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Original Research

The spatio-temporal relationship between alcohol outlets and violence before and after privatization: A natural experiment, Seattle, Wa 2010–2013

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ABSTRACT

Alcohol-related violence is a well-documented public health concern, where various individual and community-level factors contribute to this relationship. The purpose of this study is to examine the impact of a significant policy change at the local level, which privatized liquor sales and distribution. Specifically, we explored the relationship between alcohol and violence in Seattle, WA, 2010–2013, via hierarchical spatio-temporal disease mapping models. To measure and map this complex spatio-temporal relationship at the census block group level ($n = 567$), we examined a variety of models using integrated nested Laplace approximations and used the deviance information criterion to gauge model complexity and fit. For each additional off-premises and on-premises alcohol outlet in a given census block group, we found a significant increase of 8% and 5% for aggravated assaults and 6% and 5% for non-aggravated assaults, respectively. Lastly, our maps showed variation in the estimated relative risks across the city of Seattle.

1. Introduction

Alcohol-related violence is a well-documented public health concern (Gruenewald et al., 2006, Scribner et al., 2010, Watts and Rabow, 1983, Zhu et al., 2004), where various individual and community-level factors contribute to this relationship. These factors range from sociodemographic characteristics such as age, race/ethnicity, and income to neighborhood characteristics like vacant units, retail space, public transportation, and risky retailer density (Grubesic et al., 2013). Various geographic scales have been considered, including census block groups (Grubesic and Pridemore, 2011), census tracts (Zhu et al., 2004), ZIP codes (Gruenewald et al., 2006), and neighborhoods (Britt et al., 2005). Even though these scales vary in size, their general findings suggest that areas that have more alcohol outlets or greater alcohol outlet density tend to have higher rates of violence. Work to date, however, has primarily been cross-sectional, thus offering little insight into how a change over time in the number of alcohol outlets in a particular region will affect violence.

Longitudinal studies, and in particular, natural experiments, allow for a formal assessment of a discontinuous change, such as privatizing alcohol sales. These studies are more robust and generally allow for causal inference in changes in such alcohol-related harms as violence (Livingston et al., 2007). Recent research has examined the spatio-temporal relationship between alcohol outlets and violence. In particular, researchers examined how increased license fees, additional enforcement staff, and expanded powers for the alcohol license board addressed the proliferation of problem alcohol outlets believed to be the source of assaultive violence in the city of New Orleans

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(Xu et al., 2012). Their findings suggested that the implementation of the policy was associated with a significant decrease in the positive relationship between assaultive violence and off-premises alcohol outlet density. A second longitudinal study focused on 581 California ZIP codes over a 6 year period (Gruenewald and Remer, 2006). This study examined the relationship between hospital discharges related to violent assaults and alcohol availability as well as other sociodemographic characteristics. The researchers found that an average reduction of only one bar in each of the ZIP codes analyzed would have resulted in 290 fewer violent assaults per year across the 581 areas examined in their study; the average population in the study region comprised 234,344 persons over the 6 years of the study. Another study, which focused on the impact of additional alcohol outlets in a given area, assessed the state of Pennsylvania, which is currently considering a move away from an Alcohol Beverage Control state to a privatized alcohol distribution system (Grubesic et al., 2012). Here, researchers focused on the city of Philadelphia and estimated that an additional 1115 outlets could possibly open in the event of privatization. Should this happen, the tremendous increase in outlets in Pennsylvania could lead to an increase in negative health, crime, and other related harms. Therefore, more evidence is needed to determine the influence of significant alcohol-related policies on the relationship between alcohol and violence, and, in particular, the impact of additional alcohol outlets in a given area.

In 2012, Initiative 1183 [I-1183] was passed in the state of Washington, privatizing wholesale distribution and retail sales of liquor. Although state and local government agencies would continue strictly regulating the distribution and sale of liquor, the passing of I-1183 allowed for a significant increase in the number of alcohol outlets throughout the state. The overarching goal of our study was to: determine the effect I-1183 has on alcohol availability in the city at the census block group level, and characterize the policy's effect over time on the relationship between alcohol outlets and violence. We concentrated on the city of Seattle between the years 2010 and 2013, in an effort to focus on a more urban setting, and to capture the alcohol-violence relationship before and after the implementation of I-1183. To assess this relationship, we use hierarchical spatio-temporal disease mapping models in a Bayesian statistical framework (Lawson, 2013). Using integrated nested Laplace approximations (INLA), we were able to measure and map the global and local impact of I-1183, while also taking into consideration the various sociodemographic and neighborhood characteristics of the city of Seattle on violence.

In this paper, we first describe the datasets and their sources used to characterize alcohol outlets, violence, and the various sociodemographic and neighborhood measures used at the census block group level. Next, we detail the different modeling frameworks used for our analysis. Our results are then presented, after describing our model selection criterion. We also include maps of Seattle, to illustrate the spatial risk of violence during the study period. Lastly, we discuss our findings, policy implications, as well as potential future work.

2. Materials and methods

2.1. Data

This study combined data from three different sources, which are each outlined in detail below. The various data sources allowed us to gain the most accurate depiction of alcohol outlets and violence, as well as sociodemographic and neighborhood characteristics.

2.2. Units of analysis

Our spatial unit of analysis was at the census block group level, which is the smallest geographical unit for which the United States Census Bureau publishes sample data. For Seattle, WA, we examined 567 census block groups. During 2010, Seattle had a population of 608,660 residents, where each census block group, on average, had 1272 residents. Our temporal unit of analysis was year and ranged from 2010 to 2013, which was two years before the implementation of I-1183 and two years after.

2.3. Alcohol outlet data

Seattle, WA, alcohol outlets for 2010–2013 were obtained from the Washington State Liquor and Cannabis Board (WSLCB), formerly the Washington State Liquor Control Board. The Board's primary function is the licensing of alcohol outlets, as well as the enforcement of the state's alcohol, tobacco, and cannabis laws. Alcohol outlets are classified into two primary categories: off-premises and on-premises. Off-premises alcohol outlets are able to sell beer and/or wine in bottles, cans, and original containers for off-premises consumption. Under I-1183, off-premises outlets include retailers with at least 10,000 square feet, generally comprising grocery stores and warehouse clubs. On-premises alcohol outlets include restaurants, bars, taverns, and nightclubs. Active alcohol outlet addresses were successfully geocoded, 99.8%, using a hybrid method, where details of this approach are noted elsewhere (Murray et al., 2011). As the primary independent variables of interest, both off-premises and on-premises alcohol outlets were retained as counts in each census block group in each year.

2.4. Violence data

Violence data, both aggravated and non-aggravated assaults for 2010–2013, were obtained from the Seattle Police Department (SPD). The SPD uses Uniform Crime Reporting (FBI. Uniform Crime Reports 2010) definitions for all reported crimes in the city. Aggravated assaults are "an unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded." Non-aggravated assaults are "assaults or attempted assaults where no weapon was used or no serious or aggravated injury resulted to the victim." Incident reports, which indicated the occurrence of either aggravated or non-aggravated assaults, were extracted from the publicly available SPD's crime data portal

(Seattle Police Department 2014). Although the SPD reports the total number of personal crimes to the public, which includes assaults, the SPD only makes available to the public a subset of incident reports reflective of these crimes due to privacy issues. According to the SPD's Data Release Rules, "Narratives, remarks, text, entities and descriptions may contain personal, juvenile, and national security information and are not released to the public." Assaults were ultimately geocoded previously by the SPD, and are the official geographic information of record. As the primary dependent variables of interest, both aggravated and non-aggravated assaults were retained as counts in each census block group in each year.

2.6. Sociodemographic and neighborhood data

Sociodemographic and neighborhood data from 2010 were obtained from Environmental Systems Research Institute's (ESRI) Updated Demographics database (ESRI Demographics 2010). For each census block group, we examined various measures that are known to confound the relationship between alcohol and violence (Zhu et al., 2006). We included the percentage of the population aged 15–29 years, and households with an annual income below \$15,000, which is a measure of socioeconomic status. Other neighborhood characteristics included the percentage of vacant units, a density measure for public transportation stops, in addition to whether the census block group was in the downtown Seattle area. All density measures were standardized to the square mileage of each census block group. We measured the percentage of black, female-headed households, which was operationalized as a factor variable in an effort to address multicollinearity. To capture the racial and ethnic diversity of Seattle, we considered a diversity index, which ranged from 0 (least) to 100 (most diverse). The diversity index (ESRI. Major Trend Revealed in Census 2010) is defined as the likelihood that two persons, selected at random from the same area, would belong to a different race or ethnic group. The index calculations accommodate up to six single race groups and ethnicity: White, Black, American Indian or Alaska Native, Asian, Native Hawaiian or Pacific Islander, some other race, and Hispanic or Latino. Finally, since the presence of non-alcohol retailers has been shown to impact the relationship between alcohol and violence significantly (Grubesic et al., 2013), we considered two additional measures. The first measure was a location quotient (LQ) for commercial land use, which compares the proportion of commercial land use in each block group to the proportion of commercial land use in the entire city of Seattle. The second was a measure of risky retailers, which may also increase violence. This measure was operationalized as a density, and was a function of the number of check cashing stores, pawnshops, and convenience stores within each census block group.

2.7. Analysis

To determine the spatio-temporal relationship between alcohol outlets and assaults, we used a variety of spatio-temporal disease mapping models. We assumed the number of assaults, in census block group i ($i = 1, \ldots, 567$) and in year t ($t = 2010, 2011, 2012, 2013$), were Poisson distributed with intensity $E_{it}\lambda_{it}$, where λ_{it} is the relative risk of assault. The number of aggravated and non-aggravated assaults was modeled separately. The expected number of assaults is a constant and proportional to the population size for each census block group (Waller et al., 2007). Specifically, $E_{it} = R_t * n_i$, where R_t is the observed number of aggravated or non-aggravated assaults over the entire population for a specific year t, and n_i is the total population size based on 2010 estimates for each census block group. As originally proposed (Bernardinelli et al., 1995) and recently presented (Blangiardo et al., 2013), the linear predictor of our first parametric model (referred to as M1) had the following form: $\log(\lambda_{it}) = \beta_0 + u_i + v_i + (\beta_1 + \delta_i)t$, where β_0 is the intercept and represents the overall assault risk, and u_i and v_i represent the structured and unstructured census block group-specific random effects, respectively. Both spatial effects are assumed to follow an intrinsic Gaussian Markov random field (IGMRF) (Rue and Held, 2005), where the joint prior density is defined as $\pi(\boldsymbol{u}|\sigma_u^2) \propto \exp(-1/2\sigma_u^2 \boldsymbol{u}^T \boldsymbol{R_u} \boldsymbol{u})$ and $\pi(\boldsymbol{v}\ |\sigma_v^2) \propto \exp(-1/2\sigma_v^2\ \boldsymbol{v}^T \boldsymbol{R_v} \boldsymbol{v})$, and $\boldsymbol{R}$ represents the structure matrix. For the unstructured spatial effects, $\boldsymbol{R_v}$ is simply the identity matrix; whereas, for the structured spatial effects, the diagonal entries of $\boldsymbol{R_u}$ represent the number of adjacent neighbors for census block group i and the off-diagonal entries are indicators of whether two census block groups are neighbors. The parameter β_1 characterizes the overall linear trend in assaults, while $\boldsymbol{\delta}$ describes the interaction between space and time. Each δ_i can be interpreted as the differential time trend, and allows for a measurement of the specific departure in each area from the overall time trend captured in β_1. To avoid multicollinearity, time was mean-centered. While the first parametric model assumed an unstructured differential temporal trend for each census block group, defined again using an IGMRF, we also assessed a second parametric model (M2), but with a structured differential trend instead.

To relax the linearity constraint on the differential temporal trend present in the parametric models (M1 and M2), we specified a nonparametric dynamic temporal trend (Knorr-Held, 1999), such that: $\log(\lambda_{it}) = \beta_0 + u_i + v_i + \gamma_t + \phi_t$, where the overall intercept (β_0) and the structured (u_i) and unstructured (v_i) spatial effects are specified just as in M1 and M2. The new parameters γ_t and ϕ_t represent the structured and unstructured temporal effects, respectively. The structured temporal effects are assumed to have either a random walk of order 1 (M3) or of order 2 (M4), such that $\gamma_t|\gamma_{t-1} \sim N(\gamma_{t-1}, \sigma_\gamma^2)$ or $\gamma_t|\gamma_{t-1}, \gamma_{t-2} \sim N(2\gamma_{t-1} + \gamma_{t-2}, \sigma_\gamma^2)$, respectively. The unstructured temporal effect was assumed to have an exchangeable prior distribution, $\phi_t \sim N(0, \sigma_\phi^2)$.

We then examined a number of space-time interaction based models, which extended our initial models but allowed for a combination of structured and unstructured spatio-temporal effects. The basic form of the various interaction models was specified as: $\log(\lambda_{it}) = \beta_0 + u_i + v_i + \gamma_t + \phi_t + \delta_{it}$, where all parameters are defined similarly as in M3 and M4, except that the new parameter, $\boldsymbol{\delta}$, follows a Gaussian distribution. The precision matrix of this Gaussian distribution is given by $\tau_\delta \boldsymbol{R}_\delta$, such that $\tau_\delta = 1/\sigma_\delta^2$ is a scalar for the precision and $\boldsymbol{R}_\delta$ is the structure matrix that defines the spatio-temporal dependence. We examined four specific interaction models (Types I, II, III, and IV), commonly used in spatio-temporal disease mapping settings (Knorr-Held, 1999). Models 5 and 6 assumed a Type I interaction between the unstructured spatial (v_i) and temporal (ϕ_t) effects, but varying the random walk assumption, respectively, for the structured temporal effects (γ_t). Models 7 and 8 assumed a Type II interaction between the structured temporal (γ_t) and unstructured spatial (v_i) effects. Models 9 and 10 assumed a Type III interaction between the unstructured temporal (ϕ_t) and structured spatial (u_i) effects. Finally, Models 11 and 12 assessed the more complex Type IV interaction between the structured spatial (u_i) and temporal (γ_t) effects. Further details about the various interaction models considered are provided elsewhere (Knorr-Held, 1999). All models considered were fully adjusted for both types of alcohol outlets and various sociodemographic and neighborhood characteristics; each model included these as fixed effects, where their corresponding coefficients, α, were of primary interest.

Utilizing integrated nested Laplace approximations (INLA) (Rue et al., 2009), we were able to investigate these spatio-temporal disease mapping models in a Bayesian statistical framework. INLAs are a method for approximate Bayesian inference, and, in general, there are three stages considered. Stage one focuses on the observational model, stage two focuses on the latent Gaussian field, and the final stage focuses on hyperparameters, which are not always assumed Gaussian. Because it is not possible to compute the posterior distributions analytically, often times, Markov chain Monte Carlo algorithm (MCMC) methods have been used. Due to several limitations in the use of MCMC methods, however, and with these models having assumed latent Gaussian fields, the INLA approach was extremely attractive. Although the INLA approach is an approximation-based method, it is quite accurate, avoids estimation in the presence of significant Monte Carlo error, and minimizes computational time (Rue and Held, 2005, Rue et al., 2009).

To complete the Bayesian statistical framework, we assumed various prior distributions for the parameters of interest. All α and β coefficients were assumed to have traditional, weakly informative priors, such that α, $\beta \sim Normal(0,\ 10^3)$. For the unstructured and structured spatial and temporal precision components, we chose to assume fairly non-informative prior distributions, such that $\tau_v,\ \tau_u, \boldsymbol{\tau_\gamma}, \boldsymbol{\tau_\phi}, \boldsymbol{\tau_\delta} \sim Gamma(1, 0.5)$. To assess sensitivity to prior distributional assumptions for the spatial and temporal variability, we also considered two other prior distributional settings for our final model. Parallel to others (Carroll et al., 2015), we assumed moderately informative spatial variance components, and considered $Gamma(2, 1)$ as well as $Gamma(1, 1)$, instead of the traditional non-informative setting.

To compare the various spatio-temporal models, we used the deviance information criterion (DIC) which is a measure of both model complexity and fit and is analogous to the Akaike information criterion (AIC) in the traditional frequentist statistical framework (Jin et al., 2005). The INLA approach computes the DIC, which is defined as $DIC = \bar{D} + p_D$, where $\bar{D}$ is the posterior mean of the deviance and p_D is the number of effective parameters. Models that fit well have the smallest DIC score, which implies a small $\bar{D}$ and a small p_D. In considering an important difference in DIC, there have been suggestions based on AIC criterion that models receiving values within 1-2 of the best deserve consideration, while 3–7 have considerably less support (Burnham and Anderson, 1998). If DIC values are similar, a more complex model may fit better than a simpler one, but will have less precise parameter estimates; therefore, the best choice will be some intermediate degree of complexity (Kéry, 2010).

3. Results

Fig. 1 shows the reported aggravated and non-aggravated assaults, as well as the number of off-premises and on-premises alcohol outlets in Seattle, WA, 2010–2013. Overall, between 2010 and 2013, non-aggravated assaults increased 74%. More serious crimes, captured in aggravated assaults, also appeared to increase over time, but with an increase of 42% over the study period. The number of off-premises alcohol outlets increased in a relatively linear fashion to a total of 635 outlets of this type in the city of Seattle by 2013. A similar increase in on-premises alcohol outlets was apparent: in 2013, there were as many as 1760 outlets present. Basic descriptive statistics for the sociodemographic and neighborhood characteristics of Seattle are presented in Table 1. On average, each census block group has a commercial LQ of 1 and about 6% vacant units. The overall diversity index in the city's 567 census block groups is 50, indicating that for two randomly selected people, there is a 50% chance they would be of different races. In addition, public transportation stop density is approximately 20 stops per square mile, and the average percentage of household incomes below \$15,000 is only 9%. To further describe the distribution of the sociodemographic and neighborhood characteristics, histograms are presented in Supplementary Fig. 1.

We also examined the correlation between all sociodemographic and neighborhood characteristics using a variance inflation factor (VIF) (Chatterjee and Hadi, 2015), where all VIFs were less than 2.0 (results presented in Supplementary Table 1), indicating minimal multicollinearity. Lastly, Supplementary Fig. 2 includes maps of these characteristics to display their spatial correlation, and Supplementary Table 2 displays the results of the corresponding test statistic and p-value via the Moran's I using the Monte-Carlo approach (Florax and Folmer, 1992). All sociodemographic and neighborhood characteristics displayed significant evidence of autocorrelation.

DIC values for the parametric and nonparametric models are provided in Table 2, separately for aggravated and non-aggravated assaults. For both measures of violence, the nonparametric models seem better suited compared to the parametric models. Specifically, the space-time interaction models, which assumed both unstructured space and time

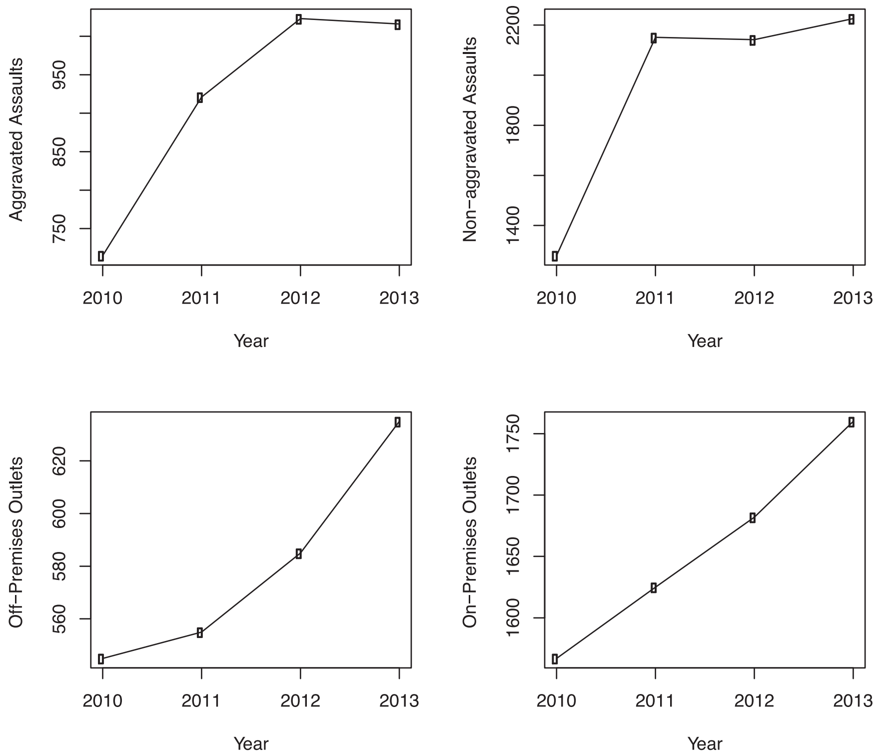

Fig. 1. Temporal trends in the number of reported aggravated and non-aggravated assaults and off-premises and on-premises alcohol outlets for Seattle, WA 2010–2013.

Table 1
Descriptive statistics for Seattle, WA census block groups ($n = 567$)*

	Minimum	Maximum	Mean	SD
Commercial location quotient	0.000	20.290	0.996	8.211
% Vacant units	0.000	0.259	0.063	0.090
Diversity index	10.400	93.400	50.080	27.931
% Household income < $15,000	0.000	0.654	0.088	0.246
Public transportation stop density	0.000	147.900	19.520	55.412
% Age 15–29 years	0.057	0.885	0.224	0.297
Risky retailer density	0.000	36.530	1.717	14.654
Black, female-headed households (factor)	-2.193	4.152	0.000	2.112
Downtown Indicator (*N*, %) Yes 29 (5.115) No 538 (94.885)				

* SD = standard deviation

(Type I), appeared to have a better fit for both types of violence. Regardless of the random walk specification, M5 and M6 have the best balance between goodness of fit and model simplicity, although their effective number of parameters is larger compared to the other models. Therefore, we chose to focus on M5 for both non-aggravated and aggravated assaults as our final models. We also assessed the DIC values for the various prior distributional assumptions to determine sensitivity for our final models; all DIC values were comparable.

Table 3 presents the posterior estimates for the fixed and random effects of Model 5, for both aggravated and non-aggravated assaults. In addition to the posterior mean and standard deviation, we also present a column labeled “RR” for the estimated relative risk, and the corresponding 95% credible intervals. For aggravated assaults, there is a positive relationship between both off-premises and on-premises alcohol outlets. Specifically, the estimated average relative risk is 1.077, indicating that for every additional off-premises alcohol outlet in a given census block group, the risk of aggravated assault increases by approximately 8%. Similarly, aggravated assaults increase by approximately 5% for each additional on-premises alcohol outlet. Census block groups that have more commercial properties and larger percentages of vacant units tend to have significantly higher risk of aggravated assault. For non-aggravated assaults, the trends are similar to the more serious crimes, but additional significant relationships are evident. For each additional off-premises and on-premises alcohol outlet, the risk of non-aggravated assaults increases

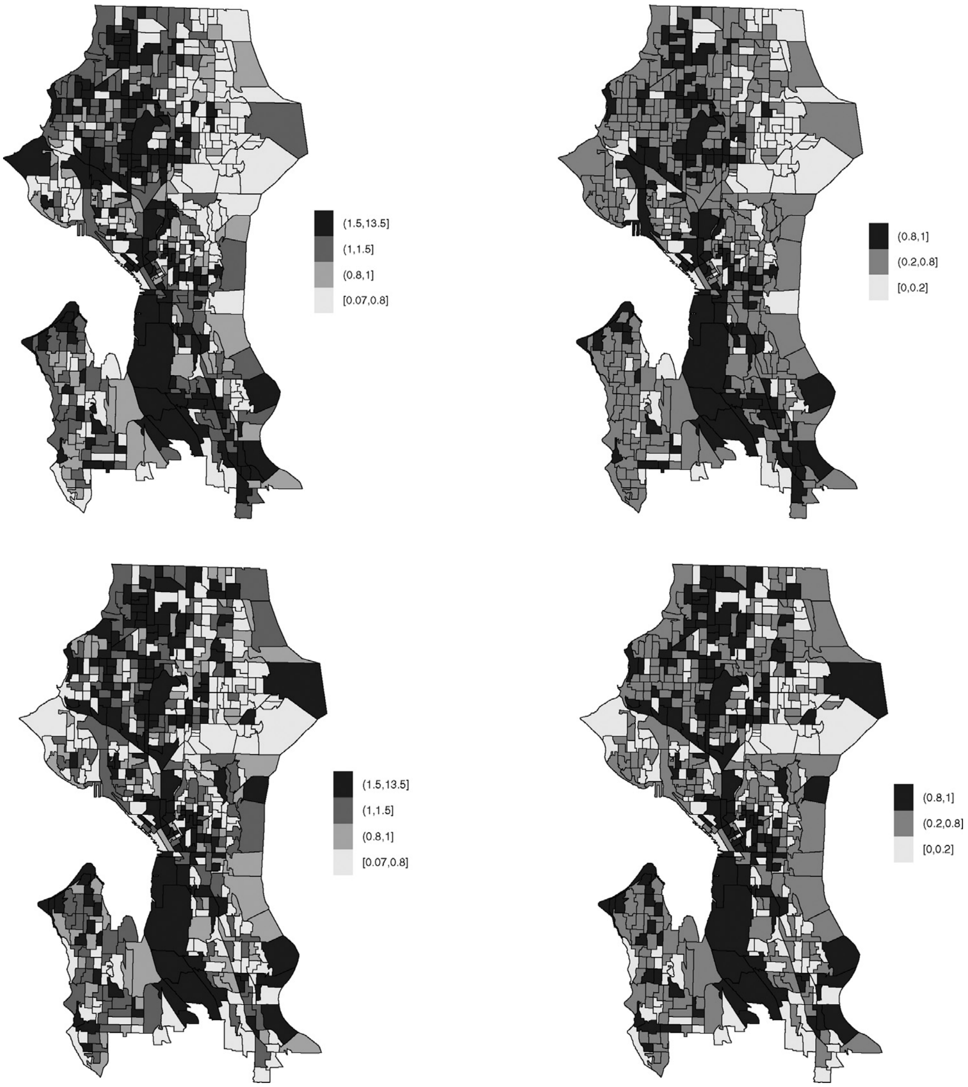

Fig. 2. Posterior mean for the census block group-specific relative risks (left), $RR_i = \exp(u_i + v_i)$, and the posterior probability of exceeding 1 (right), $p(RR_i > 1 | \boldsymbol{y})$, in Seattle, WA, 2010–2013 via Model 5 for aggravated (top panel) and non-aggravated (bottom panel) assaults.

Table 2
Summary of model selection criterion: *DIC* (Deviance Information Criterion), *pD* (effective number of parameters), and $\bar{D}$ (deviance) for aggravated and non-aggravated assault models*.

	Aggravated assaults			Non-aggravated assaults		
Model type	*DIC*	*pD*	$\bar{D}$	*DIC*	*pD*	$\bar{D}$
Parametric						
M1: Parametric (EXCH)	5031	381	4650	6879	507	6372
M2: Parametric (CAR)	5023	350	4674	6893	471	6421
Nonparametric						
M3: Differential (RW1)	5035	306	4729	6963	385	6579
M4: Differential (RW2)	5034	305	4729	6961	383	6578
M5: Space-time I (RW1)	5011	411	4600	6826	597	6228
M6: Space-time I (RW2)	5010	410	4601	6826	595	6231
M7: Space-time II (RW1)	5034	307	4727	6961	385	6575
M8: Space-time II (RW2)	5032	307	4725	6960	386	6574
M9: Space-time III (RW1)	5024	356	4669	6852	525	6327
M10: Space-time III (RW2)	5024	356	4668	6851	525	6326
M11: Space-time IV (RW1)	5033	306	4727	6961	384	6576
M12: Space-time IV (RW2)	5032	305	4727	6959	383	6576

* EXCH = exchangeable; CAR = conditional autoregressive; RW1 = random walk of order 1; RW2 = random walk of order 2.

Table 3
Posterior estimates of Model 5 for aggravated and non-aggravated assaults*.

	Aggravated assaults				Non-aggravated assaults			
Parameter	Mean	SD	RR	95% CI	Mean	SD	RR	95% CI
Fixed effects								
Intercept	−1.344	0.314	0.261	(0.141, 0.482)	−1.309	0.283	0.270	(0.155, 0.470)
Off-premises outlets	0.074	0.021	1.077	(1.033, 1.122)	0.059	0.019	1.061	(1.022, 1.101)
On-premises outlets	0.045	0.006	1.046	(1.033, 1.059)	0.049	0.006	1.050	(1.038, 1.063)
Commercial location quotient	0.134	0.042	1.144	(1.053, 1.243)	0.118	0.039	1.125	(1.042, 1.216)
% Vacant units	0.107	0.045	1.113	(1.019, 1.216)	0.121	0.042	1.128	(1.039, 1.225)
Diversity index	0.500	0.085	1.648	(1.396, 1.946)	0.432	0.072	1.540	(1.337, 1.774)
% Household income < $15,000	0.095	0.054	1.099	(0.988, 1.223)	0.152	0.050	1.165	(1.055, 1.285)
Public transportation density	0.091	0.052	1.095	(0.989, 1.212)	0.120	0.047	1.127	(1.027, 1.236)
Downtown	0.236	0.241	1.266	(0.789, 2.033)	0.166	0.221	1.181	(0.765, 1.822)
% Age 15–29 years	0.111	0.057	1.117	(0.998, 1.250)	0.060	0.050	1.062	(0.963, 1.170)
Risky retailer density	0.080	0.043	1.083	(0.995, 1.179)	0.056	0.040	1.058	(0.977, 1.145)
Black, female-headed households (factor)	-0.035	0.062	0.966	(0.856, 1.090)	-0.026	0.055	0.974	(0.875, 1.085)
Random effects (Precision, $\tau = 1/\sigma^2$)								
Unstructured spatial τ_v	2.162					1.900		
Structured spatial τ_u	2.163					4.191		
Unstructured temporal τ_γ	3.344					1.323		
Structured temporal τ_ϕ	3.848					2.525		
Unstructured space-time τ_δ	16.596					11.579		

* SD = standard deviation; RR = relative risk; CI = credible interval

by an average of 6% and 5%, respectively. Similar to the more serious crimes, census block groups with more commercial properties and larger percentages of vacant units appears to have more non-aggravated assaults. In addition, those same census block groups with more access to public transportation, more diverse populations, and more households with an annual income less than $15,000 also tend to experience more non-aggravated assaults. The census block group-specific random effects are also presented in Table 3. The unstructured and structured spatial and temporal precision terms are relatively small for both aggravated and non-aggravated assaults, indicating more spatial heterogeneity present in Seattle, after adjusting for the alcohol outlets as well as the various sociodemographic and neighborhood characteristics. However, there appears to be less spatio-temporal variability in both types of assault, as suggested by the larger unstructured space-time precision terms.

Fig. 2 presents a further exploration of the spatial risks of both aggravated and non-aggravated assaults: the posterior mean for the census block group-specific relative risks, as well as the posterior probability of these relative risks exceeding 1. The top panel of Fig. 2 displays the spatial risks of aggravated assaults, after adjusting for the presence of off-premises and on-premises alcohol outlets, as well as the various sociodemographic and neighborhood characteristics considered, in addition to the map of the exceedance probabilities for aggravated assault risk. A number of contiguous census block groups in the south-central portion of Seattle display increased risk, as characterized by a spatial relative risk greater than 1, as well as posterior probabilities above 0.8. The northwestern portion of Seattle also displays increased risk of aggravated assault. Similarly, the bottom panel of Fig. 2 displays maps related to non-aggravated assaults, where increased risks in the south-central portion of the city are also apparent. Several larger census block groups along the eastern border of Seattle display increased risk of non-aggravated assault as well.

Although we initially compared the overall DIC values for the various models considered, we also considered the patterns of local DIC by census block group for Model 5. The local DIC for aggravated and non-aggravated assaults in Seattle, WA in 2010 and in 2013 is mapped in Fig. 3. The overall pattern in local DIC values show evidence of spatial variation in DIC, with higher DIC values more apparent along the south-western borders of the city. Plotting these DIC values allows for the diagnostic visualization of our final model, where we focus on the spatial consideration of local DIC statistics for model selection and goodness-of-fit evaluation (Wheeler et al., 2010).

4. Discussion

Assessments of the spatio-temporal relationship between alcohol and violence have gained much attention in recent decades. While there is a consistent positive association between alcohol outlets and violence, even after adjusting for various sociodemographic and neighborhood characteristics, longitudinal studies examining how this relationship changes over time are essential in fully characterizing this relationship. Our study assessed the spatio-temporal relationship between alcohol and violence in Seattle, WA 2010–2013 during the implementation of I-1183, which privatized alcohol sales and distribution. We characterized violence separately as aggravated and non-aggravated assault, as opposed to an overall measure of assault. Similarly, alcohol outlet was operationalized separately as off-premises and on-premises. We were able to measure and map the spatio-temporal relationship to gauge the impact of I-1183. As both off-premises and on-premises alcohol outlets increased, the risk of assault also increased, even after adjusting for various sociodemographic and neighborhood characteristics.

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Fig. 3. Local *DIC* (Deviance Information Criterion) for Model 5 for aggravated (top panel) and non-aggravated (bottom panel) assaults in Seattle, WA 2010 and 2013.

The spatio-temporal aspect of our study allowed us to formally examine if the observed increase in alcohol availability directly impacted violence, even after adjusting for sociodemographic and neighborhood characteristics. While our spatio-temporal models did not include an overall fixed temporal component, it did include a random temporal and spatio-temporal component allowing us to estimate the relationship between alcohol and violence for every year in our study. Due to the longitudinal design of our study, our findings lend themselves to examining the causal association between alcohol availability and violence, both before and after the implementation of I-1183.

To our knowledge, this is the first study to examine this spatio-temporal relationship in Washington after the passage of I-1183, where violence and alcohol are uniquely identified to further explain this often-dynamic relationship. Our study also has notable strengths. First, the positive relationship we estimated between alcohol and violence is consistent with other spatio-temporal studies and adds to an increasing body of research concerning alcohol-related violence (Gruenewald and Remer, 2006, Popova et al., 2009, Zhang, 2015). In addition to the common confounders of this relationship, such as the presence of vacant units, household incomes below $15,000, and race/ethnicity captured in a diversity index, we also considered the presence of non-alcohol retailers. We found that census block groups with more commercial properties were at an increased risk of both types of violence considered. Although we also measured the role of potentially risky retailers, including pawnshops and check cashing facilities, we did not find any significant effects. Next, we considered various hierarchical Bayesian models to assess this spatio-temporal relationship using INLA. Although many alcohol and violence based studies use the traditional MCMC approach to estimate parameters of interests (Britt et al., 2005, Xu et al., 2012, Zhu et al., 2006, Yu et al., 2008), we chose INLA for its many features. In contrast to MCMC, this method avoids estimation in the presence of significant Monte Carlo error, minimizes computational time (Rue and Held, 2005, Rue et al., 2009); in addition, this approximation method is quite accurate. Lastly, our work adds to a growing body of literature that assesses the impact of policy on alcohol-related violence (Xu et al., 2012, Yu et al., 2008). In looking at the effect of privatization, we were able to further examine the impact of a substantial alcohol-related policy on both aggravated and non-aggravated assaults. Through these natural experiments, researchers can thoroughly assess both the spatial and temporal trends in alcohol availability and violence. For instance, our study found that areas with more vacant units and higher percentages of homes with an annual income less than $15,000 also tend to have significantly more assaults, in the presence of both types of alcohol outlets. In creating polices around alcohol outlet licensing, these specific neighborhood characteristics should, at the very least, be considered.

Although our study benefits from the longitudinal nature of our spatio-temporal data, it has a few limitations. First, assessing the effect of privatization over a 4-year period, 2010–2013, may not fully capture the magnitude of the policy impact. Since the policy became effective in 2012, there may be a lag in how this policy impacts violence or any other alcohol related harm, although, we saw immediate, significant increases in alcohol outlets in 2012 and 2013. While our research attempts to overcome the challenges of cross-sectional studies, future assessments of this spatio-temporal relationship in the city of Seattle should incorporate additional years. Another concern involves unmeasured confounders. We found that even before the implementation of I-1183, violence increased between 2010 and 2011; therefore, the causal relationship between the policy and violence is not valid during these years and it is quite possibly a function of other unmeasured individual and/or neighborhood level characteristics. A third concern involves the generalizability of our results to the entire state of Washington, which I-1183 impacts. While our study focused on a more urban setting, the Seattle-based census block groups considered are far from a random sample from the entire state; therefore, making generalizations about the impact of I-1183 on the relationship between alcohol and violence is challenging. Our analysis, nonetheless, includes a variety of sociodemographic characteristics, with somewhat of a range, such age, household income, and diversity. Lastly, due to privacy concerns, the SPD does not release a complete inventory of aggravated and non-aggravated assault data for public use and/or analysis. Only 40–60% of the data are actually made available for inspection. That said, we observed significant increases in both aggravated and non-aggravated assaults over the study period, closely mimicking the increases reported via publicly available incident reports. Further, although these observed increases are drawn from the smaller number of publicly available assault incident reports, our findings remain consistent with other studies that have pursued research in this domain. Namely, increases in alcohol outlets and alcohol availability are associated with increases in violence.

In considering next steps, we would like to examine the impact of Initiative 502, which defined and legalized small amounts of marijuana-related products for adults over the age of 21, in the state of Washington on the already documented association between alcohol outlets and violence. This policy was also implemented in 2012, similar to I-1183. Comparable to the role of alcohol outlets in communities, marijuana dispensaries may also increase availability, subsequent use/misuse of marijuana and may also be located in neighborhoods that already display a positive relationship between alcohol and violence (Mair et al., 2015). Further examining this association would provide more evidence of the role both alcohol and marijuana play on violence. In addition to examining the impact of legalization of marijuana, we would also like to consider the impact of the changes in the various sociodemographic and neighborhood measures, as opposed to using those measures captured by the US Census in only 2010. The use of projections is increasingly becoming popular (Kanaroglou et al., 2009, Preston et al., 2000, Smith and Shahidullah, 1995, Smith et al., 2006); therefore, exploring the temporal impact of these measures using these projections would provide a more clear examination of their influence on violence. Lastly, we would like to examine the impact of alcohol outlets using spatially varying coefficient models (Wheeler et al., 2010). These models expand on our current spatio-temporal models, but looks at the impact of alcohol outlets varying in each census block group, as opposed to finding one overall impact of alcohol outlets on violence.

Finally, our study's findings suggest that the relationship between alcohol and violence is complex; however, capturing this relationship over time in a spatial context is necessary to fully examine this association. More longitudinal studies are essential to provide evidence of the causal relationship between alcohol outlets and violence in the presence of significant policy changes. These additional studies could provide important insights to guide policy decisions regarding alcohol outlets in other communities, especially in those other states considering privatizing liquor sales and distribution, such as Pennsylvania, Utah, Virginia, and North Carolina.

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Supplementary Materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sste.2016.08.003.

References

Bernardinelli L, Clayton D, Pascutto C, Montomoli C, Ghislandi M, Songini M. Bayesian analysis of space—time variation in disease risk. Stat Med 1995;14(21-22):2433–43.
Blangiardo M, Cameletti M, Baio G, Rue H. Spatial and spatio-temporal models with R-INLA. Spatial Spatio-Temporal Epidemiol 2013;7:39–55.
Britt H, Carlin BP, Toomey T, Wagenaar A. Neighborhood level spatial analysis of the relationship between alcohol outlet density and criminal violence. Environ. Ecol Stat 2005;12:411–26.
Burnham K, Anderson D. Model selectionand inference. New York, NY: A practical information-theoretic approach Springer; 1998.
Carroll R, Lawson A, Faes C, Kirby R, Aregay M, Watjou K. Comparing INLA and OpenBUGS for hierarchical Poisson modeling in disease mapping. Spatial Spatio-Temporal Epidemiol 2015;14:45–54.
Chatterjee S, Hadi AS. Regression analysis by example. John Wiley & Sons; 2015.
ESRI Demographics; 2010 Available from http://www.esri.com/data/esri_data.
ESRI. Major Trend Revealed in Census; 2010 Data [cited 2016 July 7,]. Available from http://www.esri.com/news/arcnews/winter1112articles/major-trend-revealed-in-census-2010-data.html.
FBI. Uniform Crime Reports. 2010.
Florax R, Folmer H. Specification and estimation of spatial linear regression models: Monte Carlo evaluation of pre-test estimators. Reg Sci Urban Econ 1992;22(3):405–32.
Grubesic T, Murray AT, Pridemore W, Tabb LP, Liu Y, Wei R. Alcohol beverage control, privatization and the geographic distribution of alcohol outlets. BMC Public Health 2012;12. doi:10.1186/1471-2458-12-1015.
Grubesic T, Pridemore W. Alcohol outlets and clusters of violence. Int J Health Geogr 2011;10(1):30 PubMed PMID. doi:10.1186/1476-072X-10-30.
Grubesic TH, Pridemore WA, Williams DA, Philip-Tabb L. Alcohol outlet density and violence: the role of risky retailers and alcohol-related expenditures. Alcohol Alcohol 2013;48(5):613–19.
Gruenewald PJ, Freisthler B, Remer L, LaScala E, Treno A. Ecological models of alcohol outlets and violent assaults: crime potentials and geospatial analysis. Addiction 2006;101:666–77.
Gruenewald PJ, Remer L. Changes in outlet densities affect violence rates. Alcohol: Clin Exp Res 2006;30(7):1184–93.
Jin X, Carlin BP, Banerjee S. Generalized hierarchical multivariate CAR models for areal data. Biometrics 2005;61(4):950–61.
Kanaroglou PS, Maoh HF, Newbold B, Scott DM, Paez A. A demographic model for small area population projections: an application to the census metropolitan area of Hamilton in Ontario. Environ Plann A 2009;41(4):964–79.
Kéry M. ANOVA, mixed models and related analyses. Introduction to WinBUGS for ecologists: bayesian approach to regression. Academic Press; 2010.
Knorr-Held L. 1999 Bayesian Modelling of Inseparable Space-Time Variation in Disease Risk. Sonderforschungsbereich 386, Discussion Paper 147.
Lawson AB. Bayesian disease mapping: hierarchical modeling in spatial epidemiology. CRC press; 2013.
Livingston M, Livingston M, Chikritzhs T, Livingston M, Chikritzhs T, Room R, et al. Changing the density of alcohol outlets to reduce alcohol-related problems. Drug Alcohol Rev 2007;26(5):557–66.
Mair C, Freisthler B, Ponicki WR, Gaidus A. The impacts of marijuana dispensary density and neighborhood ecology on marijuana abuse and dependence. Drug Alcohol Depend 2015;154:111–16.
Murray AT, Grubesic TH, Wei R, Mack EA. A hybrid geocoding methodology for spatio-temporal data. Trans GIS 2011;15(6):795–809.
Popova S, Giesbrecht N, Bekmuradov D, Patra J. Hours and days of sale and density of alcohol outlets: impacts on alcohol consumption and damage: a systematic review. Alcohol Alcohol 2009;44(5):500–16.
Preston S, Heuveline P, Guillot M. Demography: measuring and modeling population processes. Blackwell Publishers; 2000.
Rue H, Held L. Gaussian Markov random fields: theory and applications. CRC Press; 2005.
Rue H, Martino S, Chopin N. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. J R Stat Soc: Ser (Stat Methodol) 2009;71(2):319–92.
Scribner R, Mason K, Simonsen N, Theall K, Chotalia J, Johnson S, et al. An ecological analysis of alcohol-outlet density and campus-reported violence at 32 U.S. colleges. J Stud Alcohol Drugs 2010;71:184–91.
Seattle Police Department; 2014 [cited 2014 January 9]. Available from https://data.seattle.gov.
Smith SK, Shahidullah M. An evaluation of population projection errors for census tracts. J Am Stat Assoc 1995;90(429):64–71.
Smith SK, Tayman J, Swanson DA. State and local population projections: Methodology and analysis. Springer Science & Business Media; 2006.
Waller L, Zhu L, Gotway C, Gorman D, Gruenewald P. Quantifying geographic variations in associations between alcohol distribution and violence: a comparison of geographically weighted regression and spatially varying coefficient models. Stoch Environ Res Risk Assess 2007;21(5):573–88. doi:10.1007/s00477-007-0139-9.
Watts R, Rabow J. Alcohol availability and alcohol-related problems in 213 California cities. Alcohol Clin Exp Res 1983;7(1):47–58.
Wheeler DC, Hickson DA, Waller LA. Assessing local model adequacy in Bayesian hierarchical models using the partitioned deviance information criterion. Comput Stat Data Anal 2010;54(6):1657–71.
Xu Y, Yu Q, Scribner R, Theall K, Scribner S, Simonsen N. Multilevel spatiotemporal change-point models for evaluating the effect of an alcohol outlet control policy on changes in neighborhood assaultive violence rates. Spatial Spatio-Temporal Epidemiol 2012;3(2):121–8.
Yu Q, Scribner R, Carlin B, Theall K, Simonsen N, Ghosh-Dastidar B, et al. Multilevel spatio-temporal dual changepoint models for relating alcohol outlet destruction and changes in neighbourhood rates of assaultive violence. Geospatial Health 2008;2(2):161.
Zhang X. Changes in density of on-premises alcohol outlets and impact on violent crime, 12. Atlanta, Georgia: Preventing Chronic Disease; 2015. p. 1997–2007.
Zhu L, Gorman D, Horel S. Hierarchical Bayesian spatial models for alcohol availability, drug "hot spots" and violent crime. Int J Health Geogr 2006;5(1):54 PubMed PMID. doi:10.1186/1476-072X-5-54.
Zhu L, Gorman DM, Horel S. Alcohol outlet density and violence: a geospatial analysis. Alcohol Alcohol 2004;39(4):369–75.

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