Spatial Analysis of the Relationship between Alcohol Outlet Density and Criminal Violence: An Examination at the Neighborhood Level

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Word Count: 4,388 (without abstract, references)

Figures: 4, Tables: 2

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Abstract

Misuse of alcohol is a significant public health problem, potentially resulting in unintentional injuries, motor vehicle crashes, drownings, and, perhaps of greatest concern, serious acts of violence, including assaults, rapes, suicides, and homicides. Although previous research establishes a link between alcohol consumption to increased levels of violence, studies relating the density of alcohol outlets (e.g., restaurants, bars, liquor stores) and the likelihood of violent crime have been less common. In this paper we test for such a relationship at the small area level, using data from 79 neighborhoods in the city of Minneapolis, Minnesota. Since the neighborhood is the level at which residents would likely work to limit alcohol outlet density (and also violent crime), our analysis, while aggregate, does not suffer from an ecologic fallacy. We adopt a fully Bayesian point of view using Markov chain Monte Carlo (MCMC) computational methods as available in the popular and freely available WinBUGS language. Our models control for important covariates (e.g., neighborhood racial heterogeneity, age heterogeneity) and also account for spatial association in unexplained variability using conditionally autoregressive (CAR) random effects. Our results indicate a significant positive relationship between alcohol outlet density and violent crime, while also permitting easy mapping of neighborhood-level predicted and residual values, the former useful for intervention in the most at-risk neighborhoods and the latter potentially useful in identifying covariates still missing from the fixed effects portion of the model.

Key Words: Bayesian, Markov chain Monte Carlo, alcohol, criminal violence, neighborhood
Background

Misuse of alcohol is a significant public health problem in the United States, resulting in unintentional injuries, motor vehicle crashes, drownings, and--of special concern--serious violence, including assaults, rapes, suicides and homicides. The alcohol establishment (e.g., restaurant, bar, liquor store) is an important access point for the purchase and, for on-premise outlets, the consumption of alcohol. Although evidence exists connecting alcohol consumption to levels of violence, a limited number of studies have been conducted examining the specific relationship between alcohol availability, as defined by alcohol establishment density, and violence. Scribner and co-authors conducted the first of these recent studies, examining the risk of assaultive violence and alcohol availability in cities within Los Angeles County. The authors discovered that after adjusting for sociodemographic factors, higher levels of alcohol outlet density were significantly associated with higher rates of assaultive violence (i.e., criminal homicide, forcible rape, robbery, aggravated assault and domestic violence) within a geographic unit. A subsequent replication study, examining the same relationship in New Jersey municipalities, however, did not find that higher alcohol outlet density was associated with elevated rates of violence, nor did a follow-up study focusing only on domestic violence.

In an attempt to clarify the inconsistency regarding the relationship of density to violence, researchers in New Jersey decided to focus on one city, Newark, and to geographically link violence rates to outlet density in census tracts and census block groups, rather than using larger city or municipality definitions of geographic areas. In doing so, the regression models revealed that alcohol outlet densities were significant predictors of rates of violent crime at both the census tract level and the census block group level. Similar analyses conducted on census tracts in New Orleans, block groups in California and Camden, New Jersey, and census tracts in
Kansas City, Missouri, revealed that outlet density (whether defined as outlets per square mile or outlets per person) was strongly associated with rates of various types of assaultive violence\textsuperscript{8,9,11,12}.

In the current study we attempt to address limitations in previous research. Previous studies have not used the same unit of analysis—researchers previously used counties, cities, census tracts and block groups as the unit within which to assess the impact of outlet density. In beginning our analysis, we sought a theoretical perspective to inform our choice of geographic unit. Skog\textsuperscript{13} suggests that our drinking culture is a system of interdependent actors—the density of outlets in a neighborhood is linked to the social network in which these actors live and carry out their daily activities. From that perspective, analyzing outlet density from the level of individual outlets is inappropriate, as the effect of density is a summed effect across a geographic area. We believe that a unit of analysis most appropriately reflecting neighborhoods would best estimate the effect of density, rather than a larger unit of analysis, such as a city or county. Parker and Wolz have noted that density is related to locations small enough to be influenced by a varying population structure and a stratification that exists within certain geography\textsuperscript{14}. Using larger geographic units may result in a loss of focus on the fundamental nature of outlet density\textsuperscript{14}.

In addition, most previous studies have lacked a solid theoretical model upon which to base analysis. As a result, we sought an appropriate theoretical perspective to inform our choice of covariates. Sampson, Raudenbush and Earls, in their work examining neighborhoods and violent crime, have suggested that collective efficacy (cohesion and trust within a community coupled with expectations for intervening when necessary) is an informative social theory upon which to base analysis at the neighborhood level\textsuperscript{15}. Communities with greater collective efficacy
may be able to better accommodate behaviors of alcohol establishment patrons and may be able to provide some social control restricting violent behavior within and outside establishments. Communities with less collective efficacy and facing greater structural constraints (including heterogeneity in a community, challenging economic situations, family disruption and heavy urbanization) may be less able to cope with alcohol establishments and patrons with problems. This theoretical perspective suggests a set of covariates reflecting collective efficacy and structural constraints should make up our analysis model.

Finally, much of the research into the connection between outlet density and violence has utilized multiple regression, controlling for sociodemographic variables. In evaluating spatially related data, however, problems arise because geographic units are not necessarily independent of one another. In fact, researchers would expect that the density of outlets in one neighborhood would be likely to influence health outcomes in an adjacent neighborhood. Not controlling for spatial autocorrelation may result in a false positive, i.e., concluding that outlet density has a significant effect on violence, when it fact it does not. It appears that an analysis that controls for spatial autocorrelation is necessary in evaluating whether outlet density is related to violence.

In an effort to address each of the aforementioned limitations, we conducted a cross-sectional ecologic analysis, using spatial smoothing, to evaluate the relationship between alcohol establishment density and criminal violence using neighborhood level data from Minneapolis, Minnesota. We use alcohol outlet density as our measure of collective efficacy, based upon the notion that organized communities are able to influence this density. Covariates from the U.S. Census serve as our structural constraint variables.
Methods

We needed to obtain neighborhood level data about alcohol establishments, criminal violence, and structural constraint variables to perform our analysis. In this section we review data sources and discuss analysis steps.

Neighborhoods

The City of Minneapolis is unique in that it contains 84 self-identified neighborhoods with distinctive geographic borders. Most of these neighborhoods have a neighborhood association, street signs identifying the neighborhood, and represent a combination of census tracts and block groups. Rather than selecting zip codes, census tracts, or block groups for the geographic unit of analysis for our study, we were fortunate to be able to use neighborhoods, units that we believe best represent a geographic location for the activation of collective efficacy (i.e., geographic regions whose residents can unite in an effort to change alcohol outlet density through common action). These neighborhoods are probably most similar to the “neighborhood clusters” identified by Sampson and his co-authors in their Project on Human Development in Chicago Neighborhoods. The City of Minneapolis Planning Department provided us with geographic boundaries of the neighborhoods. Of the 84 neighborhoods initially identified, we used 79 neighborhoods for the current study, as six of the neighborhoods were highly industrial areas with few residents and few alcohol establishments. The total population of the City of Minneapolis, according to the 2000 Census, was 382,618. The city is 7.6% Hispanic/Latino, 18% African American/Black, 2% American Indian, 6% Asian, and 4% two or more races. The remainder of the community is white/Caucasian. Minneapolis is 55 square miles and has an overall population density of 6,970 residents per square mile.
Alcohol Establishments

We obtained a list of all licensed alcohol outlets in 2000 in Minneapolis using two sources. Lists of all “intoxicating liquor” establishments (including name, address, phone and liquor license type) were obtained from the state Liquor Control Division. Similar lists of all low-alcohol (3.2%) beer (“non-intoxicating liquor”) establishments were obtained from the City of Minneapolis. Across the 79 neighborhoods included in the study, 446 on-premise (i.e., bars, restaurants) establishments and 129 off-premise (i.e., liquor stores, convenience stores) establishments were included in the study. Staff from the City of Minneapolis GIS Unit geocoded each alcohol establishment to one of the 79 neighborhoods. The number of establishments per neighborhood ranged from 0 to 129, with a mean of 7.28 and a median of 3. We calculated alcohol establishment density (our collective efficacy variable) by taking the total number of outlets in each neighborhood divided by the total population in that neighborhood. The skewed nature of the resulting alcohol establishment density variable suggested a natural log transformation, but because there were neighborhoods without bars (n=9), we first added \( \varepsilon = 0.00001 \) to the density in each neighborhood. The resulting log transformed alcohol establishment density has a minimum of \(-11.51\), maximum of \(-3.461\), mean of \(-7.447\), and median of \(-7.182\).

Criminal Violence Data

The second set of data, criminal violence, was obtained from the City of Minneapolis Police Department (PD). The PD provides crime data by neighborhood by month through its public website. These data are initially collected as part of the PD’s Computer Optimized DEployment – Focus On Results (CODEFOR) strategy. CODEFOR data uses the same crime
categories as the FBI’s Uniform Crime Report (UCR) Part I offenses, but counts crimes
differently (i.e., CODEFOR counts all offenses in a multiple offense scenario, as opposed to just
the most serious event, as in the FBI’s UCR). Offenses included in the CODEFOR data include:
homicide, rape, robbery, aggravated assault, burglary, motor vehicle theft and arson. Because
crime rates vary dramatically over the course of a year (with seasonal highs and lows) and can be
subject to rapid changes year-by-year\textsuperscript{21}, we collected crime data for three years (2000, 2001 and
2002) and created an average of the total number of crimes per neighborhood. Total average
yearly criminal violence per neighborhood has a minimum of 48 incidents, maximum of 2448
incidents, mean of 328 and median of 196.

\textit{Structural Constraints}

We obtained structural constraint data from the City of Minneapolis Planning Department
that specially generates Census data aligning to Minneapolis neighborhoods. Research has
demonstrated that a number of neighborhood sociodemographic characteristics (i.e., structural
constraints) are related to rates of violence, including economic structure of a community,
ethnicity, age structure, level of urbanicity and social structure\textsuperscript{4,6}. Specifically, the covariates
used include:

\begin{itemize}
\item[a)] \textit{Heterogeneity in race}. This covariate, which represents the percentage of neighborhood
residents that are non-white, was calculated by dividing the total of (black or African
American alone; American Indian and Alaska native alone; Asian, Native Hawaiian and
other Pacific Islander alone; some other race alone; and two or more races) by the total
neighborhood population.
\end{itemize}
b) **Heterogeneity in age.** This covariate, which represents the ratio of younger residents to middle age residents, was calculated by dividing the total number of 15 to 24 year olds in a neighborhood by the number of 25 to 44 year olds.

c) **Heterogeneity in home ownership.** This covariate, which represents the percentage of housing that is rented in the neighborhood, was calculated by dividing the total number of renter occupied housing units by the number of all occupied units in the neighborhood.

d) **Ratio of single headed households to family households.** This covariate, which represents the ratio of single headed households to two parent households, was calculated by dividing the sum of (female headed households; male headed households) by family households for each neighborhood.

e) **Size of households.** This covariate represents the average size of households in the neighborhood.

Due to the count nature of the independent variable, we also include the total population of each neighborhood in our models. This value ranges from 828 to 19,805, with a mean of 4,839 and a median of 4,335.

Sociodemographic information assessed at a small geographic unit is likely to more accurately reflect community composition than more aggregate measures at the municipality or city level. Assessment of these measures at the neighborhood level will provide for more heterogeneity in covariates than assessment at a larger geographic level. Recent research also suggests that aggregate census information is a relatively accurate predictor of the true sociodemographic characteristics of a geographic unit. Census data are unlikely to accurately reflect individual level characteristics, but for the purposes of this study, aggregate data are more appropriate. Because our interest is in investigating the alcohol-crime link at the neighborhood
level, as opposed to individual level, and our results will only be interpreted at the neighborhood level, we do not risk producing an ecologic fallacy.

Analysis

Because of the potential for spatial similarity across neighborhoods, a spatial smoothing analysis is warranted. We used Bayesian methods implemented via Markov chain Monte Carlo (MCMC) algorithms to obtain a full posterior distribution on the true crime level in neighborhoods and to estimate the relationship between alcohol establishment density and crime, controlling for structural constraints. To perform this analysis, we used WinBUGS 1.4 software that executes Bayesian inference using Gibbs sampling (see e.g., Section 5.4 of Carlin and Louis, 2000). This software is available for free download and was developed by the MRC Biostatistics Unit in Cambridge and the Imperial College School of Medicine in London.

We base our analysis on empirical Bayes approaches to aerial count data, following the seminal work of Clayton and Kaldor (1987), who demonstrated spatial smoothing with lip cancer rates for Scotland counties, and the celebrated conditionally autoregressive (CAR) spatial random effect models of Besag, York and Mollie (1991). We apply this approach to criminal violence levels and the impact of alcohol outlet density on these levels. We include neighborhood-level spatially smoothed random effects because we anticipate that crime levels in adjacent neighborhoods will be similar. Using $O_i$ to represent the observed numbers of crimes in the $i$th neighborhood and $urbanpop_i$ to represent the population in the $i$th neighborhood, our basic model is:
\[ O_i \sim \text{Poisson}(\mu_i) \]
\[
\log \mu_i = \log (\text{urbanpop}_i) + \alpha_0 + b_i \\
\bar{b}_i \sim \text{Normal}(\bar{b}_n, 1/(n_i \tau)) \\
\]
\[
n_i = \text{Number of neighbors of neighborhood } i \\
\bar{b}_i = 1/n_i \sum_{j=\text{neighbor}(i)} b_j 
\]

In this model, \(\alpha_0\) is given a non-informative normal prior distribution (with mean 0 and precision equal to 0.00001) and \(\tau\) (the precision parameter controlling the degree of spatial smoothing) is given a gamma prior distribution with mean 10 and precision 1.

Next, we extend this model to include covariates. We reflect the effect of a covariate \(x_i\) simply by modifying the log crime density to:
\[
\log \mu_i = \log (\text{urbanpop}_i) + \alpha_0 + \alpha_1 x_i + b_i ,
\]
where \(\alpha_1\) is given a non-informative normal prior distribution (again, having mean 0 and precision 0.00001). We evaluate an extremely simplified model with no random effects, as well as a model with only the natural log of alcohol outlet density as a covariate and our spatial random effects. Finally, we consider a “full” model with the natural log of alcohol outlet density, all of our covariates at once, and our spatial random effects:
\[
\log \mu_i = \log (\text{urbanpop}_i) + \alpha_0 + \alpha_1 x_i + \sum_{k=2}^{p=6} \alpha_k z_{ik} + b_i ,
\]
where \(k = 2 \ldots \ p\) indexes the covariates. We also consider non-spatial smoothing with the last two models, by letting the \(b_i\)’s be independently and identically distributed as Normal \((0, \tau)\) random variables, with the precision \(\tau\) given the same distribution as above.

To compare models, we used the deviance information criterion (DIC), and an associated measure, \(p_D\), which assesses the effective number of model parameters\(^{37}\). The latter quantity offers insight into the amount of Bayesian shrinkage of a model’s random effects toward their
grand mean. The DIC is a hierarchical modeling generalization of the Akaike information criterion (AIC). Although the DIC score by itself has no intrinsic meaning, differences in DIC across models is meaningful. Consistent with the AIC, smaller DIC values indicate a better-fitting model. Further, DIC values are only one measure of the appropriateness of a model. We also assessed each model by performing a collinearity analysis on all covariates, to ensure uniqueness of our structural constraints and satisfactory convergence and stability of our MCMC algorithms.

**Results**

We completed five separate WinBUGS runs for each model, allowing 50,000 iterations for MCMC burn-in in each case, and 50,000 further iterations to determine the posterior estimates. In our first model, we include only urban population, an intercept term, and our collective efficacy variable, the natural log of alcohol outlet density, with no random effects. In our second model, we test this same simplified model but add independently and identically distributed normal random effects, \(a_i\). In our third model, we test the simplified model with moderate spatial clustering in the random effects, \(b\). Our fourth and fifth models include the addition of our structural constraint covariates, with independent and spatially correlated random effects, respectively.

Table 1 presents the posterior means and standard distributions of the effect \(\alpha_1\) that corresponds to our collective efficacy variable, the natural log-transformed alcohol outlet density. Also included in Table 1 are the DIC and \(p_D\) values for each of the five models.
Table 1. Model Fitting Results

<table>
<thead>
<tr>
<th>Model*</th>
<th>Effect of Alcohol Outlet Density, $a_1$</th>
<th>DIC</th>
<th>$p_D$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Mean/Standard Deviation</td>
</tr>
<tr>
<td>1. log outlet density</td>
<td>0.2797</td>
<td>0.00500</td>
<td>56.01</td>
</tr>
<tr>
<td>2. log outlet density, $a$</td>
<td>0.1602</td>
<td>0.03119</td>
<td>5.14</td>
</tr>
<tr>
<td>3. log outlet density, $b$</td>
<td>0.1041</td>
<td>0.02432</td>
<td>5.12</td>
</tr>
<tr>
<td>4. log outlet density, other fixed covariate effects, $a$</td>
<td>0.1244</td>
<td>0.04201</td>
<td>2.96</td>
</tr>
<tr>
<td>5. log outlet density, other fixed covariate effects, $b$</td>
<td>0.0827</td>
<td>0.02896</td>
<td>2.86</td>
</tr>
</tbody>
</table>

*Here we use $a$ to signify the vector of i.i.d random effects, and $b$ to signify the vector of spatially associated random effects.

With the exception of the first model with no error terms (and an extremely high DIC), we find that the DIC and $p_D$ values remain fairly constant. The theoretical perspective used to inform this analysis suggests that either Model 4 or 5 would be the most sensible to use in evaluating the impact of alcohol outlet density on criminal violence rates. Examination of the effect of interest reveals that in each of these models, the effect remains significant despite the inclusion of the other fixed effects, with an increase in alcohol outlet density corresponding to an increase in criminal violence. The effect in Model 5 is the smallest and most conservative, but with a correspondingly small standard deviation. Based upon the intuitive appeal of including a spatial smoothing term in our model, we select Model 5 as the final model for our subsequent investigation.

The raw data are mapped in Figure 1, with the corresponding fitted values from Model 5 mapped in Figure 2. Both maps depict, for each Minneapolis neighborhood included in this analysis, the density of crimes: the number of acts of criminal violence per 1,000 neighborhood residents in one year. Unshaded neighborhoods correspond to those having so few residents that they were excluded from the analysis. The visual similarity of the maps indicates excellent fit of
the spatial random effects model. The maps reveal a concentration of violence in the central and northeastern neighborhoods in the city, with less criminal violence in the southern and outer neighborhoods. A map of the spatial random effects (b, in Model 5 above) in Figure 3 reveals that a few key neighborhoods (in dark gray) absorb much of the spatial error, indicating that those neighborhoods have unusually different criminal violence levels in comparison to their neighbors—“hot spots” of activity. A map of the fitted random effects (a, in Model 4 above) is similar, but reveals somewhat less spatial pattern. Since the DIC scores of the two models are equal up to MCMC error, we prefer the spatial model, since greater smoothness in the random effects map should assist somewhat in any search for missing spatial covariates.

[Insert Figures 1, 2 and 3 about here]

As expected, an examination of the residuals from the final model, depicted in Figure 4, reveals a reasonably normal distribution, though with three outliers. The smaller two outliers, neighborhoods 59 and 45, are both neighborhoods with unusually low bar density and number of residents for their high criminal violence rates. These two neighborhoods are both transition neighborhoods—the first (59) is going through housing and resident income improvements and the second (45) is a declining industrial area with a much larger daytime employment population than its nighttime residential population. The biggest outlier, neighborhood 45, is located in the central part of the city and is the city’s downtown business corridor. This neighborhood has an incredibly large number of on-premise and off-premise alcohol establishments serving as the social center for Minneapolis on evenings and weekends. Again, this neighborhood sees a much greater daytime employment and nighttime visitor population than its nighttime residential population.
The final model includes an intercept, the natural log of alcohol outlet density, and a number of structural constraints we believe important for this analysis. In Table 2 we present the posterior means and standard distributions of each of the final model effects. We also include the posterior distribution of $\tau$.

### Table 2. Final Model Covariates

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Covariate Effects, $\alpha_i$</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Mean/Standard Deviation</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\alpha_0$)</td>
<td>-1.958</td>
<td>0.39100</td>
<td>-5.01</td>
<td>(-2.74, -1.18)</td>
<td></td>
</tr>
<tr>
<td>LN outlet density ($\alpha_1$)</td>
<td>0.08269</td>
<td>0.02896</td>
<td>2.86</td>
<td>(0.025, 0.141)</td>
<td></td>
</tr>
<tr>
<td>Heterogeneity in race ($\alpha_2$)</td>
<td>2.083</td>
<td>0.45000</td>
<td>4.63</td>
<td>(1.18, 2.98)</td>
<td></td>
</tr>
<tr>
<td>Heterogeneity in age ($\alpha_3$)</td>
<td>-0.001071</td>
<td>0.00826</td>
<td>-0.13</td>
<td>(-0.018, 0.015)</td>
<td></td>
</tr>
<tr>
<td>Heterogeneity in homeownership ($\alpha_4$)</td>
<td>0.4706</td>
<td>0.32690</td>
<td>1.44</td>
<td>(-0.183, 1.12)</td>
<td></td>
</tr>
<tr>
<td>Household head ratio ($\alpha_5$)</td>
<td>-1.436</td>
<td>0.67070</td>
<td>-2.14</td>
<td>(-2.78, -0.095)</td>
<td></td>
</tr>
<tr>
<td>Household size ($\alpha_6$)</td>
<td>-0.2826</td>
<td>0.17310</td>
<td>-1.63</td>
<td>(-0.629, 0.064)</td>
<td></td>
</tr>
<tr>
<td>$\tau$</td>
<td>1.807</td>
<td>0.27800</td>
<td>--</td>
<td>(1.25, 2.36)</td>
<td></td>
</tr>
</tbody>
</table>
As noted previously, the natural log of alcohol outlet density is significantly related to criminal violence, although the significance of this effect is not overwhelming for our chosen model. Of the covariates included in the final model, only heterogeneity in race and household head ratio are statistically significant. Those neighborhoods with a greater heterogeneity in the race of their residents are associated with greater criminal violence, and this relationship appears strong. Neighborhoods with a greater percentage of families with single heads of household, either males or females, in comparison to households with two heads of household, are associated with less criminal violence, although the significance of this relationship is marginal. Heterogeneity in age, heterogeneity in homeownership, and household size, do not appear to be significantly related to criminal violence.

Discussion

In this study we have analyzed the relationship between alcohol outlet density and criminal violence in the neighborhoods of a large Midwestern city (Minneapolis, Minnesota) controlling for structural constraints and using spatial random effects. Our analysis revealed a statistically significant relationship between outlet density and criminal violence at the neighborhood level, in the presence of the fixed effects and a moderate degree of spatial smoothing. Central and north central neighborhoods in the city have the highest density of criminal violence, and correspond to areas with high densities of alcohol outlets, while south and outer ring neighborhoods have the lowest density of criminal violence, and correspond to areas with lower densities of alcohol outlets. In addition, two structural constraints included in the model, heterogeneity in race of neighborhood residents and ratio of single head households to two head households, were significantly related to criminal violence.
Translation of this study’s findings into magnitude of effect reveals that an addition of one alcohol establishment to a neighborhood having the average observed value of alcohol outlet density would result in an increase in the number of criminal violence acts in that neighborhood by 5 crimes per 1,000 individuals per year. Although a seemingly small increase in crime, recall that we focus on criminal violence in this study, not all crimes. For the purposes of our investigation, we included only severe crimes: homicide, rape, robbery, aggravated assault, burglary, motor vehicle theft and arson. Controlling for the spatial autocorrelation that exists between neighborhoods yielded a more conservative, but also more precise, estimate of effect than when we included independently and identically distributed normal random variables, or when we did not include substantively important fixed effects.

Previous research in this area has resulted in a call for examination of the spatial effects of neighborhood characteristics and alcohol outlet densities from a more theoretically informed perspective, and in a more diverse array of settings. The current study offers a unique contribution to the research on alcohol outlet density, analyzing relationships based upon the theoretical concepts of collective efficacy and structural constraints, appropriately controlling for spatial autocorrelation, and at an especially appropriate unit of analysis—the self-identified neighborhood unit. It is at this geographic level that we are likely to see neighbors come together in an effort to address alcohol outlet density issues and criminal violence problems.

Although unique in some ways, the current study is not without limitations. First, our measures of population are based on home residence data from the U.S. Census, and are thus not measures of daytime neighborhood populations, or, perhaps more importantly, non-residential neighborhood populations at night. This issue is especially important for those “hot spot” areas of concentrated alcohol outlet density, where evening populations frequenting alcohol
establishments may differ dramatically from residential populations. To address this issue in future research, we suggest use of better Census data (i.e., a “night” Census).

In addition, the current study does not include other aspects of community life that may influence criminal violence, including location of other spots where crime may concentrate (e.g., bus depots, nighttime business centers, major street intersections)\textsuperscript{28}. Further, this study does not include other assessments of neighborhood collective efficacy aside from outlet density\textsuperscript{15}. Future studies could include a broader array of each of these variables. Future studies might also include an aggregate measure of alcohol consumption in order to better link alcohol outlet density and resulting criminal violence\textsuperscript{12}. Finally, the current study is cross-sectional in nature and does not explore the spatio-temporal nature of the relationship between outlet density and crime. We are unable to assess a causal relationship between density and criminal violence using our study design; assistance in this regard might come from analyzing more years of data\textsuperscript{29}. One difficulty with this approach, however, is the fact that outlet density is slow in changing, so a lengthy time period would be necessary to follow a change in outlet density and to evaluate whether this leads to a detectable change in criminal violence\textsuperscript{2}.

Despite these shortcomings, the current study is congruent with other small area analysis research, revealing that areas with higher outlet density experience more criminal violence than areas with lower outlet density, even when controlling for a number of structural constraints including heterogeneity in a community, challenging economic situations, family disruption and heavy urbanization\textsuperscript{4,7,8,9,11,12,28}. Further, the current study extends the geographic area, demographic diversity, and unit of analysis where this relationship is found. Finally, the study’s fully Bayesian approach accounts for spatial correlation in the data, and also permits full
posterior and predictive inference (e.g., the probability that \( \mu_i \) exceeds some threshold \( c \) in some unmeasured or unmeasureable neighborhood \( i \)) unavailable using traditional statistical methods.
References


28 Roncek DW, Maier PA. Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of 'hot spots'. *Criminology* 1991;29(4):725-753.

Figure 1. Raw Crime Density (Per 1,000 Residents)
Figure 2. Fitted Crime Density (Per 1,000 Residents)
Figure 3. Values for Spatial Random Effects, Model 5

- (6) < -0.5
- (14) -0.5 - -0.25
- (22) -0.25 - 0.0
- (21) 0.0 - 0.25
- (9) 0.25 - 0.5
- (4) 0.5 - 1.0
- (3) >= 1.0