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Space-time Analyses of Alcohol Outlets and Related Motor Vehicle Crashes: Associations at City and Census Block Group Levels

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Abstract

Objectives—Past research has linked alcohol outlet densities to drinking, drunken driving and alcohol-related motor vehicle crashes (MVCs). Because impaired drivers travel some distances from drinking places to crash locations, spatial relationships between outlets and crashes are complex. We investigate these relationships at three geographic levels: Census block groups (CBGs), adjacent (nearby) areas, and whole cities.

Methods—We examined risks for all injury MVCs as well as 'had been drinking' (HBD) and single-vehicle nighttime (SVN) subgroups using data from the Statewide Integrated Traffic Records System (SWITRS) across CBGs among 50 California cities from 2001 to 2008. Relationships between outlet densities at the city-level, within CBGs, and in adjacent CBGs and crashes were examined using Bayesian Poisson space-time analyses controlling for population size income and other demographics (all as covariates).

Results—All injury MVCs were positively related to adjacent CBG population size (RR=1.008, 95%credible interval (CI)=1.004, 1.012), and outlet densities at CBG (RR=1.027, CI=1.020, 1.035), nearby area (RR=1.084, CI=1.060, 1.106) and city levels (RR=1.227, CI=1.147, 1.315), and proportion of bars or pubs at the city level (RR=2.257, CI=1.187, 4.125). HBD and SVN crashes were comparatively less frequent in high outlet density CBG (RR=0.993, CI=0.986, 0.999; RR=0.979, CI=0.962, 0.996) and adjacent areas (RR=0.963, CI=0.951, 0.975; RR=0.909, CI=883, 0.936), but positively associated with city-level proportions of bars (RR=3.373, CI=0.736, 15.644; RR=10.322, CI=1.704, 81.215). Overall a 10% increase in all outlets was related to 2.8% more injury crashes (CI=2.3%,3.3%), and 2.5% more HBDs (CI=1.7%,3.3%). A 10% increase in bars was related to 1.4% more crashes, 4.3% more HBDs and 10.3% more SVNs.

Conclusions—Population size and densities of bars or pubs were found to be associated with crash rates, with population effects appearing across cities and outlet effects appearing within dense downtown areas. Summary estimates of outlet and population impacts on MVCs must consider varying contributions at multiple spatial scales.

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alcohol availability; alcohol outlet density; motor vehicle crashes; spatial analysis

Alcohol-related motor vehicle crashes (MVCs) are a major problem in the United States, resulting in more than 10,000 fatalities in 2010 and imposing annual estimated costs of $37 billion (NHTSA, 2012). Approximately one third of crash fatalities since 1995 have been identified as alcohol related (Insurance Institute for Highway Safety, 2005, 2011). One policy based approach for reducing alcohol-involved traffic crashes is to limit the physical availability of alcohol and develop policies to reduce drinking and related problems (Gruenewald, 2011). Limiting alcohol outlets in a specific area is theorized to decrease the convenience of obtaining beverages and thus reduce alcohol demand and drinking-related problems (Chaloupka et al., 1998).

Some authors have argued that reductions in physical availability may be less effective at reducing motor vehicle crashes than other drinking problems because increased driving distances will increase crash exposures (McCarthy, 2003; Lapham et al., 1998; Gary et al., 2003; Gruenewald et al., 2002) Most studies, however report overall positive associations of outlet densities to MVCs (Scribner et al., 1994; Jewell and Brown, 1995; Gruenewald et al., 1996; Escobedo and Ortiz, 2002; McCarthy, 2003, 2005; Farmer et al., 2005; Treno et al., 2007). A handful of studies report negative associations with different forms of availability (McCarthy, 2003 for off-premise density; Baughman et al., 2001; Treno et al., 2007 for restaurant density). Even among those that report positive effects, estimated effect sizes relating outlets to MVCs vary widely because of differences in (1) the measurement of physical availability, (2) the selection of geographic units of analysis, (3) models used to assess alcohol-involved MVC risks relative to expectations, and (4) the degree to which each study accounts for pertinent confounders. Considering several examples, some studies use legal regulations in place of direct measures of physical availability (e.g., Baughman et al., 2001; Gary et al., 2003), others characterize physical availability in terms of overall outlet densities while others distinguish on- vs. off-premise places (e.g., Toomey et al., 2012; Ponicki, et al., 2013), yet others aggregate data into county (Jewell and Brown, 1995; Kelleher et al., 1996), city (Scribner et al., 1994; McCarthy, 2003; Farmer et al., 2005), ZIP code (Treno et al., 2007), or smaller units (Toomey, et al, 2012). Further, crash rates may be estimated relative to local population sizes (Scribner, et al., 1994), roadway miles (Gruenewald, et al., 1996) and other metrics of exposure to crash risks. It should be noted that alcohol-related MVCs may or may not occur within the geographic unit used to characterize outlet densities. Indeed, if the geographic unit of analysis is small, then alcohol use in one unit will be related to crashes in another (Gary, et al., 2003; De Boni, et al., 2013; Levine, 2015; Morrison, et al, 2017). For these reasons, of all problems related to alcohol use that occur in community environments, neighborhood and population correlates of alcohol-related MVCs are particularly difficult to characterize at the community level. Thus, based on these considerations one should expect that there will be substantial spatial variations in rates of alcohol-related MVCs across different/multiple types of community areas that may exist simultaneously in any particular urban setting. It is important to consider that there are many contexts that may produce alcohol related MVCs. Thus, place-of-last-drink studies indicate that upward of 50% of drivers stopped for drinking and drunken driving were coming from private residences (Robinson, et al., 2005; Padilla and Morrissey, 1993). In contrast, other outcomes related to alcohol outlets, like violence and property damage, appear to exhibit less spatial variation and relatively invariant effects related to specific outlet types (e.g., night clubs and bars(Cameron et al, 2016a,b)).

Obviously, no one study can address the many measurement issues and approaches related to understanding the spatial dynamics of alcohol availability/alcohol outlets and MVCs. This being said, it's important that research (1) use detailed quantitative metrics for availability whenever possible, (2) recognize that outlet effects may be multi-scale and (3) related to exposures in complex ways, and (4) keep in mind the multiple sources of crash risks across community areas. To address these concerns, we think it important to start with relatively small spatial units that allow investigators to identify local outlet effects more accurately and discriminate these from larger-scale effects related to neighborhood and city areas. Analyses at a single areal level may badly mis-measure correlates of crash outcomes. For example, Ponicki et al. (2013) found that bar densities were related to alcohol-involved MVCs across ZIP code areas, but these effects were very small; a 10% increase in outlets was related to a less than 1% rise in alcohol-involved MVCs. Zip codes may poorly estimate outlet effects in this situation because the analyses could not distinguish competing sources of crash risks at multiple geographic scales. Indeed, there may be, as we discuss above, other processes involved, occurring simultaneously, at different areal levels, that were not accounted for.

In this study we address these issues by analyzing CBG data from 50 cities in California from 2001 to 2008 in which 30,960 accidents occurred . Physical availability is distinguished in a way to minimize collinearity in measures of outlet density across outlet types. Relationships of population size (a critical covariate due to possible effects across spatial scales), income and outlets are assessed at local CBG, nearby area CBG and city levels to identify multi-scale effects and provide suitable controls across levels of analysis. Finally, availability relationships are distinguished by their effects upon all MVCs vs. alcohol-related MVCs more specifically. Areas of cities with more outlets are likely to have more motor vehicle traffic and more crashes; the key questions are whether, net of overall exposures to crash risks, alcohol-related MVCs occur more often in or around the areas where alcohol outlets are located and to what extent multiple scales of effects can be observed?

METHODS

Data on motor vehicle crashes, alcohol retail outlets, and other variables for 50 cities in California over the years 2001 through 2008 are used (see supplement X). We aggregated to the Census 2000 Block Group level for purposes of these analyses. As part of a larger study of the social ecology of alcohol problems in the state, 50 non-adjacent cities were randomly selected from a universe of 138 incorporated municipalities with between 50,000 and 500,000 residents as of the 2000 Census. Block groups were included in these analyses if their geographic centroids were within the outer boundaries of one of these 50 cities (with unincorporated "islands" within a given city being counted as part of that municipality). The

50-city data set included 3,870 of the statewide total of 22,132 block groups, with the individual cities ranging from 23 block groups in Temecula to 340 in Sacramento.

Traffic crash data within California for the years 2001 through 2008 were obtained from the widely used California Highway Patrol's (CHP) Statewide Integrated Traffic Records System (SWITRS). (Scribner et al., 1994; McCarthy, 2003; Treno et al., 2007; Ponicki et al., 2013). Crashes involving an injury or death were selected for these analyses because state law requires that crashes involving any injury or death be reported to the CHP (California Vehicle Code Section 20008). Property-only crashes are far less complete and were not included. Crash locations were geocoded to block groups in two phases. First, nearly 100% of SWITRS records listing highway post-miles were geocoded by the University of California's Safe Transportation Resource and Education Center (SafeTREC). Second, other crash locations were geocoded to StreetMap USA (ESRI, 2010) street segments within each of California's 58 counties in order to facilitate automatic geocoding. Statewide, 94.0% of SWITRS crash records were successfully geocoded to the block group level, and the un-geocoded crashes were disproportionately outside of major cities. The models below analyze three outcome measures: the block-group-by-year counts of all injury crashes, and the counts of alcohol-involved crashes as indicated by had been drinking (HBD) or single-vehicle nighttime (SVN, occurring between 8 PM and 4 AM) status. HBD crashes have shown high validity as a measure of impaired driving (McCarty et al., 2009; Brubacher et al., 2013; Grossman et al., 1996; Brick and Carpenter, 2001), while SVN crashes are a common impaired-driving surrogate that has been shown to be highly alcohol-involved (Voas et al., 2009).

California uses three general retail alcohol outlet types; restaurants (license types 41 and 47), off-premise establishments (license types 20 and 21), and bars/pubs (license types 23, 40, 42, 48, 61 and 75). We obtained active license records as of January of each year from the California Department of Alcohol Beverage Control (ABC). Premise address was geocoded for each record. The analyses allow for the three types of outlets to have differing associations with both crashes and alcohol involvement. Because local densities are somewhat correlated across outlet types, the models control for overall density (10s of outlets per square mile) as well as the proportions of those establishments that are bars or restaurants (making off-premise the implicit standard for the overall density measure). These outlet density measures were calculated at three levels of geographic resolution: within the local block group, averaged among adjacent block groups where adjacent areas are those which share a border with any CBG and adjacent area measures are unweighted averages of measures across adjacent CBGs, not including the local CBG, and across all block groups within a city, with each geographic level having an overall outlet density per area as well as proportions of that density that are bars and restaurants. We did not include CBGs that were outside city boundaries and assumed that variations in crash rates related to populations living outside city areas (edge effects) would be captured by the city random effect in the analysis model.

Annual estimates of Census-based demographic data at the block-group level were extracted from GeoLytics Estimates Premium (2010). Variables used included local population density (1000s per square mile), total population across adjacent block groups and city-wide (in thousands), inflation-adjusted household income both locally and across adjacent block groups (year 2007 dollars divided by 10,000), average household size, percentages unemployed or in poverty, and proportions of population that were male, racially white or black (with all others as the excluded group), of Hispanic ethnicity, and within four age groups (20–24, 25–44, 45–64, and 65+). Because prior research suggests that alcohol-involved crashes were strongly related to shares of population that are white or young adult, the model includes controls for proportions white and age 20–24 both locally and across adjacent block groups. The models also include an indicator variable for whether each block group touches a class 1 or 2 highway (ESRI, 2010). A single yes/no variable was chosen because a given stretch of roadway may share multiple designations (e.g., a state highway number and a Federal highway designation), which could lead to duplication in counting of the number or mileage of such routes.

Statistical Approach

Bayesian Spatial Models: Block-group crash counts were analyzed using hierarchical Bayesian space-time Poisson models (Besag et al., 1991; Bernardinelli et al., 1995; Carlin and Louis, 2000). These models allow for repeated annual measures among block groups nested within cities. This Bayesian spatial approach corrects for both large outlying risk in low-population areas as well as the effects of unexplained spatial autocorrelation. Per previous work, (Ponicki, 2013), spatial autocorrelation may be a particular issue when studying motor vehicle crash risks for a number of reasons; 1) including drinkers traveling across multiple block groups for alcohol where the effects of these longer trips may not be fully captured by the adjacent-area model variables; 2) data that control for factors such as weather patterns may be inconsistently gathered. Both of these issues can lead to biased results, if left untreated, due to standard regression assumption violations. Specific/precise model-based estimates of local rates utilizing both local and neighboring (adjacent/lagged) observations using Bayesian methods can help to resolve these problems.

By allowing each area unit to “borrow strength” from its neighbors conditional autoregressive (CAR) random effects may mitigate the leverage influence of outlying local rates and properly treat residual spatial autocorrelation (Waller and Gotway, 2004). The CAR random effects approach accounts for similarity of problem risks among block groups located near each other, while assessing non-spatial random effects allows for block group differences in unexplained risk that are not spatially autocorrelated (over dispersion can also be controlled). (Carlin and Louis, 2000). Lord et al. (2005) report that hierarchical Bayesian methods can account for “excess” zero counts that often occur in small areas with high crash risk although zero-inflated count models are generally not well suited to crash data . In a panel of Pennsylvania counties, (Aguero-Valverde and Jovanis,2006) Bayesian CAR Poisson models were reported to provide a comparable fit to negative-binomial specifications for crash risks with the former being preferred as spatial autocorrelation is controlled.

Given that the outcome measures are the counts of injury crashes (total, HBD, or SVN) in a given block group and time period, a Poisson regression model is used:

$$Y_{i,t} \Big| \mu_{i,t} \sim Poisson(E_{i,t}\exp(\mu_{i,t})) \quad (1)$$

where $Y_{i,t}$ represents the count of injury crashes in block group i during year t and $E_{i,t}$ denotes the expected number of the injury crashes. For the total crash analyses, this expectation assumes that crashes are distributed in direct proportion to block-group population. Hence $\exp(\mu_{i,t})$ may be interpreted as the relative injury-crash risk of residing in spatial unit i at time t: regions with $\exp(\mu_{i,t}) > 1$ will have greater crash counts than expected based on their population, and regions with $\exp(\mu_{i,t}) < 1$ will have fewer than expected. Because expected outcomes cannot be zero in these log-linear Poisson models, the 70 block-group observations (0.23%) with zero populations were given a minimal expectation of 0.0001 to allow for the possibility of positive crashes even in unpopulated areas. A sensitivity analysis with a dummy variable allowing for additional crash risk in these unpopulated cases produced nearly identical results. For the analyses of HBD or SVN crashes, the expectation $E_{i,t}$ assumes that statewide crashes in that alcohol-related category are distributed in direct proportion to local injury crashes that do not fall in that category, again with an expectation of 0.0001 being used in the 3.18% of block groups observations with no non-alcohol crashes. In these cases $\exp(\mu_{i.t})$ can be interpreted as a risk ratio of injury crashes being designated as alcohol involved rather than not alcohol involved. Nearly identical results were obtained in sensitivity analyses with expectations based on total injury crash rates, in which case $\exp(\mu_{i.t})$ would be interpreted as the likelihood that any given crash is designated as HBD or SVN.

Following standard generalized linear models, the log-relative risk, $\mu_{i.t}$, is modeled linearly as:

$$\mu_{i,t} = \alpha 0 + \alpha 1 * t + X'_{i,t}\beta + \Omega_i + \theta_i + \phi_i \quad (2)$$

This is a linear combination of fixed covariate effects and random effects which account for spatial and/or temporal correlation. Parameters $\alpha 0$ and $\alpha 1$ are an intercept and linear time trend that control for statewide level and growth of injury crash risks, respectively, that are not explained by other covariates. Matrix $X'_{i,t}$ contains space- and time-specific covariates and β is a vector of fixed-effects estimates of the effect of those covariates. Ω_i denotes a random effect allowing for time-invariant variation among the 50 cities within which the block groups i are nested. $\theta_{i,t}$ and $\varphi_{i,t}$ represent the pair of random effects at the block-group level capturing spatially unstructured heterogeneity and CAR spatial dependence, respectively. Models were estimated using WinBUGS 1.4.3 software (Lunn et al., 2000). Non-informative priors were specified for all fixed and random effects. Models were allowed to burn-in for 20,000 (HBD and SVN crashes) to 60,000 (total injury crashes) Markov Chain Monte Carlo (MCMC) iterations, which were sufficient for all parameter estimates to stabilize and converge between two chains with different initial values. Posterior estimates were then sampled for an additional 50,000 iterations within each MCMC chain to provide model results. Traces of MCMC iterations demonstrated good convergence for all parameters. A major benefit of this Bayesian approach is that it allows us to combine a parameter's association with population crash rates as estimated in one analysis with the estimated probability that a given crash is alcohol-involved (HBD or SVN) from another analysis. We therefore first present the results of each outcome's model separately in Table 2, below. Noting that the outcome from the model explaining total crashes serves as the basis for estimating rates of HBD and SVN crashes, we then combine the posteriors of total and HBD parameter estimates and total and SVN parameter estimates, respectively, to calculate total covariate effects across each pair of models (as presented in Table 3).

RESULTS

Table 1 presents descriptive statistics for the outcome measures and explanatory variables included in the analyses. (in supplementary table 1 we provide city specific details relevant to our analysis). The average block group had 1,706 residents in an area of 1.2 square miles, experiencing 9.5 injury crashes per year, of which 1.0 were categorized as HBD and 0.6 as SVN. It had 0.13 outlets per square mile, of which 8.0% were bars and 40.8% were restaurants. The outlet densities among adjacent areas tend to be similar, but the city-level mean is lower (0.06 per square mile) due to a few large outlying block groups.

Table 2 presents results for the Bayesian spatial Poisson analyses. The first set of columns represents effects related to all injury MVCs relative to population. The second and third sets of columns present effects related to HBD and SVN crashes, respectively, net of non-HBD and non-SVN crashes. The raw coefficients from these Poisson models are log relative rates from the posterior distribution, and for ease of interpretation all values have been exponentiated in the table to represent relative rates. The median relative rate from each model's sampled MCMC iterations represents the expected value for each effect. This median relative rate is followed in parentheses by a credible interval indicating a range of values that is expected to contain the true relative rate with 95% probability (a Bayesian concept analogous to standard confidence intervals).

The positive intercept in the all-injury-crash analysis indicates that such CBGs have crashes that grow more than one-to-one with population, whereas their alcohol-involved crashes rise less than one-to-one with population, a background population source of crash risks not recognized in previous analyses. The population risks of all injury crashes and the risk ratio that those crashes are SVN both decline with local population density. CBGs with higher populations in adjacent areas have higher population risks of injury crashes and greater likelihood that those crashes are HBD. City population has no effect in any model. Net of these population effects, injury crash rates and their likelihood of alcohol involvement are substantially influenced by alcohol outlet densities. Injury crash rates are positively related to alcohol outlet densities at each geographic level (city, local, adjacent areas), with the relative rates being higher at greater levels of aggregation (i.e., city density has the largest proportional effect, whereas local densities have the smallest). The relative risk that these crashes are alcohol involved (HBD or SVN), however, decline (are negatively associated) with the density of outlets in local and adjacent block groups.

The city-level proportion of bar outlets has a positive relationship to crash rates as well as to the likelihood that the crashes are SVN, but local and adjacent bar proportions do not have well-supported effects for any outcome (i.e. we define a covariate as “well-supported” if it’s 95% credible interval excludes no effect) . The proportion of restaurant outlets within adjacent areas has a negative association with the chances of a local crash being categorized as HBD.

Population crash risks are also negatively associated with income, household size, unemployment, and the local proportions that are older or black. They are positively related to the presence of major highways, poverty, and proportion Hispanic within the local block group, as well as to the concentration of young adults in adjacent areas. The bottom section of the table describes the spatial aspects of the model. The conditionally autoregressive (CAR) spatial random effect explained 25% of block-group variance in total crash rates as well as 79% and 30% of the relative likelihood that those crashes are HBD and SVN, respectively. The CAR random effects within these three analyses all exhibited high degrees of spatial autocorrelation, with Moran I statistics between 0.73 and 0.82.

While the detailed covariate estimates in Table 2 accurately reflect the structure of the statistical models, they are not particularly helpful for predicting the effect of specific policy changes on rates of alcohol-involved crashes. For example, the estimated effect of raising bar densities by 10% in all block groups would depend on the combined effects of nine variables: the overall outlet density as well as the proportions that are bars or restaurants, each estimated at three geographic levels (locally, in adjacent block groups, and city-wide). In Table 3 we use the MCMC posteriors to estimate the combined effects of four hypothetical increases in outlet-density on crash rates within an average block group, with well-supported estimates shown in bold. Part A hypothesizes a 10% increase in all outlet types within each block group. This would raise local, adjacent and city-level outlet densities by an equal proportion, but would have no effect on the shares of outlets that are bars or restaurants. For an average block group, this 10% increase in outlet densities is associated with a 2.8% increase in total crashes and 2.5% more HBD events but no well-supported effect on SVN crashes.

Part B of Table 3 assumes that the density of only one outlet type is increased by 10%, while the others are unchanged. This leads to smaller increases in overall outlet density as well as shifts in the proportions of outlets by type. A 10% rise in bars alone is associated with a 1.4% rise in total crashes, but related to considerably higher increases in alcohol involved events (4.3% for HBD, 10.3% for SVN). Conversely, a 10% increase in restaurants or off-premise outlets is generally associated with smaller negative changes in alcohol-involved crashes

Part C of Table 3 presents each geographic covariate’s contribution to the “bars only” row of Part B. This indicates that over two-thirds of the predicted rise in total crashes is generated by the city-level change in the proportion of bars, and this fraction is even larger for the predicted increases in HBD and SVN crashes. The remaining association for total crashes is due primarily to the resulting increases in overall outlet density across the three geographic levels.

Figure 1 illustrates how CBG, adjacent CBG and city-level bar- and population-density effects predict the geographic distribution of HBD MVCs in the city of Fresno. The left map shows HBD relative rates associated with spatial contributions of bar density, reflecting the combined parameters of the outlet-density and proportion of outlets that are bars across both the injury crash and HBD analyses. Elevated risks, indicated by darker shading, can be seen both in block groups containing bars (whose locations are displayed as circles for reference) and in neighboring areas. The color scale identifies quintiles of risk among these Fresno block groups, with the highest quintile of bar density contributing at least 14% more HBD risk than seen in the lowest-risk quintile (1.67/1.46). The right map shows the combined effects of the three population covariates (local density, plus adjacent and city-wide levels). This map's quintile scale suggests that, ignoring differences in other covariates, these population variables alone suggest HBD crash risks at least 89% higher in the darkest shaded block groups on the city's periphery than in the densely populated areas near the city center (0.89/0.47). The relative rates shown in these maps represent the combined effect of population or bar densities on HBD crash rates across the three geographic levels in the analyses. These summary effects represent the best posterior estimates from the Bayesian analyses.

DISCUSSION

Across a sample of 50 mid-size California cities we found that injury crashes were positively related to detailed quantitative measures of retail alcohol availability in general and specifically related to the density of bars. Our statistical approach allowed for outlet effects to be multi-scale, and the results suggest that crash risks within any given block group are associated not only with local outlet density but also with alcohol availability measured across neighboring block groups and whole cities. We also distinguished the association of alcohol availability with population risks for injury crashes from relationships of these crash exposures to alcohol involved injury crashes using both officers' assessments of whether drivers had been drinking (HBD) and a traditional alcohol surrogate, single vehicle night time crashes (SVN). This empirical approach whereby multiple correlates of population and outlet effects are described and elucidated is well demonstrated by the result that bar density was positively related to the likelihood that a crash was present in each of these alcohol-involved categories, and that these effects were primarily due to the proportion of bars at the city level.

Previous research is divided regarding the relationship between alcohol outlet densities and alcohol-involved traffic crashes. The lack of agreement may arise in part because a high density of alcohol outlets could imply both increased alcohol consumption and reduced driving distances, resulting in indeterminate predictions for risk of alcohol-involved crashes. Further, because individuals may drive long distances to visit an alcohol outlet (Levine, 2015), a high density of outlets may affect crash risks both locally and more distally at the same time. What must be considered is the granularity and comprehensiveness of the spatial context and the theoretical underpinnings for any particular spatial unit (or combination of units) chosen for analysis. A very local approach may be desirable to locate hot spots where specific causes can subsequently be identified. A broader city-wide approach may be desirable to identify broad city-level correlates that may indicate causally important components of crash risks (e.g., population size and composition, transportation patterns).

The local, adjacent-unit and city outlet density effects shown in Table 2 suggest that the spatial influence of some correlates of MVCs extend far beyond the size of a typical CBG. Thus, the combined effects related to outlet densities at these three geographic levels are considerably larger than predicted by a model that does not allow for lagged or city outlet effects. For example, Table 3 shows that a 10% increase in total outlet densities across all block groups would be expected to raise all injury crash rates by 1.4%, and Table 2 suggests that this is due to a large positive effect at the city level bolstered by additional well-supported positive effects of local and adjacent-area densities. This indicates that predictions regarding motor vehicle crashes can be quite sensitive to the scale of geographic units (local, adjacent/neighboring, city wide) as well as to whether models allow for spatially-lagged outlet density effects. Such sensitivity strongly suggests that multi-scale hierarchical analyses may be a preferred method for addressing some of the aggregation bias, change of support and modifiable area unit problems confronted by spatial ecological research into crash risks (Cressie and Wikle, 2011).

As shown in Figure 1, there is a clear signal indicating differences in correlates of crash outcomes across areas of the 50 cities examined in this study. The left map shows that block group variations in outlet density effects range at least 14% between highest and lowest quintiles. Within-city variations in bar concentrations appear to have substantial effects on crash risks, even as large effects are also observed between cities (Table 3); these risks appear to be concentrated, reasonably enough, around areas where most outlets, and bars in particular, are located. The right map shows that local and adjacent population contributions to HBD risk vary by at least 89% between highest and lowest quintiles. Within city variations in population size also have substantial effects on crash risks; these effects are, also reasonably enough, around residential areas where populations are most concentrated. It is tempting to conclude that crashes in these different areas are related to different processes; perhaps drinking drivers are both more likely to crash in areas where traffic is greatest (e.g., areas where outlets are most concentrated) and in areas where trips home are concentrated; or perhaps place-of-last-drink for many drivers who crash are at the homes of friends and relatives in these areas. Future research may address these points.

Limitations and Future Directions. This study has several important limitations. (1) Estimated outlet density effects could be biased by the lack of important transportation and land use variables which were not available in the block-group level data across the eight years studied (Keay and Simmonds, 2005; Ahmed et al., 2011). Further, there may be other transportation measures such as more detailed roadway segments that may also help future spatial crash modeling research related to alcohol outlets (Levin, 2017). (2) The spatial units of analysis do not necessarily match the scale of the underlying activity. Block groups tend to be physically compact in urban areas but can be much larger at the edges of cities; obviously, scale matters in assessments of alcohol use behaviors and the type and concentration of outlets. (3) The measure of spatial connections between units may be inappropriate. The current study uses simple adjacency to calculate spatial-lagged effects. An alternative approach might use inverse weighted distances or travel times to-and-from geographic units. (4) The large spatial autocorrelations that remain observed after consideration of covariate effects continue to suggest that the characteristic scale of outlet-crash relationships may be larger on average than CBGs. (5) The combination of local and spatially-lagged outlet density effects with strongly-positive spatial autoregressive effects would suggest that the effects of alcohol outlets may be much greater than has been estimated here (LeSage and Pace, 2009). (6) Although spatial lag effects were examined, temporal lag effects were not. Nevertheless, within the panel framework of the current study, estimates represent correlated effects *within* areas across time.

In summary, the current results suggest considerable complexity in the relationship between alcohol availability and alcohol-involved traffic crashes. Our estimated density effects differ by types of outlets, with bars typically having larger associations than restaurants and off-premise outlets. Our results also indicate that no one geographic scale can capture the full extent of this relationship, suggesting the importance of multi-scale approaches in future research. Lastly, the current findings indicate that availability may have different associations with total crashes than with the chances that each crash is alcohol involved, suggesting the value of detailed quantitative metrics allowing for such distinctions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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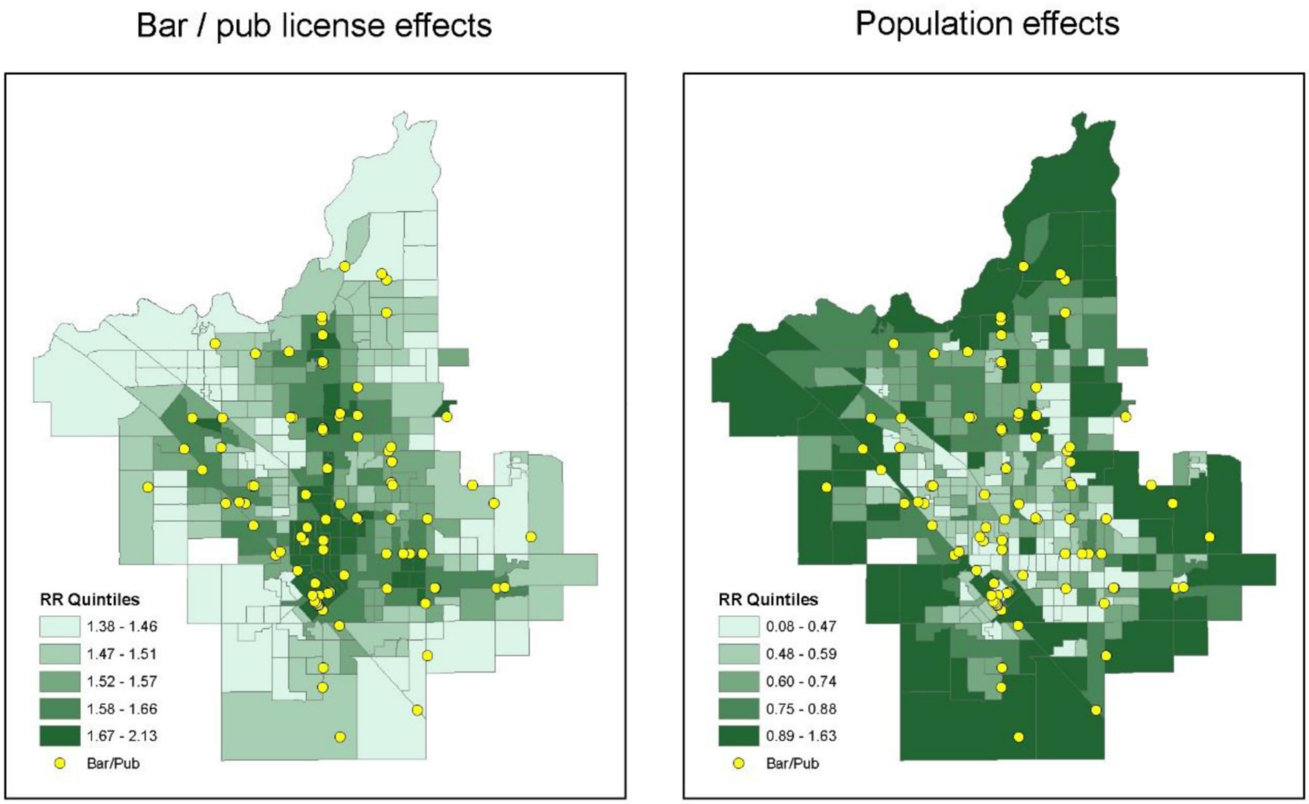

Figure 1.

Estimated contributions of bar densities and population variables to relative rates of had-been drinking (HBD) crashes in Fresno, CA 2008

Note: Each map represents the contribution of the specified community characteristic to the relative risk of HBD crashes within each block group. This combines the characteristics' impact on the rate of overall injury crashes with their effect on the odds that a crash will be HBD in that area. The left map estimates the combined risk contributions of overall outlet density and proportion bars across three geographic levels (local black group adjacent areas, and ctty-wide). The right map estimates the combined risk contributions of the local populatron density and the adjacent a city-level populations. The color scale for each map identifies quintiles of relative risk within these Fresno block groups. Locations of bars and pubs are shown for reference.

Table 1

Descriptive Statistics

Variable Description	Mean	SD	Min	Max
Block group population	1,706	1,333	0	29,778
Block group land area (square miles)	1.211	6.533	0.007	147.855
Counts of injury crashes				
Total	9.526	13.070	0.000	238.000
Had Been Drinking (HBD)	1.013	1.625	0.000	21.000
Single Vehicle Nighttime (SVN)	0.558	1.239	0.000	21.000
Alcohol outlet density (10s per square mile)				
In local block group	1.334	2.549	0.000	39.261
Mean of adjacent block groups	1.363	1.413	0.000	18.897
City-level average	0.577	0.630	0.047	3.424
Proportion of outlets that are bars or pubs				
In local block group	0.080	0.141	0.000	1.000
Mean of adjacent block groups	0.080	0.088	0.000	1.000
City-level average	0.088	0.026	0.000	0.165
Proportion of outlets that are restaurants				
In local block group	0.408	0.272	0.000	1.000
Mean of adjacent block groups	0.446	0.205	0.000	1.000
City-level average	0.499	0.084	0.311	0.773
Local population density (1000s / square mile)	7.241	6.064	0.000	75.673
Adjacent population (1000s)	11.370	6.236	0.588	67.852
City population (1000s)	209.128	160.955	58.987	550.139
Real income ($10,000s)	5.462	2.668	0.000	23.538
Adjacent real income ($10,000s)	5.447	2.141	0.956	20.479
Average household size	2.855	0.706	0.000	6.400
% Poverty	10.894	11.959	0.000	100.000
% Unemployment	7.256	8.079	0.000	153.333
Proportion age 20–24	0.072	0.029	0.000	0.612
Proportion age 20–24 in adjacent block groups	0.072	0.021	0.000	0.446
Proportion age 25–44	0.290	0.068	0.000	0.715
Proportion age 45–64	0.229	0.064	0.000	1.000
Proportion age 65+	0.119	0.086	0.000	1.000
Proportion white	0.793	0.165	0.000	1.000
Proportion white in adjacent block groups	0.794	0.142	0.105	0.990
Proportion Black	0.062	0.094	0.000	0.894
Proportion Hispanic	0.308	0.235	0.000	1.200
Proportion male	0.494	0.040	0.000	1.000
Presence of any class 1–2 highway (dummy)	0.427	0.495	0.000	1.000

Notes: Descriptive statistics of model variables for 3870 Census block groups within 50 mid-sized California cities over the years 2001–2008 (total n = 30,960). Proportions of outlets that are bars or restaurants are undefined in areas with no outlets; in such cases the sample-wide average proportions were used.

Table 2

Relative risks associated with block group and city characteristics, among total injury crashes and crash types

	Crash rates relative to block-group population		HBD crash rates relative to non-HBD crashes		SVN crash rates relative to non-SVN crashes	
Variable Description	**Median**	**(95% C.I.)**	**Median**	**(95% C.I.)**	**Median**	**(95% C.I.)**
Alcohol outlet density (10s / sq. mile)						
In local block group	1.0273*	(1.0199, 1.0348)	0.9929*	(0.9866, 0.9993)	0.9627*	(0.9507, 0.9748)
Mean of adjacent block groups	1.0836*	(1.0599, 1.1062)	0.9787*	(0.9621, 0.9956)	0.9093*	(0.8830, 0.9363)
City-level average	1.2267*	(1.147, 1.3153)	1.0097	(0.9110, 1.1196)	0.8955	(0.7975, 1.0062)
Proportion of outlets bars/pubs						
In local block group	1.0064	(0.9423, 1.0759)	1.0907	(0.9758, 1.2183)	0.9946	(0.8355, 1.1795)
Mean of adjacent block groups	1.0175	(0.8731, 1.1856)	1.2346	(0.9878, 1.5419)	1.1444	(0.8244, 1.5937)
City-level average	2.2569*	(1.1872, 4.1247)	3.3733	(0.7363, 15.6442)	10.3222*	(1.7038, 81.215)
Proportion of outlets restaurants						
In local block group	1.0290	(0.9921, 1.0670)	0.9408	(0.8833, 1.0004)	0.9593	(0.8715, 1.0566)
Mean of adjacent block groups	1.0814	(0.9885, 1.1778)	0.8135*	(0.7242, 0.9169)	0.8898	(0.7523, 1.0600)
City-level average	0.9662	(0.7176, 1.2710)	0.8400	(0.4196, 1.5270)	0.8314	(0.4216, 1.8908)
Population density (1000s / sq. mile)	0.9155*	(0.9099, 0.9211)	1.0015	(0.9974, 1.0056)	0.9797*	(0.9724, 0.9872)
Adjacent population (1000s)	1.0084*	(1.0039, 1.0123)	1.0045*	(1.0014, 1.0076)	1.0031	(0.9981, 1.0081)
City population (1000s)	1.0003	(1.0000, 1.0007)	0.9998	(0.9991, 1.0004)	1.0000	(0.9993, 1.0006)
Real income ($10,000)	0.9494*	(0.9279, 0.9680)	1.0029	(0.9881, 1.0176)	1.0193	(0.9961, 1.0432)
Adjacent real income ($10,000)	0.9588*	(0.9357, 0.9863)	0.9910	(0.9709, 1.0125)	1.0607*	(1.0286, 1.0966)
Average household size	0.8045*	(0.7676, 0.8456)	1.1124*	(1.0622, 1.1657)	1.1073*	(1.0265, 1.1900)
% Poverty	1.0074*	(1.0034, 1.0111)	0.9999	(0.9975, 1.0022)	1.0017	(0.9979, 1.0055)
% Unemployment	0.9951*	(0.9934, 0.9967)	1.0019	(0.9996, 1.0041)	1.0019	(0.9983, 1.0053)
Proportion age 20–24	0.9105	(0.6021, 1.3485)	0.6717	(0.2714, 1.6599)	2.1529	(0.6618, 7.2812)
Proportion age 20–24 in Adjacent BG	4.0755*	(2.0036, 8.1149)	1.2991	(0.3471, 4.8115)	0.3835	(0.0545, 2.5284)
Proportion age 25–44	0.5779*	(0.4174, 0.7652)	0.9290	(0.4878, 1.7034)	1.7565	(0.7803, 3.6455)
Proportion age 45–64	0.6598	(0.4218, 1.0058)	1.3409	(0.6475, 2.6698)	4.591*	(1.9753, 10.8623)
Proportion age 65+	0.3754*	(0.2516, 0.5614)	0.9054	(0.5518, 1.4342)	0.7879	(0.4083, 1.4989)
Proportion white	0.7996	(0.5739, 1.0906)	1.4659*	(1.1166, 1.9621)	1.6271*	(1.0859, 2.3533)

	Crash rates relative to block-group population		HBD crash rates relative to non-HBD crashes		SVN crash rates relative to non-SVN crashes	
Variable Description	**Median**	**(95% C.I.)**	**Median**	**(95% C.I.)**	**Median**	**(95% C.I.)**
Proportion white in Adjacent BG	0.4249*	(0.3187, 0.6162)	1.2758	(0.9109, 1.8070)	1.0851	(0.7311, 1.6659)
Proportion Black	0.2973*	(0.1691, 0.4866)	0.9826	(0.6571, 1.4508)	1.2315	(0.6943, 2.1978)
Proportion Hispanic	2.0285*	(1.6333, 2.5356)	0.8719	(0.7106, 1.0756)	0.8118	(0.5958, 1.1087)
Proportion male	0.6645	(0.4111, 1.1668)	1.9314*	(1.1264, 3.3824)	1.9477	(0.9003, 4.5481)
Presence of any class 1–2 highway	2.2733*	(2.1090, 2.4899)	0.9686	(0.9295, 1.0099)	1.2127*	(1.1349, 1.2958)
Intercept	5.9085*	(4.128, 9.1185)	0.3162*	(0.1733, 0.6827)	0.1170*	(0.0442, 0.2583)
Time trend (1–8)	0.9543*	(0.9497, 0.9593)	1.0336*	(1.0253, 1.0419)	1.0547*	(1.0424, 1.0667)
SD (city-level random effect)	0.0230	(0.0230, 0.3004)	0.2278	(0.2004, 0.2621)	0.2136	(0.1743, 0.2563)
SD (CAR spatial random effect)	0.5749	(0.5749, 0.7037)	0.3350	(0.3016, 0.3681)	0.3381	(0.2718, 0.3984)
SD (non-spatial random effect)	0.9481	(0.9481, 1.0137)	0.1740	(0.1045, 0.2209)	0.5196	(0.4755, 0.5623)
Spatial proportion block grp. variance	0.2478	(0.2478, 0.3496)	0.7876	(0.6588, 0.9241)	0.2975	(0.1957, 0.4033)
Proportion variance due to city effects	0.0004	(0.0004, 0.0618)	0.2672	(0.2172, 0.3285)	0.1060	(0.0726, 0.1471)
CAR spatial autocorrelation (Moran's I)	0.6557	(p < 0.00001)	0.6730	(p < 0.00001)	0.6890	(p < 0.00001)

Notes: Posterior results are from Bayesian space-time Poisson analyses of 3870 Census block groups within 50 mid-sized California cities over the years 2001–2008 (total n = 30,960). Each Poisson model included an exposure variable with coefficient restricted to one, calculated on the assumption that outcome counts study-wide are distributed in exact proportion to population (total crash model) or to non-alcohol crashes (HBD and SVN crash models). Raw Poisson coefficients and credible intervals have been exponentiated and are thus interpretable as relative rates.

Table 3

Predicted increases in injury crash risks due to specified outlet density changes

Type of outlet density change:	All injury crashes	HBD injury crashes	SVN injury crashes
(A) 10% rise in all types of outlets:	**2.82%**	**2.49%**	0.43%
	(2.30%, 3.34%)	(1.66%, 3.31%)	(−0.43%, 1.27%)
<u>(B) 10% rise in a single outlet category:</u>			
-- Bars only	**1.40%**	**4.26%**	**10.30%**
	(0.48%, 3.10%)	**(1.36%, 15.56%)**	**(2.18%, 76.78%)**
-- Restaurants only	1.18%	−2.41%	**−5.95%**
	(−0.15%, 2.54%)	(−7.36%, 1.12%)	**(−37.13%, −0.48%)**
-- Off-Premise only	0.48%	0.04%	−3.37%
	(−0.36%, 1.26%)	(−4.80%, 1.95%)	(−28.98%, 0.43%)
(C) Covariates' contributions to "bars only" effects above:			
-- Overall density in <u>local</u> block group	**0.03%**	**0.03%**	−0.01%
-- Overall density in <u>adjacent</u> block groups	**0.11%**	**0.08%**	−0.01%
-- Overall density at <u>city</u> level	**0.12%**	**0.13%**	0.07%
-- Proportion bars in <u>local</u> block group	0.01%	0.09%	0.00%
-- Proportion bars in <u>adjacent</u> block groups	0.02%	0.24%	0.16%
-- Proportion bars at <u>city</u> level	**1.16%**	**3.53%**	**9.98%**
-- Proportion restaurants in <u>local</u> block group	−0.01%	0.01%	0.01%
-- Proportion restaurants in <u>adjacent</u> block groups	−0.04%	0.05%	0.01%
-- Proportion restaurants at <u>city</u> level	0.02%	0.09%	0.10%

Estimated effects calculated based on sample mean outlet densities. A 10% increase in all outlet types (part A) would not affect the proportions of those outlets that are bars or off-premise outlets. A 10% change in a given outlet category (part B) will raise total density by less than 10%, and will raise the proportion of outlets for the given category but reduce it for other outlet types. Part C demonstrates the contribution of individual outlet covariates to part B's estimates of the effects of raising bars only by 10%; bold type indicates well-supported contributions based on calculations of sampled MCMC iterations across analyses. Credible intervals shown in parentheses in parts A and B.