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Longitudinal Impacts of Two Causal Drivers of Alcohol Demand on Outlet Concentrations within Community Settings: Population Size and Income Effects

Zhuxuan Jin, Ph.D.[1], **Howard H. Chang, Ph.D.**[1], **William R. Ponicki, M.S.**[2], **Andrew Gaidus**[2], **Lance A. Waller, Ph.D.**[1], **Chris Morrison, Ph.D.**[3,4], and **Paul J. Gruenewald, Ph.D.**[2,*]

[1]Department of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, 1518 Clifton Road NE, Atlanta GA 30322

[2]Prevention Research Center, Pacific Institute for Research and Evaluation, 180 Grand Avenue, Suite 1200, Oakland, CA 94612

[3]Penn Injury Science Center, University of Pennsylvania, 423 Guardian Drive, Philadelphia, PA 19104

[4]Monash University, Department of Epidemiology and Preventive Medicine, 99 Commercial Road, Melbourne VIC 3004, Australia

Abstract

We analyzed counts of licensed bars, restaurants and off-premise alcohol outlets within 53 California cities from 2000–2013. Poisson models were used to assess overall space-time associations between outlet numbers and population size and median household income in local and spatially adjacent block groups. We then separated covariate effects into distinct spatial and temporal components (“decomposed” models). Overall models showed that densities of all outlet types were generally greatest within block groups that had lower income, were adjacent to block groups with lower income, had greater populations, and were adjacent to block groups that had greater populations. Decomposed models demonstrate that over time greater income was associated with increased counts of bars, and greater population was associated with greater numbers of restaurants and off-premise outlets. Acknowledging the many negative consequences for populations living in areas of high outlet density, these effects are a predictable and powerful social determinant of health.

INTRODUCTION

This paper is concerned with two very general questions in the assessment of public health problems related to alcohol use: (1) Are there detectable long-term effects of alcohol

*Correspondence to Paul J. Gruenewald, Prevention Research Center, Pacific Institute for Research and Evaluation, 180 Grand Avenue, Suite 1200, Oakland, CA 94612; Fax: (510) 644- 0594; Phone: (510) 883-5738; paul@prev.org.

demand on alcohol markets within cities and communities of the US? If so, (2) can we estimate the relative magnitude of these effects? This will hopefully allow us to begin to predict some of the known long-term health consequences for populations living in and near to such markets. If the answer to both questions is “yes,” then we can use this information to inform simulation models used to predict health outcomes related to alcohol markets across community areas (Holder, 1998; Fitzpatrick and Martinez, 2012). These, in turn, can be used to help guide regulatory policies intended to ameliorate some of the most significant problems related to these markets in community settings (Gruenewald, 2011). One difficult problem for such models is the representation of reciprocal relationships between alcohol supply and demand at the largescale community and fine-scale neighborhood levels; it is expected that alcohol outlets will open to sell alcohol and meet market demand, that subsequent greater supply will induce yet greater demand, and this system will come to equilibrium at some new level of use. The dynamics are, on-the-face-of-it, trivial. That is, in any case, until one realizes that both supply and demand are expressed across neighborhoods and communities linked by transportation systems that provide greater or lesser access to markets and populated by drinkers who will travel greater or lesser distances to obtain alcohol. At that point, the problem becomes more complex, requiring comparative static geographic models applied in urban economics to help elucidate the causal factors that determine market locations relative to sources of demand (O‟Sullivan, 2007; Hanson, 2005).

To keep some of this complexity at bay it is helpful to consider some basic theoretical ideas and empirical observations that have been used to analyze the geography of alcohol markets across community areas. Deriving their hypotheses from urban economic and economic geographic theory, Morrison and colleagues (2015a,b, 2016) used community level data to empirically assess expected impacts of population size and income on alcohol market locations: In both metropolitan and rural areas, outlets locate near to residential neighborhoods with high alcohol demand (e.g., high income areas with large populations); outlets locate in areas with low land and structure rents (to minimize costs of operation); outlets are excluded from residential areas with high land and structure rents (the „not in my backyard‟ phenomenon); and outlets locate near to one another (to share resources, economic agglomeration). While there are some minor distinctions as to effects across outlets of different types (i.e., bars, restaurants and offpremise establishments), over time these processes concentrate outlets in low income, often minority, areas of communities near to high income residential neighborhoods, a fact long known in the alcohol research literature (Gorman and Speer, 1997; LaVeist and Wallace, 2000).

The work of Morrison and colleagues also established, first, that expected demand and land rent effects can be observed in cross-sectional data and, second, that population size and income are differently related to outlet locations: While demand across community areas is strongly related to population size and income, land and structure rents are reflected in income alone. Population size has one effect, to increase the volume of demand. Income has two effects, to increase demand and, to the degree that income acts a surrogate for land and structure rents, exclude alcohol markets. More critically, it appears that the effects of income are expressed at two different spatial scales with the demand effects operating across larger geographic areas (e.g., cities) and rent effects operating locally (e.g., within Census block group areas). Importantly, population and income effects are spatially separable. Finally, as these economic forces shape locations of alcohol markets, over-concentrations of outlets, especially bars, lead to greater harms like violent assaults, accidents and injuries (Popova, et al, 2009; Campbell, et al, 2009). Thus, as we come to better understand the social and economic forces that affect the development of alcohol markets in community settings we also come to identify those neighborhoods and communities most affected by problems related to those outlets.

In this study we consider the extent to which population and income effects are sustained across spatially adjacent units over time. As motivation, we note individual consumers may purchase alcohol either near to their homes or across broader adjacent neighborhood and city areas as they travel as part of their routine daily activities. Thus, concentrations of alcohol markets may be affected by population and area characteristics of a local geographic region, nearby regions, and broader retail market areas such as a city. Because alcohol licenses require some effort to obtain and are not easily moved, outlets in a given location may respond slowly to temporal changes in alcohol demand and may be related to spatial variations in demand at differing resolutions (i.e., local, nearby and city areas). To-date, a major weakness of all studies of community level impacts of alcohol outlets on public health problems has been the failure to assess these multi-scale spatio-temporal effects (Morrison, et al, 2015c). Thus, the main contribution of the current study is to utilize a statistical modeling approach that decomposes multilevel spatial and temporal influences of two key drivers of alcohol demand – income and population – as they relate to densities of alcohol outlets in 53 California cities from 2001 to 2013. The covariate decomposition approach detailed in the sections below provides a method to separate the *overall* spatiotemporal association of population size and income with alcohol outlets into different spatial and temporal scales. Cross-sectional spatial components of the model reflect the impacts of long-term spatial segregation of alcohol outlets into specific community areas (e.g., population segregation into wealthy and poor areas) at different spatial-scales (e.g. neighborhood versus city). Temporal components reflect relatively short-term impacts of income and population on locations of outlets over the 13 years of available data.

METHODS

We collected data on alcohol retail outlets and other variables for 53 medium-sized cities in California over the years 2001 through 2013. As part of a larger study of the social ecology of alcohol outlets and related problems in the state, these 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 53 cities. U.S. counties are subdivided into census tracts of approximately 3,000–6,000 people, which in turn are subdivided into block groups of approximately 600–3,000 people. The 53-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 328 in Sacramento.

Alcohol Outlets.

We considered three broad categories of alcohol retailers: off-premise establishments (license types 20 and 21), restaurants (license types 41 and 47) and bars/pubs (license types 23, 40, 42, 48, 61 and 75). Active license records as of January of each year were obtained from the California Department of Alcohol Beverage Control (ABC) and geocoded to the premise address listed within each record. Annual counts of each outlet type were aggregated to the Census 2000 block group-level for 53 cities in California during the period 2001 to 2013.

Covariates

Annual block-group demographic and economic estimates were obtained from GeoLytics, Inc. (2014). These data included two key contributors to alcohol demand: population and median household income. Other covariates were included to account for population characteristics also related to outlet market locations (Morrison, et al, 2016) but not central to the current study: percentages of local populations identifying as black, Hispanic, or Asian, percentage of male, percentage of population in the 15–24 age groups, average household size, unemployment rate, and percentage of population with income under 150% of the Federal poverty level. The GeoLytics demographic estimates for years 2011 to 2013 were supplied for Census 2010 block groups, and these measures were reallocated to 2000 Census block groups using captured Census block characteristics as weights. Because retail outlets tend to be located on major arterials, we also included an indicator of whether a block group was served by a class 1 or 2 highway (ESRI, 2010). A yes/no indicator 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 the number or mileage of such routes.

Analysis model.

We modeled the spatial-temporal areal count data using hierarchical Bayesian models, separately for each type of alcohol outlet. Let *cst* denote the number of alcohol outlets in city, *c*, block group, and year *t*We begin with a Poisson log-linear model explaining alcohol outlet counts relative to land area:

$$
\begin{aligned}
&Y_{cst} \mid \theta_{cst} \sim \text{Poisson}\left(E_{cs}\theta_{cst}\right)\\
&\log\theta_{cst} = \beta_0 + \beta_{Inc} Inc_{cst} + \beta_{Pop} Pop_{cst} + \beta_{NInc} NInc_{cst} + \beta_{NPop} NPop_{cst}\\
&+\beta_{Other} X_{cst} + \alpha t + u_{cs} + v_{cs}.
\end{aligned}
$$

with $_{cst}$ having mean $E_{cs}\ \theta_{cst}$ where E_{cs} denotes the square miles of block groupin city *c* and denotes the corresponding prevalence of alcohol outlets per square miles in year *t*. We considered four spatial-temporal covariates of interest relating to population and income: (1) local block group real household income (Inc_{cst}) in \$10,000 2013 dollars; (2) local block group population size Pop_{cst} in 1,000; (3) average real household income of neighboring adjacent block groups ($NInc_{cst}$) in \$10,000 2013 dollars weighted by population, for measuring the spatial lag effect of neighboring real household income; and (4) total population size of neighboring adjacent block groups ($NPop_{cst}$) in 1,000 per square miles for measuring spatial lag effect of neighboring population. Block group adjacency was defined by sharing a common border. Population density was chosen to measure potential demand from non-residents living near the local block group‟s border while avoiding the issue that some census block groups are very large in geographic extent, especially near the boundary of a city.

The above model also includes additional covariates for the block group population and roadway characteristics (X_{cst}), a linear temporal trend (αt), the city-level population density ($PopDens_{ct}$) in 1,000 per square-mile, and two random effects: (1) a block group-level spatially-dependent random intercept u_{cs} which follows an intrinsic conditional autoregressive (ICAR) model (Banerjee at el. 2015, Chapter 4); and (2) an unstructured block group-level random intercept u_{cs} which follows N(0,σ^2). The ICAR random effects account for potential spatial dependence between observed outlet counts not explained by the covariates, while the unstructured random intercepts account for extra Poisson variation (over-dispersion).

We next considered a model where the spatially and temporally-varying covariates of interest were decomposed into several additive and conditionally independent components. This allows us to examine how covariates at different spatial-temporal scales may impact differently on annual alcohol outlet counts. Let X_{cst} be a covariate that varies across cities, block groups, and years. First, a city-level average $\overline{X}_c$ was obtained by averaging X_{cst} across block groups and years within each city. Second, a block group-level average $\overline{X}_{cs}$ was obtained by averaging X_{cst} across years within each block group. Here we suppress the subscript corresponding to the indices over which the averages are calculated. The spatial-temporal covariate X_{cst} was then decomposed into three components: $X_{cst} = \overline{X}_c + \left(\overline{X}_{cs} - \overline{X}_c\right) + \left(X_{cst} - \overline{X}_{cs}\right)$. The first component $\overline{X}_c$ captures between-city variability and is static in time and across block groups. The second component $\overline{X}_{cs} - \overline{X}_c$ captures within-city variability due to block group locations. The third component $X_{cst} - \overline{X}_{cS}$ captures within-block group variability due to temporal changes. We refer to the three components, respectively, as city variation, block group variation, and temporal variation. The three independent components were included simultaneously in the model. We refer to the effects associated with each component, respectively, as the *city* effect, the purely *block group* effect, and the purely *time* effect. We note that if the coefficients associated with the three components are identical, then the coefficient is identical to that obtained using the original covariate X_{cst}. This covariate decomposition separates the *overall* spatial-temporal association of alcohol outlets and a covariate into different spatial and temporal scales, while limiting collinearity between the measures.

The Poisson log-linear model with decomposed spatial-temporal covariates becomes:

$$\log\theta_{cst} = \beta_0 + \beta_{Inc,city}\overline{Inc}_c + \beta_{Inc,bg}\left(\overline{Inc}_{cs} - \overline{Inc}_c\right) + \beta_{Inc,time}\left(Inc_{cst} - \overline{Inc}_{cs}\right) + \beta_{Pop,city}\overline{Pop}_c + \beta_{Pop,bg}\left(\overline{Pop}_{cs} - \overline{Pop}_c\right) + \beta_{Pop,time}\left(Pop_{cst} - \overline{Pop}_{cs}\right) + \beta_{NInc,bg}\overline{NInc}_{cs} + \beta_{NInc,time}\left(NInc_{cst} - \overline{NInc}_{cs}\right) + \beta_{NPop,bg}\overline{NPop}_{cs} + \beta_{NPop,time}\left(NPop_{cst} - \overline{NPop}_{cs}\right) + + \beta_{Other}X_{cst} + \alpha t + u_{cs} + v_{cs}$$

Specifically, we decomposed Inc_{cst} and Pop_{cst} into three components as described above. City-level averages for spatial lagged covariates ($NInc_{cst}$ and $NPop_{cst}$) were not included because the effects of these covariates were only meaningful at the block group-level.

Integrated Nested Laplace Approximation.

Parameter estimation was performed under a Bayesian framework and the following priors were assigned to all the unknown parameters. All fixed effect coefficients were assigned normal distributions with mean 0 and variance 1,000. For all random effect variance components, we assumed the precision (inverse of the variance) followed a log-gamma distribution with parameter 1 and 0.00005. To analyze the large spatialtemporal dataset, the model was fitted via the integrated nested Laplace approximation (INLA) in R Version 3.3.2. INLA performs approximate Bayesian inference for structured additive regression models such as a Poisson log-linear model (Rue et al. 2009). While Markov chain Monte Carlo (MCMC) methods are more commonly used for Bayesian inference, they can suffer from convergence issues and increased computational burden when the sample size is large or when high-dimensional parameters are present. INLA provides a solution for faster Bayesian inference by numerically approximating the marginal posterior density for the hyper-parameters and the latent variables. It has been successfully applied in many spatial and spatial-temporal analyses due to its computational efficiency (Kinyoki et al. 2016, Halonen et al. 2016). INLA results from spatial models have been shown to be comparable to results obtained from MCMC (Beguin et al. 2012, Carroll et al. 2015).

RESULTS

Summary statistics (means and standard deviations) of block group-level alcohol outlets and other variables Pearson correlations are provided in Tables 1 and 2. Summary statistics for local and neighborhood income and population size are provided at the city-level (“Overall”), block group-level (“Block Group Variation” from city means) and over time (“Temporal Variation” from block group averages). We note that means of decomposed block group and temporal variations are zero because they are residuals from city averages.

Results of the spatial Poisson models are presented in Table 3. Coefficients can be interpreted as the mean estimate and credible interval for the percent changes in alcohol outlets associated with income and population across block groups of the 53 cities. We distinguish overall effects obtained from a model without covariate decomposition (“Overall”) and those from a model with decomposition at city, block group, and temporal levels. For all three outlet types and all models with or without decomposition, the Moran‟s I for the posterior mean of the fitted alcohol outlet counts $\hat{Y}_{cst}$ indicated an average positive spatial autocorrelation of 0.179 (ranging from 0.142 to 0.200 for bars and restaurants in decomposed models), providing evidence that outlets agglomerate across block groups. Using the deviance information criterion as a measure of model fit (Spiegelhalter et al. 2002), we also found that the decomposed model outperformed the overall model for all three alcohol outlet types (Supplementary Table S1).

Household income

The spatial-temporal association of block group real household incomes was negative for all three types of outlets. With covariate decomposition, these associations were driven mainly by income variations at the block group-level. Within cities, a $10,000 greater difference between a block group‟s average income across years and its city average was associated with −36.1% (95% PI: −41.7%, −30.1%) fewer bars and pubs, −30.7% (95% PI: −34.6%, −26.6%) fewer restaurants, and −26.8% (95% PI: −30.0%, −23.6%) fewer off premise outlets. All outlets were less likely to be in block groups with high income.

Adjacent average household incomes also exhibited negative spatial-temporal associations with restaurants and off-premise outlets. The overall associations again were driven mainly by variations at the block group-level. $10,000 greater adjacent block group average incomes were associated with −32.0% (95% CI: −41.0%, −21.7%) fewer bars and pubs and 14.8% (95% CI: −20.5%, −8.8%) fewer off-premise outlets. However, adjacent block group incomes were also associated with greater temporal growth in numbers of bars and pubs, +5.4% per $10,000 (95% CI: 1.3%, 9.7%). We note that for bars and pubs, the overall spatial-temporal negative association was weakened by the opposite effects of the decomposed covariate.

Looking at both local and neighborhood effects, within cities all outlet types were less numerous within block groups with greater incomes and within block groups with greater neighboring incomes. Upward pressure on outlet growth over time was observed for bars and pubs within block groups with higher income neighbors.

Population effects.

The overall spatial-temporal associations per 1,000 increase in a block group‟s local population size were positive: +1.8% (95% CI: 0.3%, 3.1%) for bars and pubs, +2.4% (95% CI: 1.9%, 2.9%) for restaurants, and +2.6% (95% CI: 2.0%, 3.2%) for off premise outlets. By decomposing the covariate, we found different associations for city-level averages vs. temporal changes related to local population size. A 1,000-person increase in a city‟s average block-group population size was associated with −93.3% (95% CI: −99.0%, −54.8%) fewer bars and pubs and −62% (95% CI: −84.9%, −3.6%) fewer off-premise outlets. These were counterbalanced by positive temporal associations for restaurants (+2.3% per 1,000; 95% CI: 1.8%, 2.8%) and off-premise outlets (+2.4% per 1,000; 95% CI: 1.8%, 3.0%). Larger city size and density was related to fewer numbers of outlets, but the spatial-temporal interactions indicate nevertheless that numbers of restaurants and off-premise outlets exhibit proportionately greater growth in areas with greater population sizes.

Overall spatial-temporal associations were positive for all three types of alcohol outlets with respect to adjacent populations. A 1,000-person per square mile increase in adjacent population was associated with a +7.8% (95% CI: 4.6%, 11.2%) more bars and pubs, +4.6% (95% CI: 3.2%, 6.0%) more restaurants, and 5.7% (95% CI: 4.3%, 7.1%) more off-premise outlets. In decomposition, both restaurants and off-premise outlets were more numerous where neighborhood areas were more populous (+8.3% and +11.7% respectively) with upward pressure over time observed for restaurants (+2.5% per year).

Estimated percent change in the number of outlets associated with other block grouplevel covariates are presented in supplemental Table S2 (without covariate decomposition) and Table S3 (with covariate decomposition). Covariate relationships were generally stable across models with some variations related to decomposition.

DISCUSSION

Noting that population size should be directly related to alcohol demand, the results of the current study support the argument that growth in demand is generally related to growth in alcohol markets. Overall measures of population size in local Census block group areas were positively related to numbers of all types of outlets within those areas and within nearby areas over time (“Population” “Overall” effects in Table 3). Further decomposition of these effects by block groups and time showed that greater local population size (a) put upward pressure on the continued growth of numbers of restaurants and off-premise outlets within areas over time (b) was associated with greater numbers of restaurants and off-premise outlets in nearby areas, and (c) put upward pressure on the continued growth of restaurants over time in nearby areas.

The income effects observed here told a different but similarly detailed story. Overall income effects generally supported the observation that this measure represented land rent or “not in my back yard” (NIMBY) effects; fewer outlets were found in higher income local and adjacent areas. Decomposition of these effects showed that greater incomes in local block groups were related to (a) fewer outlets of all types within areas, (b) fewer bars and pubs and offpremise outlets in nearby areas, and (c) continued upward pressure on growth of bars and pubs in nearby areas over time. Income effects had negative, generally stable, relationships to numbers of outlets of all types, but a positive effect upon numbers of bars and pubs that appeared in nearby areas over time. With this one exception, the income effects observed here appear to reflect land rent effects, excluding outlets from opening in neighborhoods while encouraging growth of bars and pubs in nearby neighborhoods. It is perhaps no surprise that population size would reflect the hypothesized demand effects, whereas income would reflect the hypothesized land rent effects. Population density can vary across geographic areas by orders of magnitude, whereas income will vary by no more than a few fold, so population size will be the dominant driver of geographic variation in demand for alcohol (Morrison et al, 2015b).

As noted in the introduction, the covariate decomposition approach was implemented to provide a method by which to distinguish spatial vs. temporal associations between correlates of demand and changes in numbers of alcohol outlets within block group and adjacent areas. If factors of demand maintain continued upward pressure on numbers of alcohol outlets over time, whether within or across adjacent block group areas, we should also see support for these temporal effects. Support for such temporal effects was observed for adjacent area incomes (for bars), local and adjacent area population sizes (for restaurants) and local population size (for offpremise outlets). By contrast, while these positive demand effects were extended over time, the negative impacts of land and structure rents were relatively fixed in time; over the 14-year span of the study the block group specific effects of household income were uniformly negative with but one well supported temporal impact observed across local and adjacent areas. Evidently, areas of cities with higher income residents consistently exclude alcohol outlets from opening in those areas.

This longitudinal analysis extends a previous cross-sectional study conducted using the same dependent measures (bars, restaurants, off-premise outlets) and similarly composed independent measures (population, income) in the same California cities and at the same spatial scales (local Census block groups, adjacent block groups, city) (Morrison et al, 2015a). Results of our longitudinal analyses are very similar to the results of the cross-sectional analyses, in that outlet densities are greatest where the populations of local and adjacent block groups are largest, and where incomes in local and adjacent block groups are lowest but city-level incomes are greatest. These findings suggest that numbers of alcohol outlets are positively associated with alcohol demand across entire cities, but non-demand factors can dominate at a local level.

While the current study brings us a step closer to understanding the impacts of some economic geographic forces that affect concentrations of alcohol outlets across areas of cities, it does not provide a complete analysis of temporal effects related to changes in income and population size. The temporal effects observed here are assumed constant across years and may be better represented as time varying effects. In addition, other temporal covarying effects may be missing from the analysis model; the time of study bridges the great recession and, although one would expect much of the recession‟s impacts on demand to be mediated by income effects, impacts on alcohol supply will not. During this time retailers and employers may have been relatively unwilling to expand or open new retail businesses, including those selling alcohol. The current analyses are also somewhat limited by the lack of publicly available information on both outlet characteristics (e.g., size and sales volumes) and planning or zoning policies affecting where alcohol outlets can operate within each city. Finally, we modeled residual temporal trend as a common linear term across cities, while other more flexible spatially-varying temporal trends may also be considered.

This study represents a substantial advance in our understanding of the way alcohol outlets are spatial-temporally distributed within cities. The results confirm that relationships between population size, income, and outlet locations, which have previously been observed cross-sectionally in rural (Morrison, 2015b) and metropolitan areas (Morrison et al, 2015a, 2016) and across multiple geographic settings (Gorman and Speer, 1997; LaVeist & Wallace, 2000), are relatively stable over time. These relationships are mostly consistent across outlet types, and are concordant with a clear theoretical mechanism that will cause outlets to concentrate in lower income areas. Importantly, these findings have clear utility beyond simply describing historical economic geographic processes. Effect estimates for the decomposed covariates can be used to inform predictions of the likely impacts of population growth, economic development, and changes to regulatory systems on alcohol outlet distributions, and, because the presence of alcohol outlets in neighborhoods is related to increased incidence of alcohol-related harms (Popova, et al, 2009; Campbell, et al, 2009), on an important and mutable social determinant of health. The focus of future studies in this area should be on understanding the effects of the observed spatial dynamics on health disparities.

(a) Overall

(b) City Variation

(c) Block Group Variation

(d) Temporal Variation

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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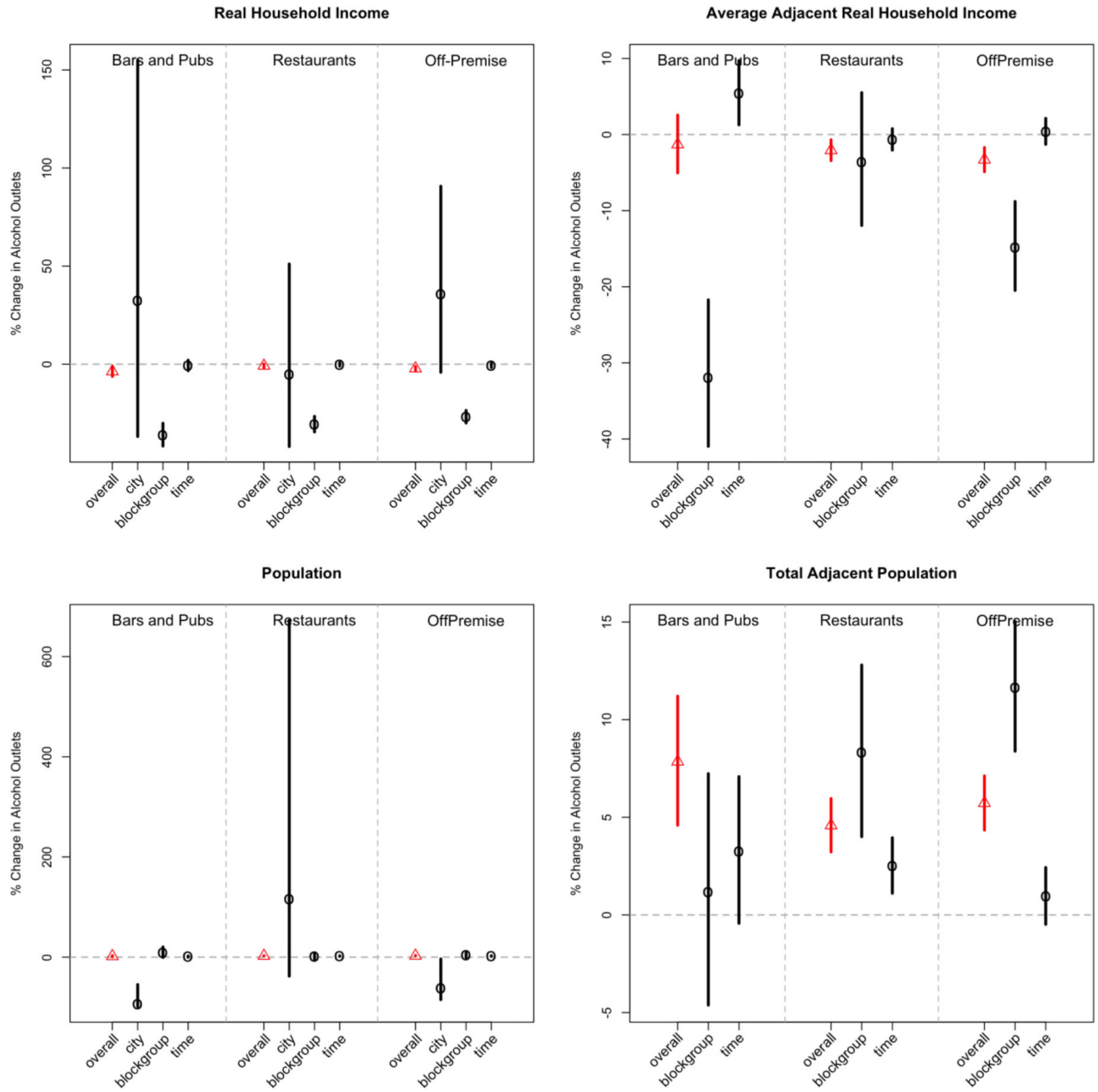

Figure 1.
Estimates and 95% posterior intervals for the percent changes in alcohol outlets associated with income (per $10,000) and population (per 1,000) in 53 Californian cities, 2001 to 2013. The overall effects, indicated in red, were obtained from a model without covariate decomposition. The city, block group, and time associations were obtained from a model with covariate decomposition.

Table 1.

Means and standard deviations (SD) of block group-level alcohol outlets and other variables across 53 Californian cities during 2001 to 2013.

	Mean	SD	Min	Max
Active Alcohol Outlets				
Bars and Pubs	0.28	0.82	0	22
Restaurants	1.71	4.12	0	102
Off-premise Outlets	1.34	1.91	0	22
Real Household Income (×$10,000)[1]				
Overall	6.08	3.00	0.00	26.49
City Variation	6.08	1.73	3.56	1.42
Block Group Variation	0.00	2.28	-8.04	14.95
Temporal Variation	0.00	0.89	-8.55	16.94
Average Adjacent Real Household Income (×$10,000)[2]				
Overall	6.07	2.41	1.03	23.62
Block Group Variation	6.07	2.34	1.23	20.84
Temporal Variation	0.00	0.57	-3.24	3.69
Population (×1,000)				
Overall	1.76	1.61	0.00	64.50
City Variation	1.76	0.54	0.87	5.72
Block Group Variation	0.00	1.32	-4.06	19.29
Temporal Variation	0.00	0.73	-13.2	49.32
Total Adjacent Population Per Square Mile (×1,000)				
Overall	6.80	3.86	0.49	39.98
Block Group Variation	6.80	3.82	0.14	38.69
Temporal Variation	0.00	0.56	-12.63	5.24
% Population near or below poverty level[3]	24.19	19.21	0.00	103.29
% Unemployment	9.39	10.78	0.00	153.00
Presence of Major Arterial Highways	0.43	0.49	0	1
Average Household Size	2.95	1.30	0.00	5.24
Race/Ethnicity				
Proportion Black	0.06	0.09	0.00	0.90
Proportion Hispanic	0.33	0.24	0.00	1.20
Proportion Asian	0.10	0.12	0.00	0.95
Proportion Male	0.49	0.04	0.00	1.00
Proportion Aged 15–24	0.14	0.04	0.00	1.00
Area (square miles)			0.01	147.86

[1] In 2013 dollars;

[2] population weighted in 2013 dollars;

[3] under 150% of the Federal poverty level.

Table 2.

Correlations averaged across years of between main covariates of interest: real household income (Inc), population (Pop), averaged real household income of the adjacent block groups (NInc), and population density of adjacent block groups (NPop): (a) overall spatialtemporal variation. Moreover, the covariates are also decomposed to further reflect (b) betweencity variation (if any), (c) within-city block group variation, and (d) within-block group temporal variation.

(a) Overall

	Inc	NInc	Pop	NPop
Inc	1.00			
NInc	0.78	1.00		
Pop	0.05	0.08	1.00	
NPop	−0.20	−0.27	−0.07	1.00

(b) City Variation

	Inc	Pop
Inc	1.00	
Pop	0.09	1.00

(c) Block Group Variation

	Inc	NInc	Pop	NPop
Inc	1.00			
NInc	0.45	1.00		
Pop	0.06	0.06	1.00	
NPop	−0.24	−0.27	−0.03	1.00

(d) Temporal Variation

	Inc	NInc	Pop	NPop
Inc	1.00			
NInc	0.25	1.00		
Pop	0.07	0.10	1.00	
NPop	0.11	0.15	0.15	1.00

Table 3.

Estimated percent change in alcohol outlets associated with income and population in 53 Californian cities, 2001 to 2013. 95% posterior intervals are given in parentheses. The overall effects were obtained from a model without covariate decomposition. The city, block group, and time associations were obtained from a model with covariate decomposition.

	Bars and Pubs	Restaurants	Off-premise Outlets
Real Household Income			
Overall[1]	**−3.7 (−6.3, −1.1)**	−0.8 (−1.8, 0.1)	**−2.2 (−3.3, −1.1)**
City[2]	32.5 (−36.9, 155.1)	−5.3 (−42, 51.1)	35.7 (−4.1, 90.7)
Block Group[3]	**−36.1 (−41.7, −30.1)**	**−30.7 (−34.6, −26.6)**	**−26.8 (−30, −23.6)**
Time[4]	−0.7 (−3.4, 2.1)	−0.1 (−1, 0.9)	−0.6 (−1.7, 0.5)
Adjacent Household Income			
Overall	−1.3 (−5, 2.6)	**−2.1 (−3.4, −0.7)**	**−3.3 (−4.9, −1.7)**
Block Group	**−32.0 (−41, −21.7)**	−3.6 (−12, 5.5)	**−14.8 (−20.5, −8.8)**
Time	**5.4 (1.3, 9.7)**	−0.6 (−2.1, 0.8)	0.4 (−1.3, 2.1)
Population			
Overall	**1.8 (0.3, 3.1)**	**2.4 (1.9, 2.9)**	**2.6 (2, 3.2)**
City	**−93.3 (−99, −54.8)**	116.5 (−38, 672.9)	**−62.0 (−84.9, −3.6)**
Block Group	9.3 (−0.7, 20.4)	1.5 (−5.2, 8.7)	3.8 (−1.3, 9.2)
Time	1.1 (−0.3, 2.4)	**2.3 (1.8, 2.8)**	**2.4 (1.8, 3.0)**
Adjacent Population			
Overall	**7.8 (4.6, 11.2)**	**4.6 (3.2, 6)**	**5.7 (4.3, 7.1)**
Block Group	1.2 (−4.6, 7.2)	**8.3 (4.0, 12.8)**	**11.7 (8.4, 15)**
Time	3.2 (−0.4, 7.1)	**2.5 (1.1, 4.0)**	1.0 (−0.5, 2.4)

[1] Overall associations measure how alcohol density varied spatial-temporally with covariates. For example, a $10,000 increase in real household income, either across block groups or across years, was associated with a −3.7% decrease in bars and pubs density (per square miles).

[2] City associations measure how alcohol density varied across cities spatially. For example, a $1,000 increase in citywide 2001–2013 average real household income was associated with a −93.3% decrease in bars and pubs density.

[3] Block group associations measure how much variation in alcohol density was associated with within-city spatial variation in covariates. For example, block groups with a $1,000 higher average real household income (over 2001–2013) compared to the city-average were associated with a −36.1% decrease in bars and pubs density.

[4] Time associations measure how much variation in alcohol density was associated with within-block group temporal variation in covariates. For example, years when block groups had a $1,000 higher adjacent household income than the block group-average were associated with a 5.4% increase in bars and pubs density.