Article

Urban Analytics and City Science

EPB: Urban Analytics and City Science
0(0) 1–16

DOI: 10.1177/2399808320965569
journals.sagepub.com/home/epb
SAGE

Spatiotemporal patterns of alcohol outlets and violence: A spatially heterogeneous Markov chain analysis

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Abstract

Alcohol-related violence remains a serious social and public health problem in the United States. A large corpus of work suggests a positive statistical relationship between alcohol outlet density and violence. However, questions remain as to how neighborhood violence evolves in response to varying access to alcohol outlets. This paper introduces an approach for analyzing the spatial and temporal dynamics of violence and its association with alcohol outlets by embedding the evolution of assault events and outlet density within a spatially heterogeneous Markov chain framework. This framework enables the exploration of spatiotemporal dynamics of alcohol outlets and violence and controls for potentially confounding impacts and spatial heterogeneity. Using a case study at the block group level in Seattle, Washington, the results of this paper suggest that violence is spatially heterogeneous at the local level and locations with sparsely distributed alcohol outlets are less likely to see an increase in violence when compared to areas with higher densities of outlets. Further, the modeling approach helps identify locations that might "tip" into more violent conditions if more outlets were allowed to operate. This paper concludes with a brief discussion of how the methods and results can help improve the management, licensing, and policy development for alcohol outlets in a community.

Keywords

Alcohol, violence, spatiotemporal, Markov chain, spatial analysis

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Introduction

Violence, which manifests in many forms, is a serious social and public health problem in the United States. In particular, violent crime which includes murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault remains a persistent feature in many communities throughout the United States (Hipp, 2015; Wintemute, 2015). For example, although violent crime rates have been steadily declining for many years, 2015 realized the first uptick in violent crime since 2006, registering 372.6 crimes per 100,000 inhabitants (USDOJ, 2016). The most recent UCR statistics from the FBI (USDOJ, 2018) indicate a violent crime rate of 380.6 per 100,000.

There are many factors at the neighborhood level that influence violent crime, including community structure and social disorganization (Sampson and Groves, 1989), collective efficacy (Sampson et al., 1997), labor stratification (Crutchfield, 1989), income inequality (Hsieh and Pugh, 1993), and ethnicity (Peterson and Krivo, 2005). The common theoretical framework(s) for this type of research can be broadly categorized as *social integration*, where the effects of neighborhood sociodemographic characteristics can be connected to crime (Gorman et al., 2013). The underlying processes that link these characteristics to crime can differ, sometimes quite significantly, but all are structured to help develop a deeper understanding of the relevant social mechanisms that fuel violence. A second suite of theories, broadly categorized as *place-based*, are concerned with the specific places or locales in which crime occurs. Routine activities theory (Clarke and Felson, 1993; Cohen and Felson, 1979) is central to this second group, as is the ability to differentiate between crime generators and crime attractors (Parker, 1993). Over the past decade, place-based research has gained momentum in the study of violence. This is particularly true in studies that attempt to connect alcohol outlets to crime (Gorman et al., 2018; Grubesic and Pridemore, 2011; Gruenewald and Remer, 2006 ; Snowden and Freiburger, 2015; Tabb et al., 2016; Wheeler, 2019). In short, these studies and others like them have established a positive statistical relationship between outlet density and violence.

It is interesting to note, however, that the bulk of these previous studies use a cross-sectional approach for evaluating the relationship between outlets and violence, providing little spatiotemporal insight (Tabb et al., 2016). This is problematic for several reasons. First, neighborhoods are dynamic, exhibiting changes in socioeconomic structure and quality of life indicators, over time (Delmelle et al., 2016; Kirk and Laub, 2010). Of course, the velocity in which neighborhoods change can be variable. As detailed by Sampson and Morenoff (2006), poverty traps can be quite persistent in urban locales, but shocks to the system can (and do) occur, fundamentally changing the structure of neighborhoods both directly and indirectly (Chamberlain, 2018). Cross-sectional studies do not have the ability to capture or integrate these dynamics. Second, the process of neighborhood change, including gentrification and its effects on small business activity (some of which may be related to alcohol sales), are also important to contextualize. Third, it is well established that crime is spatially and temporally dynamic (Contreras and Hipp, 2019; Grubesic and Mack, 2008; Rey et al., 2012), often reflecting changes in neighborhood conditions (Nobles et al., 2016). Again, cross-sectional studies are typically ill-equipped to capture these dynamics. Lastly, local changes in policy, including the privatization of alcohol sales, are important to consider when exploring the connections between alcohol outlets and violence. For example, in Washington State, Initiative I-1183 ended the state's monopoly on liquor retailing and allowed the private sector to begin selling liquor in June 2012 (Grubesic et al., 2016). Not only did this lead to an explosion of outlets selling alcohol (Tabb et al., 2016), it increased the cross-border competition in sales (e.g. Washington and Idaho) (Brunt, 2012).

The purpose of this paper is to introduce an approach for analyzing the dynamics of violence and alcohol outlet density over time. Specifically, we embed the evolution of assault events and its association with alcohol outlet density within a spatially heterogeneous Markov chain framework, allowing for the exploration of the spatiotemporal patterns of violence and outlets. This type of approach is both important and instructive for three reasons. First, the use of a spatially informed Markov chain framework helps deepen our understanding of how violent crime evolves in neighborhoods in response to varying landscape of alcohol outlets. Second, this information helps policymakers and law enforcement agencies improve the management and licensing practices for a community by pinpointing locations that may disproportionately suffer from violence when more alcohol outlets are licensed. Finally, Seattle, Washington, provides a perfect natural experiment for this paper. Using data from 2010 and 2011 (i.e. pre-deregulation), 2012 (i.e. trans-deregulation) and 2013 (post-deregulation), the dynamism of outlets and violence captured during an interesting time in the city and state—one that can be instructive for other locations considering the deregulation of alcohol sales (Linnekin, 2019).

The remainder of this paper is organized as follows. In the next section, we situate this investigation in the broader literature on alcohol outlets and violence, highlighting previous spatiotemporal and/or longitudinal work. This is followed by the details of our study area, Seattle, Washington, and the data used for analysis. Next, the general Markov chain framework and its adaption to the dynamics of alcohol outlets and violence are presented. Finally, we detail key findings and conclude with a discussion of relevant policy implications.

Background

Although the literature concerning the spatiotemporal dynamics of alcohol outlets and violence is relatively thin, there are several notable contributions in the literature that address general space–time analysis, as well as work that is alcohol/violence specific. In fact, the development of exploratory space–time methods has greatly accelerated in recent years. Rey et al. (2012) provide an excellent review of these methods. Many of the recent developments include work in space–time visualization (Xiao and Zhou, 2020), spatiotemporal interaction (Grubesic and Mack, 2008; Hu et al., 2018), Bayesian spatiotemporal modeling (Li et al., 2014; Quick et al., 2019) eigenvector filtering (Chun, 2014; Murakami and Griffith, 2019), and network-based analytics (Shiode et al., 2015).

Both longitudinal and spatiotemporal work related to alcohol and violence is relatively sparse, but there are a handful of important contributions in this domain. For example, Gruenewald and Remer (2006) examined alcohol outlet densities and hospital discharges related to assault events over 6 years at California, highlighting how outlet densities affect violence rates. The results suggest that every six outlets accounted for one additional violent assault that required an overnight stay at a hospital. Tabb et al. (2016) investigated the changes in alcohol outlets and its impact on assaultive events in Seattle between 2010 and 2013. The results suggest that for every new off-premises outlet that sold liquor, aggravated assault increased by about 8% in a given block group. Similarly, non-aggravated assaults increased by 6%. Further, for every on-premises outlet in a given block group, both aggravated and non-aggravated assaults increased by about 5%. Yu et al. (2008) leverage hierarchical Bayesian analysis and changepoint models to explore the impacts of outlet closures in Los Angeles after the 1992 Civil Unrest related to Rodney King. The results suggest that drops in assaultive violence occurred one year after the reduction in availability, but with a significant statistical effect that lasted approximately five years. Livingston (2011) explores the longitudinal relationship between outlets and domestic violence. The results suggest that outlet density, regardless of type (e.g. off-premises, on-premises), has a positive and statistically significant impact, over time, on domestic violence in Melbourne. Rowland et al. (2016) examined how outlet density impacts adolescent consumption in Australia. The results suggested that a 10% increase in density of outlets was associated with a 17% increase in odds of adolescent alcohol consumption.

All these studies suggest that there is a significant positive relationship between alcohol outlet density and violence rates, which is consistent with findings of most cross-sectional studies. But the connection between alcohol outlets and violence is not necessarily a permanent condition. For example, Xu et al. (2012) used a hierarchical change-point model to explore the impacts of several new alcohol outlet control policies implemented in New Orleans, Louisiana, during 1997. The results suggest that the policies yielded a statistically significant decrease in the positive association between assault events and off-premise outlet density. This is an important result because it suggests that policy interventions, which seek to reduce alcohol-related violence, can work.

The major weakness of cross-sectional analyses is that they cannot account for neighborhood dynamics or the variable spatiotemporal nature of violence. Longitudinal studies are more robust in detecting the relationship between violence and alcohol availability, minimizing the possibility that changes in outlet density are attributed to unobserved variables (Livingston et al., 2007). However, the vast majority of cross-sectional and longitudinal studies in the literature focus on exploring the causal relationship between alcohol availability and violence. Thus, while the study area, context, and variables might change, the results are largely consistent, reflecting a positive association between outlets and violence. That said, significant questions remain as to how neighborhood violence evolves in response to varying alcohol access and availability. For example, are neighborhoods with high densities of alcohol outlets more likely to transition to a more violent state, compared with those with low densities of alcohol outlets? If so, when?

Previous studies have demonstrated that Markov chain framework can be used to effectively quantify changes in crime through space and time (Rey et al., 2012). However, it remains unknown how to assess the extent to which these changes in crime are associated with other variables. To this end, we explore the evolution of violence and its association with alcohol outlet density by using a combination of spatially explicit clustering and conditional Markov chains. Specifically, we cluster block groups into nine contiguous regions based on a set of socio-economic and demographic variables that are known to confound the relationship between alcohol and violence; then we use conditional Markov chains to assess the extent to which the dynamics of violence is conditioned upon alcohol outlet density in each region. This type of analysis is critical for neighborhoods, public health, and law enforcement officials that are grappling with alcohol-related problems, as well as agencies charged with the regulation, management, and licensing processes associated with alcohol outlets.

Study area and data

Seattle, Washington, serves as the study area for this analysis. Seattle is a large and growing city. At the time of alcohol deregulation, it had approximately 650,000 residents (Balk, 2014).[1] As mentioned previously, data from this era provide a good natural laboratory for this research because of the passage of I-1183, which ended the state's monopoly on liquor retailing and allowed retail stores with at least 10,000 square feet (e.g. grocery stores, wholesale clubs, drug stores) to begin selling liquor in June 2012 (Grubesic et al., 2016). The bill was controversial because it was largely sponsored by the warehouse club Costco, which injected a record setting \$22 million into the campaign to support the passage of I-1183 (Allison, 2011). Although I-1183 was a statewide measure, it is important to note that many of precincts and/or neighborhoods in the city of Seattle voted against passage, while many of the suburban areas in King and Snohomish counties voted in favor of I-1183 (Wagoner, 2011).[2]

The 2010 block group data ($n = 567$) for the city of Seattle serve as the geographic base files for this analysis. We recognize that these types of administrative boundaries cannot hope to capture all of the important ecological, cultural, and political subtleties that percolate within complex urban environments, but they do provide more spatial resolution than tracts or ZIP codes (Grubesic, 2008).

Alcohol outlet data were obtained from the Washington State Liquor and Cannabis Board (WSLCB, 2013) for 2010–2013. Outlet density calculations were generated using a simple container metric—outlets per square kilometer—in each block group. There are alternative density measures, such as per-capita and/or roadway metrics (Grubesic et al., 2016), but spatial density proves to be intuitive, realistic, and bias reducing for these types of small area units (Pridemore and Grubesic, 2012). Both on-premises and off-premises outlets were used for the analysis.

Aggravated and non-aggravated assault data for 2010–2013 were obtained from the Seattle Police Department (SPD, 2014) and their crime data portal. Assault density calculations were also generated using a simple container metric—assaults per square kilometer—in each block group.

A suite of demographic and socioeconomic measures was also obtained for analysis (Table 1) (Esri, 2010). There were three core demographic measures. The first was age, operationalized as the population in each block group between 15 and 29 years. We also measured the percentage of black, female-headed households—operationalized as a factor variable to address issues of multicollinearity. In addition, we used the diversity index from Esri (2010), which captures the likelihood that two persons, selected at random in a block group, will belong to a different race or ethnic group. As the measure approaches 100, more diversity is present; as it approaches a value of 0, less diversity is present.[3] Our socioeconomic measure was households with an annual income below \$15,000. Additional neighborhood measures included the percentage of vacant housing units, a density measure for public transportation stops, and a binary variable that denoted block group location relative

Table 1. Descriptive statistics for the demographic, socioeconomic, and neighborhood data in Seattle, Washington, block groups ($n = 567$).

Variable	Minimum	Maximum	Mean	SD
Percent Age 15–29 (Age15_29_P)	0.057	0.885	0.224	0.297
Black, female-headed households (factor) (FAC1_1)	–2.193	4.152	0.000	2.112
Diversity Index (DIVINDX_CY)	10.400	93.400	50.080	27.931
Percent Household Income < \$15,000 (HINB_15000)	0.000	0.654	0.088	0.246
Percent vacant housing units (VACANT_per)	0.000	0.259	0.063	0.090
Commercial location quotient (COM_LQ)	0.000	20.290	0.996	8.211
Public transportation stop density (Stop_Den)	0.000	147.900	19.520	55.412
Risky retailer density (Retail_Den)	0.000	36.530	1.717	14.654
Central business district indicator (Downtown) (*N*,%)				
Yes 29 (5.115) No 538 (94.885)				

SD: standard deviation.

to the central business district (1 = in CBD; 0 = out of CBD). Our last suite of measures captures additional neighborhood context. We used a location quotient (LQ) for commercial land use. In short, the LQ captures the proportion of commercial land use in each block group, relative to the entire city. Higher values for the LQ indicate a greater than expected share of commercial activity. Lastly, we estimated the spatial density of risky retailers (Grubesic et al., 2013), including check cashing stores, pawnshops, and convenience stores within each block group.

Methodology

Spatial clustering

We employ one of the most widely used spatial clustering methods, *max-p-regions*, to identify mutually exclusive and geographically contiguous regions for Seattle. The max-p-regions approach is a bi-objective spatial optimization model. The first objective is to maximize the number of identified clusters/regions. The second objective is to minimize within-cluster heterogeneity. For more details on the method and its formulation, see Duque et al. (2012). One major advantage to using this approach is that unlike other spatially explicit clustering methods, max-p-regions does *not* require users to pre-specify the number of clusters to be identified (Folch and Spielman, 2014). Instead, it allows the users to specify criteria that define a cluster, then it identifies a clustering scheme that satisfies these criteria. Typical criteria include cluster size constraints (e.g. at least 10% population or households), which is then combined with the objective of maximizing the number of clusters to enable the preservation of as much geographic detail as possible. As mentioned earlier, max-p-regions is structured with constraints to ensure that each identified region is spatially contiguous and that within-region heterogeneity is minimized so that each identified cluster/region is as homogeneous as possible. While the max-p-regions rarely look like traditional neighborhood boundaries in a city, the underlying regional structure helps facilitate meaningful local analysis for evaluating the interaction between alcohol outlets and violence.

Markov chains and dynamics of alcohol outlets and violence

Motivated by Rey et al. (2012) and their use of a discrete Markov chain framework to explore the spatiotemporal dynamics of residential burglary patterns, we structure the discrete Markov chain framework to generate a spatially heterogeneous probabilistic framework that will help us understand how violence evolve across time, as well as how the alcohol outlet densities impact the evolution of violence across regions. The classic Markov chain and associated properties are presented in the online Supplemental Material.

Markov chains for dynamics of violence. Our first task is determining *if* and *how* block group violence changes annually between 2010 and 2013 in Seattle. In order to capture and represent this dynamism as a Markov chain, we define a set of different violence rate classes—each providing a discrete approximation of violence distributions. There are a variety of strategies to accomplish this task for continuous rates, but here we rely upon a popular and easily accessible/repeatable method, *quantiles*. For this work, we classify continuous violence rates into three disjoint states based on the first, second, and third tertiles, denoting low (L), medium (M), and high (H) states of violence, respectively. By defining this state space, we can then estimate the transitional probability matrix associated with the Markov chain and track the temporal evolution of violence rates among block groups.

The transitional probability matrix of violence rate, M_v, can be conceptualized as

$$M_v = \begin{pmatrix} m^v_{L,L} & m^v_{L,M} & m^v_{L,H} \\ m^v_{M,L} & m^v_{M,M} & m^v_{M,H} \\ m^v_{H,L} & m^v_{H,M} & m^v_{H,H} \end{pmatrix} \tag{1}$$

where each of the diagonal elements represents the staying probability of a block group at the correspondent violence state and the nondiagonal elements represent the transition probability to a different state. For instance, $m^v_{M,M}$ is the probability of staying at the medium state of violence across two consecutive years (e.g. 2010–2011, 2011–2012, or 2012–2013) and $m^v_{M,H}$ is the probability of transitioning from the medium state of violence to the high state of violence.

The chi-square test for time homogeneity in the online Supplemental Material equation (S7) is easily adjusted for testing spatial homogeneity, spatial dependence, and conditional transition probabilities (Bickenbach and Bode, 2003; Kang and Rey, 2018; Rey et al., 2016). To provide important local context, we also construct M_v for each region and use the chi-square test to examine whether the temporal dynamics of violence density is spatially homogenous.

Markov chains for the transitions of violence conditioned on alcohol outlets. After examining the dynamics of violence using Markov chains, our goal is to explore how alcohol outlet density impacts the evolution of community violence. Specifically, we are interested in determining if the transitional dynamic of violence in block groups varies by outlet densities. In other words, given a consistently low (or high) outlet density across two years (e.g. 2010–2011) at the block group level, is the assaultive violence rate in a given locale more likely to increase or decrease?

To address this question, we discretize the alcohol outlet density into three disjoint states denoting sparse (S), moderately dense (MD), and dense (D) based on its tertiles. Then, for the entire Seattle area, as well as for each region delineated by the spatial clustering algorithm, we develop two sets of conditional Markov chains—one for block groups with *consistently sparse* outlet densities, and the other for block groups with *consistently dense* outlet densities. If outlet density has no association with transitions in violence while accounting for spatial heterogeneity in confounding variables, the null hypothesis shown in equation (2) holds

$$H_0 : m^v_{i,j} = m^v_{i,j}|S = m^v_{i,j}|D, \ \forall i,j \in \{L, \ M, \ H\} \tag{2}$$

$$H_1 : m^v_{i,j}|S \neq m^v_{i,j}|D \tag{3}$$

where $m^v_{i,j}|S$ is the probability of a block group transitioning from violence state i to j across two consecutive years, given that the block group has a sparse distribution of outlets in both time periods; $m^v_{i,j}|D$ is the probability of a block group transitioning from violence state i to j given that the block group has a dense distribution of outlets in both time periods. The alternative hypotheses can be further refined to reflect the potential impacts of alcohol outlet density on violence. Recalling that the states of violence rate are defined as low (L), medium (M), and high (H), the alternative hypothesis becomes

$$H_1 : m^v_{L, \ M} + m^v_{L, \ H} + m^v_{M,H}|S \ < \ m^v_{L, \ M} + m^v_{L, \ H} + m^v_{M,H}|D \tag{4}$$

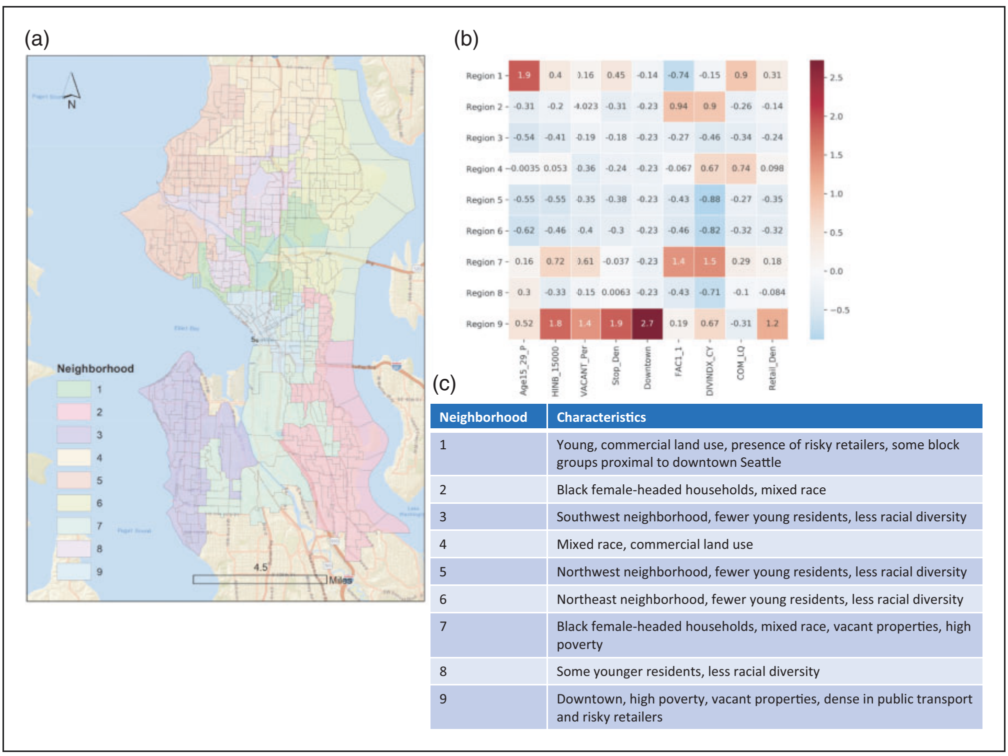
$$m^{v}_{H,M} + m^{v}_{H,L} + \ m^{v}_{M,L}|S > m^{v}_{H,M} + m^{v}_{H,L} + \ m^{v}_{M,L}|D \tag{5}$$

In short, the probability of a block group with sparse alcohol outlet density transitioning to a more violent state is lower than a block group with high outlet density. Further, the probability of a block group with sparse alcohol outlet density transitioning to a less violent state is likely to be higher than one dense with outlets. The chi-square tests described in the online Supplemental Material equation (S7) where the two subsamples represent these transitions in violence for block groups with sparse alcohol outlet density and those with dense alcohol outlet density, will be performed to test these hypotheses in each region.

Results

Region delineation

Nine mutually exclusive and geographically contiguous regions are identified by applying the max-p-regions approach using the variables detailed in Table 1. We require that each region includes at least 10% of the total population in Seattle.[4] All nine regions are displayed in Figure 1.[5] Their socioeconomic and demographic profiles are obtained by examining the average z-score for each variable (in each region). These results are visualized in Figure 1(b). Figure 1(c) provides some additional context and a summary overview of these characteristics. For example, Figure 1(c) notes that region 1 exhibits a high percentage of



Neighborhood	Characteristics
1	Young, commercial land use, presence of risky retailers, some block groups proximal to downtown Seattle
2	Black female-headed households, mixed race
3	Southwest neighborhood, fewer young residents, less racial diversity
4	Mixed race, commercial land use
5	Northwest neighborhood, fewer young residents, less racial diversity
6	Northeast neighborhood, fewer young residents, less racial diversity
7	Black female-headed households, mixed race, vacant properties, high poverty
8	Some younger residents, less racial diversity
9	Downtown, high poverty, vacant properties, dense in public transport and risky retailers

Figure 1. Region delineation and characteristics. (a) Region delineation. (b) Heatmap of mean z-scores of nine variables for each region. (c) Region characteristics.

population aged 15–29 years, a high density of public transport stops, a relatively high presence of risky retailers, commercial land use, and some block groups with geographic proximity to downtown. Again, for more details on the other regions, see Figure 1(c).

Fig. S1 provides a snapshot of assaultive violence in Seattle for 2010 to 2013, including the relative change map for assault density. Areas highlighted in green represent growth and those highlighted in red represent a decline. In aggregate terms, downtown Seattle was subject to the most significant growth in the spatial density of assaultive violence. At this juncture, it is important to remember that the trends identified in Fig. S1 are not directly connected to the Markov process models. These are simply cartographic representations of growth and decline in assaultive violence densities for the city.

The dynamics of violence

As detailed above, for the Markov chain analysis, each block group is assigned to a tertile that best represents its violence density: low (L: $x \leq 0.551$), medium (M: $0.551 < x \leq 9.221$) and high (H: $x > 9.221$). The estimated Markov transition probabilities M^v for violence density at the block group level for all of Seattle are reported in the upper leftmost heatmap in Figure 2. The corresponding number of transitions is also reported in Fig. S2. The result of the chi-square test for time homogeneity of the Markov chain for violence density suggests that the chain is also time homogeneous at the 5% significance level ($Q^{(3)} = 16.743$, $p-\text{value} = 0.16$).

Several interesting patterns can be found when examining the number of transitions and transition probabilities of violence density for Seattle. First, the transition probabilities for each violence class are far from uniform. For example, block groups classified as (L) have an estimated probability of 0.40 for shifting toward medium or high violence density in the following year. Conversely, block groups classified as (H) have a 0.21 probability of shifting toward medium or low violence in subsequent years. Put more simply, the results suggest a higher probability of (L) block group transitions toward more violent states, than (H) block groups transitioning to less violent states. For block groups starting at (M) levels of violence, there is a higher probability of transitioning to low violence density (0.31) than high violence density (0.19).

To control for the potentially confounding impacts as well as spatial heterogeneity, we explored the transitional dynamics in each of the nine regions. The transition counts and the estimated transition probabilities are highlighted in Fig. S2 and Figure 2, respectively.[6] There are several interesting patterns worth noting. First, the initial states of violence

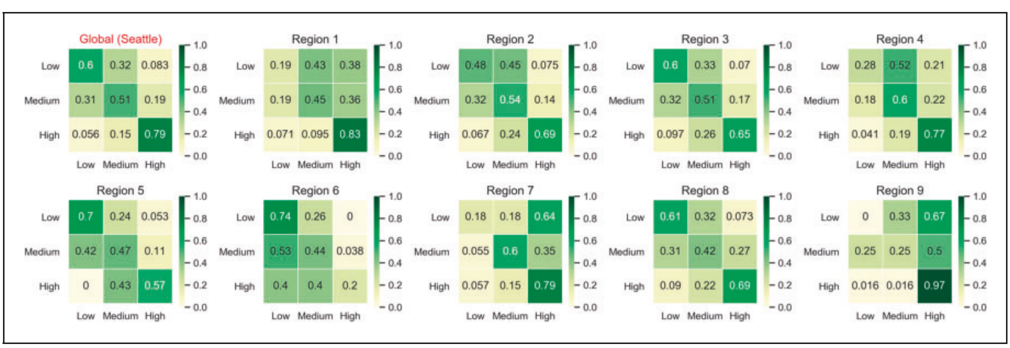


Figure 2. Markov transition probabilities of block group assault density tertiles for the entire Seattle and nine regions.

density for each region are relatively distinct. For example, the violence densities of most block groups in regions 1, 7, and 9 are classified as (H) in the initial period, while a majority of block groups in regions 3, 5, and 6 belong in the (L) and (M) tertiles.In addition, the transition dynamics among violence classes are also quite different across nine regions. For example, in the poorer regions (1, 7, and 9), the block groups classified as (L) have an average probability of 0.12 for remaining low violence in the following year. In wealthier regions (3, 5, and 6), block groups classified as (L) have a much higher probability (0.68) of remaining low violence (Figure 2). Other regions (2, 4, and 8) have an average probability of 0.46 of remaining low violence in the following year. In other words, the block groups in poorer neighborhoods are more likely to transition toward more violent states, than those in wealthy neighborhoods. The chi-square test for spatial homogeneity detailed in equation (S7) yields a value of $Q^{(9)} = 265.78$ with a $p-$value of 0.00, confirming that the temporal dynamics of violence density is spatially heterogeneous across each region.

Violence analysis conditioned on alcohol outlet

In an effort to explore how alcohol outlet density impacts the evolution of violence in neighborhoods, our last test explores the impacts of alcohol outlet density across two time periods. As discussed earlier, the alcohol outlet densities can take one of three states: sparse (S: $x = 0$), moderately dense (M: $0 < x < 9.696$), and dense (D: $x > 9.696$). Specifically, two conditional Markov chains are developed at each region, one for block groups with consistently sparse (S) alcohol outlet densities, and the other for block groups with consistently dense (D) alcohol outlet densities. The number of transitions and estimated transition probabilities for the case conditioned on the sparse alcohol outlet density ($M^v|S$) as well as that conditioned on the dense alcohol outlet density ($M^v|D$) are reported in Fig. S3 and Figure 3.

Overall, 622 block group transitions are associated with consistently sparse (S) alcohol outlet densities across two consecutive years, whereas 516 are associated with consistently dense (D) alcohol outlet densities for the same time period. Interestingly, the initial marginal distributions for these two conditional chains are distinct. For (S) block groups, 52% started at a transition period with low (L) violence density, 35% with medium (M), and 13% block groups with high (H). Alternatively, for block groups dense (D) with outlets, 12% of block groups start a transition period with low violence density, 23% with medium (M), and 66% with high (H) violence density. Again, this is consistent with previous empirical work that suggests alcohol outlet density is positively correlated with violence. However, efforts to deepen our understanding of the impacts of alcohol outlet density on the local dynamics in violence require further investigation and comparison of the $M^v|S$ and $M^v|D$.

Inspection of the $M^v|S$ (Figure 3) shows that when outlets are sparsely (S) distributed in a block group across two consecutive years, the total probability of block groups transitioning to more violent states ($m^v_{L,M} + m^v_{L,H} + m^v_{M,H}$) is 0.41, while it is 0.75 for transitioning to less violent states ($m^v_{H,M} + m^v_{H,L} + m^v_{M,L}$). However, when outlets are densely (D) distributed in a block group for two consecutive years, $M^v|D$ suggests that the total probability of transitioning to more violent states is 0.98, while that of transitioning to less violent states is 0.33. Specifically, block groups with a low density of outlets are only half as likely to transition to more violent states. But, they are twice as likely to transition to less violent states than those with a high density of alcohol outlets.

Similar patterns can be observed when examining the conditional transition probabilities for each region separately. For example, in Region 2, there is a total probability of 0.58 for block groups with sparse alcohol outlet density to transition to more violent states and 0.75

Figure 3. Markov transition probabilities of block group assault density tertiles conditional on consistent alcohol outlet density state for the entire Seattle and nine regions.

to transition to less violent states—but this shifts to 1.33 and 0.37 for those with densely distributed alcohol outlets, respectively. This same pattern emerges for both wealthy (e.g. Regions 3, 5, and 6) and poor neighborhoods (e.g. 7 and 10). As a result, a formal test of Hypothesis (2) is rejected for all neighborhoods at the 5% significance level except for Region 1. This is likely due to the small sample size which satisfies the condition of consistently sparse alcohol outlet densities in the area. This is confirmed by the visualized transition counts in Fig. S3. There were 0 block groups with consistently sparse outlet densities transitioning to medium violence density. This is indicative of a small sample testing issue for Markov chains which has not been properly resolved in the literature.

In sum, the dynamics of violence for Seattle is not homogeneous across neighborhoods with sparse or dense alcohol outlet footprints, even after controlling for spatial heterogeneity or the potential factors confounding the relationship between alcohol and violence. Thus, the results suggest that alcohol outlet density has a statistically significant impact on the evolution of violence and block groups with sparse outlet densities are less likely to increase in violence when compared to those with higher densities of alcohol outlets.

Discussion and conclusion

The application of the spatially heterogeneous Markov Chain framework in this study reveals a number of insights regarding the dynamics of alcohol outlets and violence, which were not discovered in previous studies. First, it is important to note that while only a few block groups were subject to variations in violence density, those variations were quite significant. Portions of downtown Seattle were especially impacted, with some block groups exhibiting growth greater than 2.5 standard deviations in assault density between 2010 and 2013. Second, the evolution of violence density is spatially heterogeneous across each region. Specifically, the block groups in poor neighborhoods are more likely to transition toward more violent states when compared to those located in wealthier neighborhoods. At face value, this may not be a surprising result; however, it does suggest that many of these neighborhoods exist in a precarious position, where a small stimulus (e.g. the addition of one or two alcohol outlets) may tip the neighborhood to a more violent state. Finally, our analysis suggests that block groups with sparsely distributed alcohol outlets are less likely to increase in violence when compared to those with higher densities of alcohol outlets. It is also worth mentioning that this finding also applies to scenarios where only on-premises or off-premises outlets are considered. Again, this seems to be an intuitive result. As detailed throughout this paper and the associated literature, outlet densities have a strong, positive association with violence. But the results uncovered here suggest a more nuanced association in both time and space. Specifically, for areas which are already dense in outlets, the addition of any additional outlets increases the probability of higher violence. In other words, neighborhoods already disadvantaged by high outlet densities and violence are more likely to get worse when new outlets arrive. The same cannot be said for areas with sparsely distributed alcohol outlets. Our results suggest that they have more flexibility in absorbing additional outlets and a lower probability of tipping into more violent conditions.

From a policy perspective, these results are significant for several reasons. First, communities that are concerned about the associations between alcohol outlets and violence must maintain their ability to control outlet densities. This can take several forms. First, policy mechanisms to confirm or deny license requests are imperative, not only in Seattle, but also in other locales around the United States and beyond. This is especially true when the license of a problematic outlet is set to expire. The ability to deny a license renewal is an important management and control tool for licensing boards, cities, and neighborhoods. The same can be said for new license applications, especially if the license request is located in an area already dense with outlets. As detailed in this paper, the addition of outlets can increase the probability of a locale transitioning into a more violent condition. A second approach would require a more proactive stance toward outlet densities through the development and use of geographic dispersion laws (Grubesic et al., 2012). Dispersion laws require a minimum distance (e.g. 200 m) between outlets, but also may include a minimum distance between outlets and sensitive facilities (e.g. schools, churches, etc.). Of course, communities must have the political willpower to develop and adhere to these types of dispersion laws, which can prove challenging in locales where there is a history of poor oversight or the need for licensing revenues (Grubesic et al., 2012; Zullo, 2017).

There are several limitations to this study worth noting. First, although our study period between 2010 and 2013 provided an excellent natural experiment, with deregulation occurring in June 2012, there is reason to believe that a spatial and temporal equilibrium in outlet density and violence may occur further down the road. In some ways, this is to be expected in newly privatized markets, where there is an initial burst of new activity, but in time, the competition between outlets, alcohol pricing strategies, and licensing oversight will interact to stabilize the outlet/violence landscape for a community. More work is needed here, with data from 2014 and beyond. Second, the Markov chain analysis requires the discretization of violence density distribution. Here we employ tertiles as the classification method, but other discretization methods could be used. For reference, we explored the use of median and quartile classifications, and both generate similar transition probabilities and provide identical insights. Finally, more confirmatory statistical works regarding the relationship(s) between alcohol outlet densities and violence are needed for Seattle. Although preliminary work in this area suggests a strongly positive relationship, when controlling for socio-economic status, land use, and a host of important structural variables, there may be local nuances such as university districts, large entertainment venues, and a challenging local topography that will make Seattle's story unique.

In sum, this work suggests that alcohol outlet densities have a statistically significant impact on the evolution of neighborhood violence in Seattle. For areas already dense with outlets, the addition of any additional outlets increases the probability of more violence. Of course, the underlying story for each region with a high transition probability is likely complex, and more work will be needed to determine the exact mechanisms at play. Regardless of the specifics, it is clear that more aggressive policy approaches are required both to manage outlet licensing and to control the geographic distribution of outlets. The methods and associated results detailed in this paper provide policy makers with tools to deepen our understanding of the process, as well as empirical evidence for exploring the contingencies associated with the growth of alcohol outlets.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Notes

1. Seattle continues to grow. The population estimate for 2019 is 747,300 (State of Washington, 2019).
2. For more details on the spatial distribution of the vote for I-1183 and an accompanying map, see Waggoner (2011).
3. Six race groups and ethnicities are included in the diversity index: White, Black, American Indian/Alaska Native, Asian, Native Hawaiian/Pacific Islander, Hispanic/Latino, and other.
4. Sensitivity tests for alternative size constraints were also explored, including constraints set to 15% and 20% of population. However, the results suggest that the 10% constraint is the best fit for these data.
5. Again, readers should not expect these regions to look like traditional neighborhood boundaries for Seattle. They are structured for statistical analysis, not cultural or historical analysis.
6. Please note that readers should exercise caution when reading the heatmaps for each neighborhood in the online Supplemental Material Figure S3 because the transition counts vary on the *y*-axis.

Supplemental material

Supplemental material for this article is available online.

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