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The Spatial Extent of Criminogenic Places: A Changepoint Regression of Violence around Bars

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Crime scientists have long known that crime clusters near certain places such as drinking establishments, although the spatial parameters of that clustering are less established. This article proposes a methodology to estimate a distance beyond which there is significantly less evidence of a correlation between locations and concentrations of crime. The technique uses changepoints derived from a segmented regression applied to spatial buffers emanating from around particular crime-generating land uses. Geographic information system techniques are used to create a series of buffers to determine the density of crime around sites. A changepoint Poisson regression of the buffer midpoints is used to estimate the distance beyond which crime densities do not appear to decline significantly with increasing distance. A case study of violent crime around 1,282 bars in Philadelphia, Pennsylvania, for 2008 reveals that violence is highly clustered within 25.9 m (85 feet) then dissipates rapidly, a pattern that is not replicated using control sites (fire stations). This is an estimate of the spatial extent of violence around bars, and the technique could be used to estimate the extent of other crimes around a variety of crime-generating locations.*

Introduction

Overwhelming evidence suggests that a relationship exists between violent crime and alcohol (Graham and Homel 2008; Newton and Hirschfield 2009). A British government report estimates that, in 2002–2003, 1.2 million violent crimes were alcohol related, and 70% of cases attending hospital emergency departments between 12 AM and 5 AM also were alcohol related, all at a cost of £7.3 trillion a year (DCMS 2005). In the United States, it was estimated that alcohol played a part in 19%–37% of all violent crimes between 1997 and 2008, and while the majority of alcohol-fueled violence occurred in domestic residences, it was more than twice as likely (than other types of violence) to occur in bars, nightclubs, or restaurants (Rand et al. 2010). Significant evidence exists to suggest that premises that serve alcohol on-site bear a considerable responsibility for this alcohol-fueled violence type of event (Roncek and Maier 1991; Newton and Hirschfield 2009), and that extending hours for on-site consumption may increase traffic accidents and other alcohol-related problems (Stockwell and Chikritzhs 2009).

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Problems at on-site alcohol outlets and their immediate environment are focused temporally and spatially. Temporally, the broad connection between alcohol and violence is stark. A 2007 U.S. study identifying the time of day of alcohol-involved and other violent incidents known to law enforcement found that during the 8 PM–4 AM 8-h period about one-third of nonalcohol-related violence occurred (37%), compared with two-thirds (67%) of alcohol-related violence (Rand et al. 2010, table 18). A growing literature identifies a general spatial association between the density of alcohol outlets and violence, as well as specific details of the characteristics of bars and bar management that can fuel violence. For example, Graham and Homel (2008, p. 170) list a range of bar security policies that can incite violence, including unfair or confrontational entry practices, and aggression between security staff and people who have been ejected. Therefore, the interior of establishments is not the only place where alcohol-fueled violence can occur. Environmental criminologists have long understood that crime has a contagious component, spilling over from one area to another either by accident or design (Hakim and Rengert 1981). For example, often police are called to deal with violence outside a bar that has spilled out from within the establishment. Issues of proximity affect the likelihood of offender behavior and victimization. Offenders search for criminal opportunities near their normal travel paths (Brantingham and Brantingham 1993) or near their home and the homes of their friends (Wiles and Costello 2000). The daily and routine patterns of offenders and potential offenders also can draw them to particular locations, such as subway stations (McCord and Ratcliffe 2009), bus stops (Levine, Wachs, and Shirazi 1986; Brantingham and Brantingham 1995), bars (Roncek and Maier 1991), grocery or convenience stores (Schweitzer, Kim, and Mackin 1999), and schools (Roncek and LoBosco 1983). These locations can be classified as crime *generators* or *attractors*, locations that can attract criminal activity in and around the sites (Brantingham and Brantingham 1995). One British government report estimates that "one in five violent incidents take[s] place *around* pubs or clubs" (DCMS 2005, p. 3, emphasis added). Furthermore, nearly one-quarter of respondents to a survey in Sydney, Australia, who lived within 500 m (about a third of a mile) of at least five alcohol outlets reported problems with drunkenness in their neighborhood, compared with only 12%–14% of respondents in the 0.5–1.6-km range (Donnelly et al. 2006). Groff (2011) and Pridemore and Grubesic (2011) also identify spatial concentrations of violence within the vicinity of alcohol outlets.

Estimating the spatial extent of crime spillover is the subject of this article. Modern spatial analytical tools are of sufficient caliber to enable the relatively easy extraction of incidents at a particular spatial location from police crime and incident records. It is also possible with geographic information systems (GISs) to extract incidents near a problem location, but this raises the question of *how* near? Given the increased interest by environmental criminologists, epidemiologists, and geographers in crime at and around noxious land uses (such as bars and nightclubs), this article presents a novel quantification of the spatial extent of crime problems that cluster around particular facilities. The primary research question addressed here is: How far do assaults cluster around bars? To put it another way: How near is near?

Estimating an aggregate distance within which incidents appear to cluster has potential policy significance. As police increasingly focus on crime hot spots and hot times, having an estimate of the distance within which a problem bar is likely to have an influence aids resource allocation and the development of preventative policies. At a minimum, it provides an estimated distance beyond which additional police patrols may be neither effective nor required. Furthermore, as people are perpetually concerned about perceived harmful land uses (e.g., bars, nightclubs, casinos) within their communities, some estimate of the spatial extent of any negative influence of a facility type may help to alleviate concerns regarding the spillover influence of certain types of sites.

From an analytical perspective, methods to determine the spatial limit of problems may inform a more refined analysis of displacement and/or diffusion of benefits (Clarke and Weisburd 1994; Weisburd and Green 1995) and may assist in the selection of theoretically grounded parameters for spatial analyses. Such studies often require analysts to determine a buffer zone around areas experiencing crime-prevention activity (Bowers and Johnson 2003), but at present the methods to define appropriate distances within such an analytical regime are largely subjective (Ratcliffe and Breen 2011).

This study contributes to the existing literature in several ways. First, it uses a narrower buffer bandwidth than previous studies. Second, the changepoint regression approach provides a methodology to estimate a distance beyond which significantly less evidence exists of a correlation between location and clusters of crime. Third, this regression approach allows the estimation of changepoints at distances that fall between buffer boundaries. Finally, the approach permits researchers to determine varying distance decay parameters for crime concentration as distance from particular land use changes.

What counts as "near" a bar?

Madensen and Eck (2008), drawing on a variety of research and theory, propose four reasons why some bars may experience more crimes than others. First, the neighborhood hypothesis suggests that bars in areas with a subculture of violence will experience more crime. Second, management can significantly influence behavior within an establishment irrespective of any neighborhood characteristics (management hypothesis). Third, some bars can act as crime attractors (Brantingham and Brantingham 1995), drawing in more offenders (patron hypothesis). Fourth, the general characteristics of an area, patrons, and management will establish a normative behavior that is tolerant of violence (behavior-setting theory). Clearly, some of these hypotheses are not mutually exclusive; furthermore, some of these operating principles may influence crime around and within a location. Madensen and Eck (2008) found that in Cincinnati "good" (nonviolent) bars could be located close to violent bars and that the local environment moderated, but did not predict, the violence level at an establishment. They concluded that "bars function as relatively autonomous microenvironments that are at least partially insulated from external neighborhood-level effects" (Madensen and Eck 2008, p. 7). They also noted that the decisions of bar managers directly impact the likelihood of crime and that, if these managers can inadvertently create violent environments, it is possible their actions can have the reverse effect. A possible corollary of their research is the potential impact on the neighboring environment of the behavior of bouncers and door staff, the nature of patrons, and the policies of bar managers. If so, how far does the influence of a bar extend outside its door?

From a geographical analysis perspective, a limitation of many of the studies mentioned to this point is one of spatial resolution. The observational study from Australia does not clearly define "around" for assessing the impact of spillover violence that extends outside a door, but given the nature of the requirements placed on student observations, it is unlikely to stretch any great distance (Homel and Clark 1994). In later research, Graham and Homel (2008) identify particular congestion points where alcohol-fueled violence can carry over from bars and clubs to continue at taxi stands, transport interchanges, and food outlets—all at varying distances from the bars where the trouble started. Other researchers have chosen a particular distance a priori. Roncek and Maier (1991) use the spatial resolution of a city block. Rengert, Ratcliffe, and Chakravorty (2005) use concentric bands equivalent to a city block, and Rice and Smith's (2002) study of vehicle theft and criminogenic locations in an undisclosed American city also uses the surrounding area of the containing face block. Newton and Hirschfield (2009) employ a distance of 50 m (about 165 feet) around the geocoded location of an alcohol establishment, and Pridemore and Grubesic (2011) regress the crime rate on a density measure of alcohol outlets within city block groups in a spatial lag model based on a queen contiguity spatial matrix.

These distance parameter choices appear to be largely arbitrary or based on distances of convenience, such as the average length of a city block or the availability of census units, but there is the possibility that the criminogenic influence of certain land uses may have a lesser or wider contagion. Research by Rengert, Ratcliffe, and Chakravorty (2005) and McCord and Ratcliffe (2007) suggest this. Furthermore, a distance measurement of one block is dependent on the study area in question. In the current study location, one Philadelphia city block is, on average, 122 m (about 400 feet) in length; however, most city blocks are rectangular, and this average block measurement is more of a descriptive convenience than a definitive articulation. In a comparative study of two approaches, Murray and Roncek (2008) compare crime events measured at nearby blocks with crime events within an arbitrary buffer distance of 153 m (500 feet), finding considerable difference in the results. Although they note that their results are not definitive, they nevertheless correctly conclude that the methods used to explore the spatial analysis of crime adjacency to criminogenic land uses is an important topic for study. Groff (2011) recently studied violence around drinking places in Seattle, Washington, by comparing buffers emerging from alcohol outlets derived from both Euclidean distance and street network distance, and across buffer bandwidths ranging from average street block length up to 402.3 m (one-quarter mile). She concludes that street network distances and smaller bandwidths are preferable, the latter because quarter-mile buffers are too coarse to represent usefully the precipitous decline in crime as one moves away from drinking places.

Therefore, the issue of "near" within the context of bars and violence is one of *theoretical significance* (how much crime near a bar can be associated with the bar?), *analytical significance* (what are the techniques and parameter choices to model crime appropriately in the local environment?), and *policy significance* (if there is a relationship, what should be done about it?). The analytical approach presented in this article attempts to address the second question with a methodology that has the capacity to be of value to the third question (policy relevance). In other words, knowing that violence concentrates around bars can be better addressed by local legislators and police if they have some distance estimate of how near is near. If crime is concentrated around bars to a distance of 30.5 m (100 feet), then the policing response can be local and targeted. If violence is found to be generally concentrated around bars to hundreds of meters/feet and numerous blocks, then police are forced to respond with more generalized patrols, and the impact on the wider community is greater. Thus, while the studies of location quotient values in wide buffers around bars show an inverse distance decay of violence declining as distance increases (Rengert, Ratcliffe, and Chakravorty 2005; Groff 2011), they are unable to give policy makers the sort of specific numbers that they often require to implement legislation. Analytically, there is significant scope to use a measure of the spatial influence of crime around a facility to explore a variety of different crime types in different cities. However, the spatial ranges of crime found in this article may not be appropriate distances for other cities or for more suburban or rural locales. Therefore, the first stage is to determine an appropriate analytical methodology.

Analytical approach

In an attempt to quantify empirically the aggregate diffusion of crime into the areas surrounding alcohol establishments, this article applies a changepoint regression model of crime density measured at concentric spatial buffers emanating from bar locations. This methodology involves four stages.

First, concentric buffers are generated around every bar at 1.7 m (5.5 feet), 15.2 m (50 feet), and then at subsequent 15.2-m intervals up to 457.2 m (1,500 feet). Because of the technicalities of geocoding—the process by which an address location is represented by *x* and y spatial coordinates—all crime events taking place at a single address are usually assigned the same spatial coordinate (*x*, *y*) (Chainey and Ratcliffe 2005). As a result, the initial 5.5-foot buffer is used to isolate assaults happening at an individual establishment.[1] Although bars are larger in space than an 11-foot diameter area, for geocoding purposes this serves to isolate individual events at a location. The next band from 5.5 to 50 feet serves as an indication of crime geocoded to the immediate vicinity of a bar (e.g., the street intersection if a bar is located on a corner or for crime outside a neighboring or adjacent property), and then subsequent bands (at 50-foot intervals for convenience) represent crime potential expanding outward. That the bands are not of equal bandwidth or area is not a factor because the eventual density score for each band is corrected for area during the analysis. Once the buffers are created, all those of equivalent distance are merged. This aggregation resolves an issue of overlapping buffers for different locations. In many cities, some areas have high concentrations of bars, and, therefore, individual buffers overlap with those of neighboring bars. This merging process allows the spatial model to describe a distance parameter from any bar. In other words, any crime event found in the distance band of 61–76 m* (200–250 feet) is at least 200 feet from *any* bar.

The second stage involves removing areas that would not normally have a crime event. In GIS parlance, this is termed "clipping" (Chrisman 2002). Again, the purpose of this stage is related to geocoding practice. In some cities, crime-reporting techniques are not sufficient to allow crime events to be geolocated with precision. For example, in most jurisdictions, street addresses or intersections are required for a geolocating service, with the result that assaults happening inside city parks or on areas of wasteland are usually given a mapped point at the nearest street intersection. For the study area in question, this practice was confirmed by visually examining recorded crime data of a number of years. For this reason, areas of park-land and water (rivers and lakes) were clipped from the buffer areas. This stage improves the likelihood that the resulting density measure (crimes/area) accurately reflects the actual crime density.

The third stage involves the standard GIS operation of point-in-polygon (Chainey and Ratcliffe 2005) to count the number of crime events in each buffer. In the fourth stage, the results are charted and examined with a changepoint regression process to identify statistically significant break points. Boyd et al. (2007) propose that the decay of crime concentration around drug treatment centers can be confirmed by examining the direction and significance of a slope coefficient from a regression estimation based on density values for a similar concentric arrangement of buffers. They propose a single regression parameter across buffers covering a 300-m distance (just under 1,000 feet), arguing that crime clusters around a site if the slope parameter is significance and negative. Unlike their method, a changepoint regression may provide greater clarity regarding where any crime concentration ceases to be significant. In other words, while the Boyd et al. (2007) approach may indicate that crime decreases inversely with distance from a drug treatment center, their approach cannot ascertain where the decrease becomes insignificant within their 300-m (984.5-foot) buffer area. For example, crime might decrease out to 50 m (164.0 feet), beyond which the crime density remains constant. The changepoint regression, described in the next section, is designed to address this issue.

Changepoint regression

Changepoint regression also is known as segmented regression (Williams 1970), piecewise regression, broken-line regression, two-phase regression, joinpoint regression, and multiphase regression with a continuity constraint (Kim et al. 2000). Unlike multiphase regressions, where piecewise regression functions are not required to be continuous at a changepoint, changepoint regression is a nonlinear regression model that identifies a changepoint in regression models consisting of continuous segments, where a changepoint marks a change in direction from one segment to another. Changepoints (Osorio and Galea 2006) also are called breakpoints, joinpoints, transitionpoints, switchpoints, and sometimes "thresholds" (Muggeo 2003). The purpose of introducing changepoints is twofold: first, to identify the changepoint parameter where a regression line changes along the *x* axis and, second, to examine the regression parameters for the slopes on either side of a changepoint.

This article employs the methodology as summarized by Kim et al. (2000, 2001) to estimate changepoint parameters and the regression coefficients for segments associated with changepoints. The method is applied using the Joinpoint Regression Program (2009). This methodology is demonstrated with a linear model, given a series of observations $(x_1, y_1), \ldots, (x_n, y_n)$, where $x_1 \leq \ldots x_n$, and unknown segments have the form:

$$E[y|x] = \beta_0 + \beta_1 x + \delta_1 (x - \tau_1)^+ + \cdots + \delta_k (x - \tau_k)^+ \tag{1}$$

where each τ_κ represents an unknown changepoint and the superscript plus symbol ($^+$) suggests the preceding calculation converts to zero whenever the calculation is less than zero (i.e., $a^+ = a$ when $a > 0$, and zero otherwise). Parameters β, δ, and τ are to be estimated from data in such a way that contiguous regression slopes connect at the intervening τ.

The locations of τ_κ are determined by a search across a range of possible transition points, not only at each iteration of *x* but also at intermediate locations between observations (Hudson 1966; Lerman 1980). Under normal conditions, the appropriate locations of τ_κ are determined by minimizing the total of the residual sum of squares for the least-squares estimates for each slope $[\beta_1 x, \delta_1 (x - \tau_1)^+, \ldots, \delta_k (x - \tau_k)^+]$ using normal linear model methods. For skewed distributions, a Poisson distribution function is available (Kim et al. 2000). The grid search approach proposed by Lerman (1980) is advantageous for studies such as the current one due to the arbitrary nature of the bandwidth process. Decisions regarding the width of buffers (bandwidth) and the nominal start position for the concentric circles they describe potentially can have an impact on the density score outcome for each bandwidth and are potentially susceptible to the modifiable areal unit problem (MAUP) (Openshaw 1984; Unwin 1996; Ratcliffe 2005; Andresen and Brantingham 2008). The MAUP, also known as the spatial aggregation problem (Paelinck 2000), occurs when the results of any geographic aggregation process are affected by the number, size, shape, and orientation of the geographic areas as much as any underlying spatial distribution of the data (Chainey and Ratcliffe 2005). The grid search enables potential transition points to occur between the midsections of the buffers, an improvement to the sensitivity and fit of the final result. This mitigates (but does not entirely eliminate) one negative impact of the MAUP, namely that of arbitrary boundary selection (Larson 1986); data are still aggregated to the midpoint of spatial buffers, but an improved model fit is likely given the removal of the constraint to find changepoints at data points.

Adding additional changepoints usually improves the fit of any model, such that more than one changepoint can be the parsimonious model (Williams 1970). Therefore, either an approximate permutation test can be conducted (for details, see Kim et al. 2000) or the Bayesian information criterion (BIC) (Weakliem 1999) can be used to select an appropriate model. The BIC is the log-likelihood value but with a penalty correction added for extra parameters, the upshot of which is a tendency to select simpler models. This approach is recommended for segmented regression models (Muggeo 2008).

The Philadelphia bar study

The study area is the city of Philadelphia, Pennsylvania. Philadelphia is the fifth largest city in the United States, with nearly 1.5 million people. There are about 6,300 police officers in this city recently ranked as the 21st most dangerous in the country (Morgan, Morgan, and Boba 2009). As of 2008, there were nearly 2,000 places legitimately providing alcohol for on-site consumption.

Violent crime incidents for the calendar year 2008 were provided by the Philadelphia Police Department and are compiled from incidents recorded in its incident database. Therefore, a slight discrepancy exists between the number of violent crime victims reported to the FBI in the annual Uniform Crime Report (UCR) function (FBI 2008). The current data are defined as "incidents" that generally originate as calls for service that have been initiated or deemed by a police officer to be a genuine incident. In other words, in the context of violence, each incident represents a recorded crime. An event outside a bar may have multiple victims but is still a single incident for police administrative and incident-recording purposes. The focus of violent crime reporting with the UCR system is the number of victims; therefore, a homicide incident with two victims is reported to the FBI as two records but appears in our records as a single incident. This practice is preferable for the study herein, because this article addresses the number of violent incidents rather than the number of victims. A victim count would map the frequency of victimization rather than the frequency of incidence. The list of included incidents appears in Table 1, along

Table 1 Incident Frequencies by Crime Type and Time Period, Philadelphia, PA, 2008

Crime type	All (total)	All (geocoded)	Nighttime (total)	Nighttime (geocoded)
Homicide incidents	297	294	159	158
Rapes and attempted rapes by strangers	338	332	126	124
Robberies by handgun	3,047	3,013	1,755	1,740
Other robberies	3,599	3,525	1,517	1,480
Purse snatches with force or injury	234	230	75	73
Aggravated assault (handgun)	2,299	2,277	1,206	1,191
Aggravated assault (other)	3,686	3,628	1,520	1,489
Assault (simple)	7,098	6,978	2,546	2,500
Assault (on Philadelphia police)	1,172	1,153	603	594
Total	21,770	21,430	9,507	9,349

with the 2008 incident frequency (second column), and the number of those incidents that were successfully geocoded (third column).

Given the (previously mentioned) findings of Rand et al. (2010) that alcohol-fueled violence is concentrated in the period from 8 PM to 4 AM, this study focuses only on reported violent incidents reported in this time interval. Focusing on the nighttime events, it was not possible to geocode 158 of the 9,507 incidents (1.66%), resulting in a geocoding hit rate well above an empirically derived minimum acceptable geocoding threshold (Ratcliffe 2004) and a final geolocated nighttime violent crime count of 9,349. The remainder of this article refers to this geolocated nighttime violence data set.

Fig. 1 portrays the temporal pattern of violent crime in the city, with darker columns indicating the hours considered nighttime for the purposes of this study. This nighttime period is when 43.6% of violent crimes took place in 2008.

Location data for alcohol establishments were initially sourced from the 2008 records of the Pennsylvania Liquor Control Board (PLCB). The 2008 data file has 1,902 licenses in the city of Philadelphia. For the purposes of this research, a bar is an alcohol outlet that is classified in Pennsylvania as a restaurant or club that fulfills certain additional criteria beyond the license code. Excluded from this definition are restaurants at the international airport, eating places, hotels, and public venues such as sports stadiums. Also excluded are performing arts facilities and golf club bars. These locations were largely excluded because the primary focus in this study is on sites where the on-site drinking of alcohol at an easily accessible location is the primary function of the place. Arts facilities were excluded because they often serve just a single drink during the intermission of an evening performance. Eating places and hotels were excluded by virtue of being locations that have a primary function other than the on-site consumption of alcohol. The airport bars were excluded because the airport is a large complex away from the normal street pattern that dominates the city. Golf club bars were excluded for the same reason; distance calculations may be adversely affected. Sports stadiums also are places where the nearest public street intersection can be hundreds of feet from the location of a bar, and these are also locations where drinking is concentrated into very short time periods and only on certain days. While there is no doubt that violence associated with bars at sports stadiums is a potentially fruitful area of research, sports stadiums restrict public access to ticket holders and any incidents that may be related to a bar are very difficult to map accurately given that the facility street address is likely to be hundreds of feet from the actual incident location. This problem of geocoding accuracy (Chainey and Ratcliffe 2005) provides a significant hindrance to the

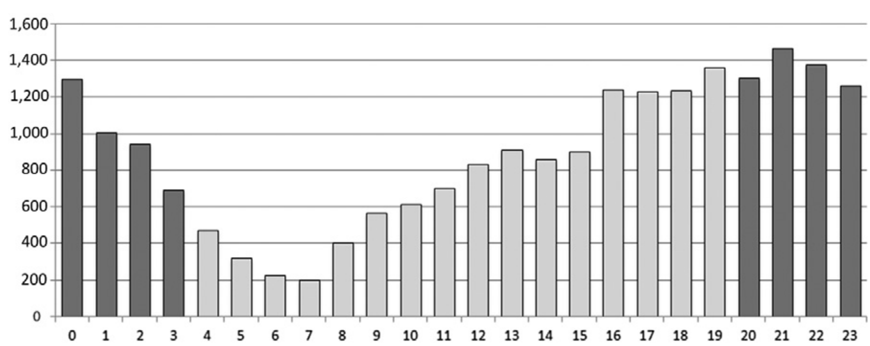

Figure 1. Violent crime incidence frequency by hour, Philadelphia, 2008.

inclusion of sports stadium bars in this study. While a stadium might have numerous bars, the geocoded location of violence within any of the Philadelphia-area stadiums is recorded at the formal street address of the entire facility (to repeat, often hundreds of feet from the actual event location). Because this discrepancy would put stadium crime events at significantly different levels of accuracy compared with events in the rest of the city, the stadium bars were excluded from this study.

From an initial list of 1,902 city establishments, 1,630 locations remained in the study as "bars." As pointed out by Newton and Hirschfield (2009), studies of the complex relationship between violence and alcohol outlets requires a consistent and reliable evidence base for alcohol retail locations. Accordingly, the PLCB records required some cleaning and verification. Through a process of visiting Web sites, making telephone contact, or visiting sites directly, two enterprising graduate students established that from this list, 1,282 locations fit the "bar" criteria of being open to the general public rather than being restricted to members or rented out as a entertainment spot to private parties; serving hard alcohol for on-site consumption; having some proportion of patrons who frequent the place for the primary purpose of consuming alcohol; and having a designated physical area within the place that serves as a drinking area (this could be the entire place or a portion of it). All 1,282 confirmed bar locations were successfully geocoded.

Buffers for each distance band were merged to prevent bands of different distances from overlapping, and the result was a mosaic of buffers that covered much of the city. The buffers were clipped to remove areas that had any of the rivers that pass through the city (the two main ones being the Schuylkill and the Delaware). The clipping process also removed any buffer areas that were outside of the city limits. A further clipping process removed any areas designated as parks or open space. The resultant buffers total 69.7 square miles of a city whose physical size is 135.6 square miles. In other words, half of the street network of Philadelphia is within 1,500 feet of a bar. Fig. 2 portrays an example area of the city; it confirms that the buffers from bars near each other merge and that the buffers are clipped by water and park areas.

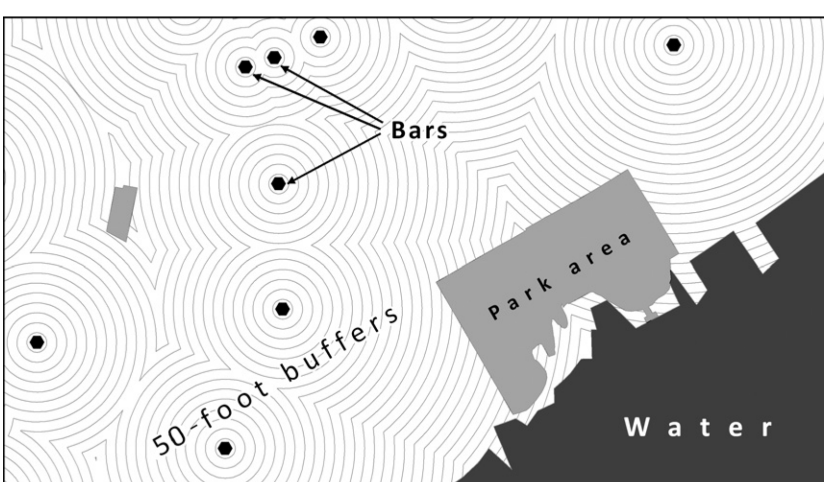

Figure 2. Example area of Philadelphia, Pennsylvania, showing 50-foot buffers around bars. Bars appear as black symbols, buffers at every 50 feet appear as concentric gray lines, parks and open areas appear as light gray, and water areas appear as dark gray.

Regression results

Of the geolocated 9,349 nighttime violent crime incidents, 8,406 (≈90%) were located within 1,500 feet of a bar. Each buffer was labeled with its midpoint distance. The midpoints are 3 (for the 0–5.5-foot buffer), 28 (for the 5.5- to 50-foot buffer), 75 (for the 50- to 100-foot buffer), and subsequent midpoint values incrementally increase by 50 feet after that (125, 175, . . . , 1,475). Buffer midpoints, buffer areas, and violent crime frequency and density scores appear in Table 2 for the first eight buffers.

Some caution should be exercised when interpreting the numbers in Table 2. The phenomenally high density of crime events appearing in the first buffer is partly an indication not only of violent events at bars but also of the impact of selecting a small buffer of only 5.5 feet in diameter as a way to capture crime events geocoded to the same (x, y) coordinate as the bar itself. The initial buffer size is arguably a measure of analytic convenience, and a more sensible argument is that 383 violent crimes occurred inside city bars during 2008 rather than to highlight the existence of a high density of crime. After the first row, interpretation of the density values is more indicative of actual crime density in the immediate environment of bars.

The purpose of the changepoint regression is to examine if there are any abrupt changes in the density of violent crime as distance from bars increases. Therefore, the first data row was excluded from the analysis because it references the bar locations themselves. Given the highly skewed nature of the data set, a Poisson model with crime counts corrected for buffer area was calculated for a variety of different changepoint frequencies (0–3), with a minimum of two observations from a changepoint to either end of the data, a minimum of three observations between changepoints, and a search regime that grids nine potential changepoints between each data observation. The results appear in Table 3.

The BIC results in Table 3 show that a changepoint model (of any form) is a substantially better fit than a no changepoint model (model 0), even after the penalty imposed through the BIC by the addition of model parameters. The drop in BIC from $\tau = 0$ to $\tau > 0$ is considerable, although less differentiation exists among the various changepoint models themselves. The most parsimonious is $\tau = 1$, for which the changepoint occurs 25.9 m* (85 feet) from the centroid of the bars.[2] This is a relatively consistent distance across all models. Both the slope prior to and after the changepoint is significant at the $P < 0.01$ level, suggesting a rapid decrease in crime density up to 85 feet from bars, followed by a less precipitous (but still significant) decline.

Table 2 Violent Crime at and around Bars, Philadelphia, PA, 2008

Buffer midpoint (ft.)	Buffer area (100,000 sq. ft.)	Violent crime (f)	Density (crime per 100,000 sq. ft.)
3	3.85	383	99.601
28	86.23	395	4.581
75	252.54	256	1.014
125	393.23	259	0.659
175	509.90	391	0.767
225	607.93	315	0.518
275	685.11	412	0.601
325	748.20	354	0.473

Note: Calculations are for the first eight buffer zones.

Table 3 Intercept, Slope Parameters, and BIC Scores for Various Changepoint Models

	Number of changepoints (τ)			
Models	0	1	2	3
Initial intercept (β_0)	0.75 *(0.14)*	2.45** *(0.23)*	2.41** *(0.19)*	2.39** *(0.20)*
τ_1		85	90	85
τ_2			575	420
τ_3				540
β_1	–0.0014** *(0.0002)*	–0.0329** *(0.004)*	–0.0317** *(0.0038)*	–0.0312** *(0.0039)*
β_2		–0.0009** *(0.0001)*	–0.0006* *(0.0003)*	–0.0018* *(0.0006)*
β_3			–0.001** *(0.0001)*	0.0016^{ns} *(0.0017)*
β_4				–0.0012** (0.0001)
β_2–β_1		0.0319** *(0.004)*	0.0311** *(0.003)*	0.0295** *(0.004)*
β_3–β_2			–0.0004^{ns} *(0.0003)*	0.0034^{ns} *(0.002)*
β_4–β_3				–0.0028^{ns} *(0.002)*
BIC	3.949	2.195†	2.344	2.278

Note: $*P < 0.05$; $**P < 0.01$; ^{ns}not significant; †model selected with BIC; standard errors appear in parentheses.

This model resolves the issue of whether crime clusters around bars but is less clear about a definitive distance.

Model $\tau = 2$ is less parsimonious and, after a similar initial changepoint at 90 feet, introduces a second changepoint at a distance of 575 feet. Model $\tau = 3$ has a slightly higher BIC value. The three changepoints in this model are at 85, 420, and 540 feet from bars. Both of the negative slope parameters for 85 and 420 feet are significant; however, the slope from 420 to 540 feet has a (nonsignificant) positive parameter.

Comparing bars and fire stations

Notwithstanding the significant research literature that finds a correlation between bars and nearby violence, this clustering could be an artifact of the analytical technique rather than an indication of a criminogenic environmental condition. Therefore, a comparison data set was used to determine if the clustering of violence around bars is stronger than for other land uses. With this in mind, the clustering of violence around fire stations in Philadelphia was estimated. In 2008, Philadelphia had 58 fire stations, and the same analytical approach described previously was used to determine the density of 2008 nighttime violence crimes in buffers expanding out from these fire stations.

Table 4 summarizes the violent crime count and density at and around fire stations up to 350 feet. It reveals a complete absence of recorded violence within 50 feet of fire stations during 2008. This is likely attributable to two factors. First, fire stations often are larger than neighborhood bars. Second, the 24-hour-a-day operation of fire stations may provide a localized surveillance of the immediate area and a suppressive effect on violence. Rengert, Ratcliffe, and Chakravorty (2005) hypothesized that the 24-hour-a-day surveillance provided by fire stations was a potential explanation for why they did not find clusters of drug arrests close to fire stations in Wilmington, Delaware. The changepoint regression model was estimated with the same conditions and parameters as the bar model, again with the first buffer at the actual locations (0–5.5 feet, with a midpoint at 3 feet) excluded. Table 5 summarizes the two models with the lowest BIC values; the

Table 4 Violent Crime at and around Fire Stations, Philadelphia, PA, 2008

Buffer midpoint (ft.)	Buffer area (100,000 sq. ft.)	Violent crime (f)	Density (crime per 100,000 sq. ft.)
3	0.05	0	0
28	4.32	0	0
75	12.97	12	0.925
125	21.78	20	0.918
175	30.50	16	0.525
225	39.19	14	0.357
275	48.14	23	0.478
325	56.92	36	0.632

Note: Calculations are for the first eight buffer zones.

Table 5 Intercept, Slope, and BIC for the Two Most Parsimonious Fire Station Changepoint Models

	Number of changepoints (τ)	
Models	0	1
Initial intercept (β_0)	–0.62** *(0.095)*	–0.417** *(0.130)*
τ_1		1005
β_1	–0.00005^{ns} *(0.0001)*	–0.0004^{ns} *(0.0002)*
β_2		0.0005^{ns} *(0.0003)*
β_2–β_1		0.0009^{ns} *(0.003)*
BIC	0.903	0.913

Note: *$P < 0.05$; **$P < 0.01$; ^{ns}not significant.

most parsimonious model has no changepoints.[3] The next most appropriate model has one changepoint, at 1,005 feet; however, both slope coefficients (prior to and after the changepoint) are not significantly different from a zero slope.

Comparing results reported in Tables 4 and 5 with the bar results (Tables 2 and 3) suggests a number of interesting characteristics. First, fire stations (unlike bars) have no reported violent crime within them or within the first 50 feet of them. Fire stations have a slightly greater density at distances of 50–150 feet, almost 1 per 100,000 square feet, and thereafter the density remains level at around 0.5 per 100,000 square feet per year. For bars, the initial distance outside a bar (up to 50 feet) is at 4.5 per 100,000 square feet per year and then 1 per 100,000 square feet per year for the next buffer. Both series settle to an average of about 0.5 per 100,000 square feet per year within less than one block of their respective locations (although the bar slope continues to decline at a shallow but statistically significant rate). Fig. 3 graphically portrays this finding with both bar and fire station density values, along with the regression slopes for their respective most parsimonious changepoint models.

Therefore, while a slightly elevated density of violence exists within 150 feet of fire stations (compared with greater distances from fire stations), this initial elevated state is minimal compared with the fourfold comparable level of violence within the immediate vicinity of bars. At no point does the density of violent crime around fire stations exceed the bar violence level at

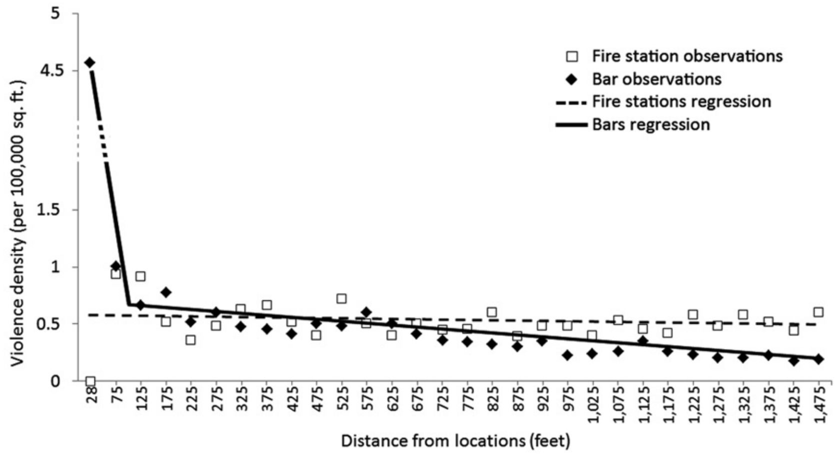

Figure 3. Crime density and distance from bars and fire stations, with regression lines (dashed line for fire stations, thicker black line for bars) and changepoints for the most parsimonious changepoint models. Note the jump in the *vertical scale*.

50–100 feet (with a midpoint of 75 feet), let alone come close to the level at the midpoint of 28 feet, which is 4.5 crimes per 100,000 feet. This lack of violence close to fire stations is reflected in the observation that the most appropriate fire station/violence model has no changepoints and is represented by a regression line that is statistically indistinguishable from a zero slope model.

Discussion

One current analytical challenge in the crime science community is to establish a methodology for estimating the spatial influence that potentially criminogenic locations have on their surrounding environments. Such a methodology has implications for assessing the impact of a variety of locations, such as drug treatment centers, pawnshops, adult entertainment locations, casinos, sports stadiums, schools, and nightclubs. Buffering around potentially criminogenic locations has been studied before, but this article demonstrates a mechanism to determine a distance beyond which crime density does not significantly change. This first attempt to establish a spatial range has theoretical and policy potential, as well as analytical implications.

This first estimate does not incorporate interaction effects with other land uses. Because it estimates individual crime spillover distances, it offers the potential in the future to assess in more depth and with more accuracy interactions between land uses of the same type (clusters of bars) and mixed land uses. To date, attempts to establish interaction effects have been hampered by rudimentary methods for establishing the spillover range of land uses. The decision about the appropriate distance at which to limit estimates of interaction has been largely driven by researcher intuition or the use of location quotients to identify when concentric buffers are no longer significant. The buffers usually are quite wide and rarely longer than a street block, a unit that Groff (2011) refers to as a “logical” unit. The evidence in this article suggests that the spillover effect of land uses such as bars may be much smaller than previously estimated and that (in agreement with Groff 2011) distance bands of hundreds of feet may be too crude to gauge accurately the magnitude or spatial concentration of the subject. While the work summarized in this article also employed buffers, they have been at a finer bandwidth, and the changepoint regression has enabled the interpolation of an estimated changepoint that can fall at a distance within bands.

Although the analytic approach adopted here constrains the model to follow a connected series of regression functions, this approach was undertaken to establish a numeric estimate that may have policy significance. Policy makers have a tendency to adopt seemingly arbitrary distances for legislative purposes, often without any apparent rationale. Examples include legislation to limit the residency of convicted sex offenders or to create additional penalties for drug sales around schools. The methodology proposed here does not necessarily identify a limit beyond which no location-related crime occurs. Also, not all offenses within an identified distance necessarily connected to the activities of their focal sites. Rather, the methodology establishes a distance beyond which there is significantly less evidence of a correlation between location and clusters of crime.

Of 1,282 bars, 149 had nighttime violence at their immediate sites, while a greater number had violence within 85 feet of their locations. This ability to be more specific regarding a distance beyond which there is significantly less evidence of a correlation between location and clusters of crime can guide an initial triage approach for more strategic interventions. As depicted in Fig. 4, many bars did not have a violent incident at or near them during 2008. Furthermore, the problem is more pronounced in some police districts than others. The tendency for violence to cluster at certain bars correlates strongly with the research literature on the subject (Homel and Clark 1994; Briscoe and Donnelly 2001) and with a recent study of nearly 200 bars in Cincinnati, Ohio, which found that 75% of assault incidents were reported near one-fifth of the bars (Madensen and Eck 2008).

Bars identified in Fig. 4 with a cross are locations that had violent incidents both inside and outside, and black crosses indicate a few locations where the number of incidents outside of them exceeded five (the maximum was 14) within 85 feet of their geocoded centroids. This cartographic approach provides a starting point for a more detailed analysis of the particular determinants of violence-oriented bars and locales.

As portrayed by Fig 4, not all bars (and their environments) are the same, in much the same way that high-crime bus stops have crime for different reasons (Levine, Wachs, and Shirazi 1986). As Groff (2011, p. 173) points out, comparing bars that are open for only a few hours with those that have extended hours, or to compare locations with gross sales in the millions with small neighborhood bars is unreasonable. Looking forward to more refined analyses, she notes that "what is needed is an exposure measure which would incorporate influence in the form of distance, activity level at the facility, and the duration of time the facility is open." Additional variables could include the possible deleterious effect of other potentially harmful types of location that might exist close to a bar. The analytical technique shown here could be adapted to incorporate these additional variables into an analysis.

As the spatial resolution shrinks, data limitations become increasingly apparent. The initial buffer used here is 5.5 feet from each geocoded bar location; however, a buffer distance of only one or two feet may be appropriate if a researcher is confident that no crime events occurring at the location would be excluded under such a regime. For crime in the vicinity of a criminogenic location, the selection of the initial buffer should be a judgment call based on examination of the crime data and an understanding of local geocoding practice. A variety of initial buffer sizes will be appropriate as long as events at a site are excluded and all other events nearby are ascribed to other buffers. Philadelphia has a relatively sophisticated crime geocoding process, but the spatial accuracy of geocoded locations varies across the city. It certainly does not reach the

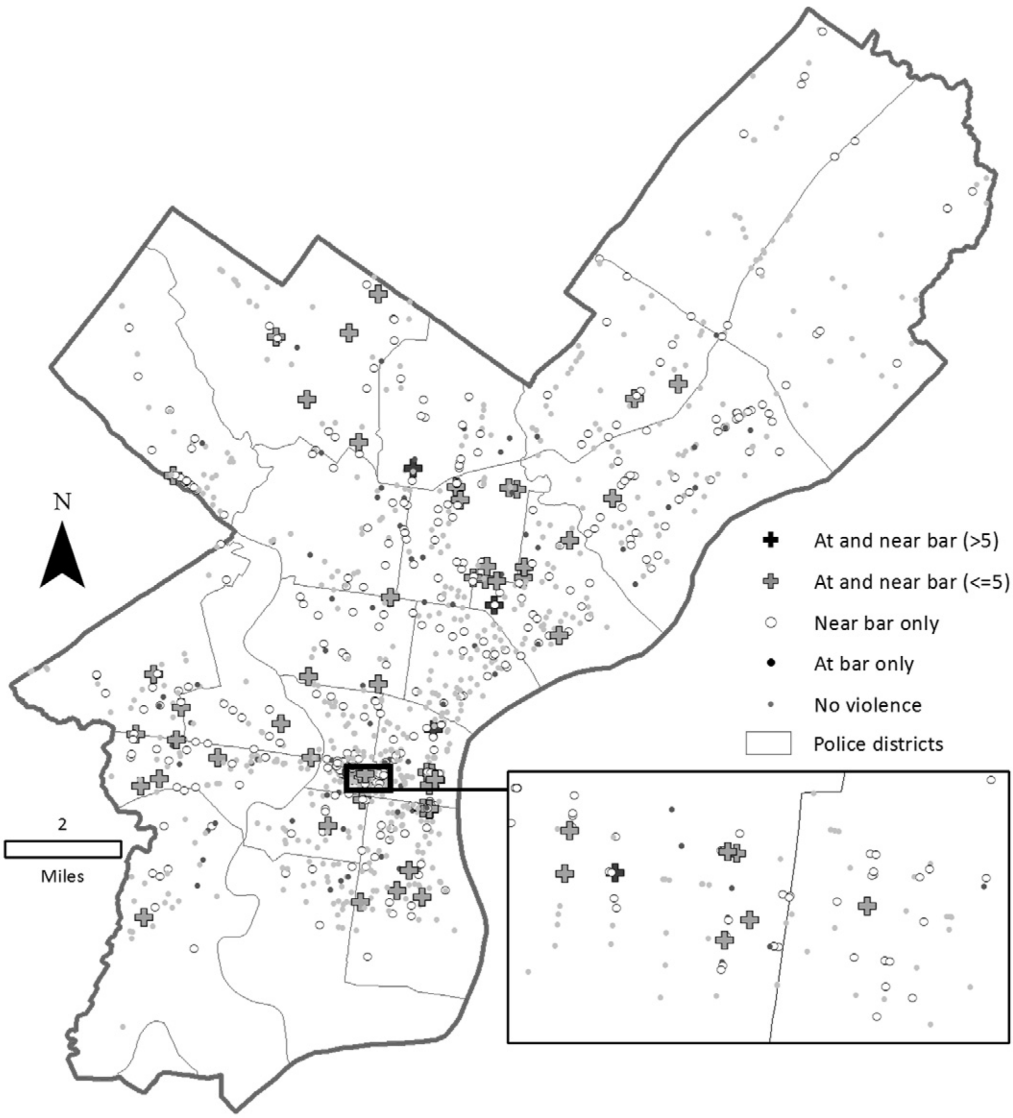

Figure 4. Map indicating 2008 violent crime levels at and near (within 85 feet) bars in Philadelphia, Pennsylvania. A heavy black cross indicates a location that had at least one violent incident within a bar, and more than five violent incidents outside the bar but within 85 feet of the location. Inset shows a detail of the Center City area with a cluster of bars.

address-based gazetteer levels of accuracy found in the United Kingdom (see Chainey and Ratcliffe 2005). Analysts in all locations should be cognizant of the geocoding accuracy available to them.

As with much social science data, the interpretation of the analytical output requires a little nuance. The most parsimonious model has a definitive changepoint at about 85 feet; however, the estimated slope after the changepoint continues to decline with a slope parameter significantly different from zero (β_2 in Table 3). The decline in slope as distance increases after

Table 6 Limitations and Advantages of the Methodology

Limitations	Advantages
○ Uses spatial buffers to aggregate crime events ○ Does not guarantee that all crime is explicitly tied to the facilities in question ○ Requires careful interpretation when involving models with multiple changepoints ○ Does not completely resolve the MAUP	○ Uses buffers with a much finer resolution than previously employed ○ Is the first approach to estimate quantitatively a distance beyond which no significant crime clustering occurs ○ Adds an additional analytical opportunity to map crime correlated at *and around* locations

this limit could be attributable to a real component of the crime/bar relationship or to an increase in space within the larger buffers that could not contain crime. From an environmental criminology perspective, a weaker theoretical foundation exists for crime associated with a land use as distance increases. Without a doubt, inherent in the approach adopted in this article is a clear need for careful interpretation of the results. Future work could incorporate a measure of bar density, similar to that done by Pridemore and Grubesic (2011). Potential exists for expanding the technique introduced here to incorporate a weighting for bars based on proximity to other bars or on turnover or on patron capacity. This may help to refine analyses of well-known drinking areas. The problem of violence in high-traffic entertainment areas is of interest to police and crime-prevention practitioners, and understanding crime in these public areas is of value—once a distance for crime contagion from bars has been identified, the primary purpose of this article. The limitations and advantages of the technique presented here are summarized in Table 6.

Conclusion

As spatial crime research advances, examination of the spatial influence of land uses and places suspected of generating crime is possible not only at the location in question but also in its surrounding area. A limiting factor for spatial crime researchers has been the absence of a methodology to estimate the spatial extent to the criminogenic influence of a bar or other site. The technique presented here is not without some limitations, yet it does provide an estimate of a distance that has, until now, been guessed or selected arbitrarily, namely a distance beyond which there is significantly less evidence of a correlation between locations and clusters of crime. One caveat to consider is that other cities and areas may have a spatial constraint distance different from the 85 feet calculated for the bars in the city of Philadelphia. Researchers in other locations need to calculate their own distances; but as NIMBY (Not In My Back Yard) communities look to exclude drug treatment facilities, bars and nightclubs, and other establishments deemed to be detrimental to community well-being, and as local governments adopt legislation to prevent everything from casinos to sex offenders from locating near vulnerable locations, the issue of distance and crime contagion will only increase as a concern for the general public. Tools to better quantify these distances are certainly needed and may in the future form the foundation for more spatially specific interaction studies that can directly inform policy planning.

Notes

* Corrections added on 29 October 2012 after initial online publication on 2 October 2012. The measurements have been corrected in this version of the article.

1 Five point five feet is clearly an unusual choice of distance parameter. It was based on a visual inspection of both the bar coordinates and the violent crime plotted locations. Investigation of the mapped street addresses revealed that occasionally a bar address and a crime event with an identical street address were a few feet apart. The most likely cause was a different process being employed to geocode the points. Bars were geocoded by academic researchers, while the violent crime reports were geocoded by an automated process employed by the Philadelphia Police Department, which uses a slightly different offset parameter. A distance of 5.5 feet was estimated to be sufficient to include crimes with the same street address and to exclude crime events at nearby addresses.

2 A visual examination of the residual plot and a Durbin–Watson statistic of 1.66 indicated no significant residual autocorrelation.

3 Additional models were calculated, but their BIC values were greater than those shown here. With two changepoints, the BIC value was 1.06, and for three changepoints the BIC was 1.21. All of the slopes for both of these models were not significant at the $P = 0.05$ level.

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