Published in final edited form as:
Addiction. 2021 July ; 116(7): 1908–1913. doi:10.1111/add.15420.

Availability of Medical Cannabis Dispensaries and Cannabis Abuse/Dependence-Related Hospitalizations in California

Christina Mair, Ph.D.,
University of Pittsburgh Graduate School of Public Health, Department of Behavioral and Community Health Sciences, 6136 Public Health, 130 DeSoto Street, Pittsburgh, PA 15261

Natalie Sumetsky, M.S.,
University of Pittsburgh Graduate School of Public Health, Department of Behavioral and Community Health Sciences, 130 DeSoto Street, Pittsburgh, PA 15261

Christiana Kranich, M.S.W.,
College of Social Work, The Ohio State University, 1947 College Road N, Columbus, OH 43210

Bridget Freisthler, Ph.D.
College of Social Work, The Ohio State University, 1947 College Road N, Columbus, OH 43210

Abstract

Aims.—To estimate associations between both current- and prior-year medical cannabis dispensary densities and hospitalizations for cannabis use disorder in California, USA between 2013 and 2016.

Design.—Spatial analysis of ZIP code-level hospitalization discharge data using Bayesian Poisson hierarchical space-time models over 4 years.

Setting and cases.—California, USA from 2013 through 2016 (6,832 space-time ZIP code units).

Measurements.—We assessed associations of annual hospitalizations for cannabis use disorder (assignment of a primary or secondary code for cannabis abuse and/or dependence using ICD-9-CM or ICD-10-CM (outcome)) with the total number of medical cannabis dispensaries per square mile in a ZIP code as well as dispensary temporal and spatial lags (primary exposures). Other exposure covariates included alcohol outlet densities, manual labor and retail sales densities, and ZIP code-level economic and demographic conditions.

Findings.—One additional dispensary per square mile was associated with a median 2.1% increase in cannabis abuse/dependence hospitalizations in a ZIP code (95% Credible Interval 0.1–4.1% increase). Prior-year dispensary density did not appear to be associated with hospitalizations (median RR 1.006, 95% credible interval [0.986, 1.026]). Higher median household income, higher unemployment, greater off-premises alcohol outlet density, and lower on-premises alcohol outlet density and poverty were all associated with decreased ZIP code-level risk of cannabis abuse/dependence hospitalizations.

cmair@pitt.edu, 412-624-3613.

Conclusions.—In California USA, increasing density of medical cannabis dispensaries appears to be positively associated with same-year but not next-year hospitalizations for cannabis use disorder.

Keywords

Medical cannabis dispensaries; cannabis abuse; cannabis dependence; cannabis use disorder; hospital discharge data

INTRODUCTION

While the legal availability of cannabis for both medical and recreational use continues to expand throughout the United States, the impacts of this increased availability on cannabis use, problematic use, and related problems on local communities remain largely undetermined. Preliminary evidence relating cannabis availability to increased problematic use has been mixed, partially due to the range of analytic methods (e.g., difference-in-difference analyses, basic statistical association studies). Studies among adult and adolescent populations have found that greater medical cannabis availability at the local (e.g., city) and state level is related to higher prior-year cannabis use, though the details of these findings vary between studies (1–6). Other studies have found that medical cannabis laws do not appear to be related to increased adolescent or young adult cannabis use (7–11) or overall cannabis hospitalizations (12), though they are associated with higher rates of treatment among males (13). One potential explanation for the heterogeneity in these findings is that the impact of cannabis availability is not evenly distributed throughout states and cities, among age groups, or on different types of cannabis use (e.g., cannabis use disorders vs. adolescent initiation of use). For example, one study found that medical cannabis dispensaries in California were more likely to be located in Census block groups with lower median household incomes and higher levels of cannabis use, indicating that exposure to dispensaries varies at a relatively small geographic scale (14).

It is important to better quantify the impacts of neighborhood ecology and cannabis dispensary density on cannabis use, abuse, and dependence as cannabis policies continue to be liberalized across the country. There are several reasons for the discrepancy in findings of the relationship between cannabis availability and cannabis abuse/dependence in the published literature. First, there is a lack of geographic specificity in reported findings. Effects of dispensaries may only be seen at lower levels of geography where cannabis is purchased and consumed, such as smaller neighborhood areas like US Census tracts (populations around 4,000), and not higher ones such as states and counties. Second, the lack of longitudinal studies has led to confusion in the causal associations or direction of links (15). It may be that cannabis availability increases more rapidly in areas with higher preexisting demand. Understanding the impact of dispensary density on current and future cannabis abuse/dependence can help shape state and local laws and policies about the numbers and restrictions on cannabis dispensary and outlet permits. In a prior analysis utilizing cross-sectional information about cannabis dispensary density in California in 2012, we found that an additional one dispensary per mile^2 in a ZIP code was associated with a 6.8% increase in the number of hospitalizations with a cannabis abuse/dependence code (16). The aim of this paper was to extend this analysis by including data from 2013 through 2016 to estimate the impacts of current- and prior-year cannabis dispensary densities on hospitalizations for cannabis abuse/dependence.

METHODS

We analyzed ZIP code-level California hospitalization discharge data from 2013 through 2016 (6,832 space-time units) to assess associations between current- and prior-year medical cannabis dispensary densities and cannabis abuse/dependence hospitalizations using Bayesian space-time models. Our findings did not arise from pre-registered analysis plans.

Measures

Aggregate counts of cannabis abuse and dependence for each year were calculated by ZIP code using patient-level records from California's Office of Statewide Health Planning and Development (17). The hospital discharge data include all events that required at least one overnight stay. As the classification system for patient-level records switched from ICD-9-CM to ICD-10-CM in the last quarter of 2015, we used two sets of codes to compute outcome totals. ICD-9-CM codes included 304.3x (cannabis dependence) and 305.2x (nondependent cannabis abuse), excluding 304.33 and 305.33 (remission codes). Analogous ICD-10-CM codes were F12.1x (cannabis abuse) and F12.2x (cannabis dependence), excluding F12.21 (remission).Eighty-five percent of diagnostic codes indicated abuse only, 14.8% indicated dependence only, and 0.2% had diagnostic codes for both abuse and dependence. Less than 1% of the cannabis abuse or dependence codes were the primary diagnostic code. Almost half of the primary diagnosis codes were for mental health disorders.

We included measures of the total number of medical cannabis dispensaries per mile^2 as well as dispensary temporal and spatial lags (18). We obtained dispensary locations from Weedmaps.com from 2012 through 2016 approximately monthly and aggregated to the ZIP code level. All unique medical cannabis locations in a given year were included in a year-specific ZIP code count, regardless of whether they were open for the entire or a partial year. Spatial lags were calculated as the total number of dispensaries in all neighboring ZIP codes (i.e., ZIP codes sharing a border, regardless of length) divided by the total area of neighboring ZIP codes. Temporal lags were calculated by matching ZIP codes to their respective previous-year ZIP codes based on greatest area overlap, since the shape and number of ZIP codes were inconsistent across years.

We included a number of other ZIP-code level variables based on prior analyses (see Mair et al. 2015 for details). Alcohol outlet densities were calculated using annual retail license data from the California Department of Alcoholic Beverage Control (19). Outlets were classified as off-premise (license types 20 and 21) or on-premise (restaurants with license types 41 or 47, and bars/pubs with license types 23, 40, 42, 48, 61, or 75). Alcohol outlet densities were calculated as the number of relevant outlets per mile^2.

We generated measures of manual labor and retail sales densities using counts of North American Industry Classification System (NAICS) codes from Zip Code Business Patterns data (20). For manual labor, we used NAICS Sector 11, 21, 22, 23, 31–33, 42, and 48–49. NAICS Sectors 44–45 and were used to create the retail sales variable. To control for ZIP code area, we divided counts of these establishments by the total area of each ZIP code.

Three variables represented ZIP code-level economic conditions. These included percent of the population below 150% of the poverty level, percent unemployed, and the median household income (per $10,000). We also included a spatial lag for percent below 150% of poverty level, calculated as the average of the main poverty variable in all neighboring ZIP codes. ZIP-code-level estimates of each of these variables were calculated based on Census block group-level GeoLytics data (21), as they are not provided by the Census at the ZIP-code level, using a method successfully implemented in prior analyses (16).

ZIP code-level demographic variables were similarly derived from block group-level GeoLytics data. Measures included racial/ethnic distributions (percent Asian, non-Hispanic Black, and Hispanic), age distributions (percent of the population aged 0–19, 20–24, 25–44, and 45–64), and percent male. Population density was included as quartiles. The overall hospitalization rate (total number of discharges per capita per ZIP code) was also included.

One hundred and nine ZIP codes had total population counts of fewer than five people. Since our models adjusted for the expected counts of each outcome based on the total population count in each ZIP code, we increased the total population to five people in these areas to allow for non-zero risks. These areas were also assigned the mean value of all other ZIP codes for variables derived from GeoLytics data.

Data analysis

We used a Bayesian hierarchical approach to analyze four years of space-time ZIP-code-level data. A spatially autocorrelated conditionally autoregressive (CAR) random effect and a spatially unstructured random effect for each space-time unit were included to account for similarity among neighboring spatial units. We used Poisson regression:

$$Y_{i,t} \mid \mu_{i,t} \sim Poisson(E_{i,t} exp(\mu_{i,t}))$$

$$\mu_{i,t} = \boldsymbol{\beta} \boldsymbol{X}_{i,t} + \phi_{i,t} + \theta_{i,t}$$

$Y_{i,t}$ is the count of cannabis abuse and/or dependence in each ZIP code i per year t. $E_{i,t}$ is the expected count of each outcome calculated relative to the total population count for each space-time unit i,t. $exp\,(\mu_{i,t})$ is each unit's relative rate. $\mu_{i,t}$ is composed of $\boldsymbol{\beta}$, a vector of coefficient estimates for the intercept and each fixed effect as observed in $\boldsymbol{X}_{i,t}$, and $\phi_{i,t}$ and $\theta_{i,t}$, vectors of spatially structured and non-spatial random effects, respectively (22). As ZIP codes change shape across years, we used misalignment models that take into account the change in area over time (23). These models include year-specific spatial structures and a variable that represents the level of change of a given ZIP code from the prior year (ZIP code instability) in the final analytic models. The model included medical cannabis dispensary density and spatial and temporal lag variables, as well as the ZIP code-level economic conditions, population demographics, retail sales and manual labor establishments density, and overall hospitalization rate, all described above. We used the R package R-INLA to estimate our models (24).

RESULTS

There were an average of 41.5 cannabis abuse/dependence hospitalizations per ZIP code per year (SD 54.6), with a total of 283,826 (Table 1). There were 2,739 dispensaries in 2013, which reduced to 1,549 in 2016 due partially to restrictions passed by many California jurisdictions as to where dispensaries could be opened (25–27). The average density of these dispensaries was 0.3/mile^2 for the main measure as well as the temporal and spatial lags. As expected in a heterogeneous state like California, there was a wide range of values for most demographic and environmental covariates. For example, 26.3% of the population lived under 150% of the poverty line per ZIP code, with a range of 0–89.4%.

In our Bayesian spatial misalignment model (Table 2), after adjustment for demographic and environmental covariates and economic conditions, an additional cannabis dispensary per mile^2 was associated with a 2.1% increase in cannabis abuse/dependence hospitalizations (95% credible interval 1.00, 1.04). An increase of one dispensary/mile^2 in spatially adjacent ZIP codes was associated with a decrease in cannabis hospitalizations (risk ratio (RR) 0.95 (95% CI 0.92, 0.98). Prior-year dispensary density was not associated with cannabis hospitalizations. Prior to including both the temporally and spatially lagged dispensary effects in the same model, we ran two models with each effect separately. This did not substantively change posterior distribution estimates. Increasing population densities were associated with increased risk for cannabis hospitalizations; ZIP codes in the highest population density quartile had a 14.9% increased risk vs. the lowest quartile (95% CI 1.07, 1.23). A one-percent increase in the percent under 150% of the poverty level was associated with a 1.9% increase in risk for cannabis hospitalizations, while a one-percent increase in the poverty rate among neighboring ZIP codes was associated with an additional 0.4% increased risk. Higher median household income, higher unemployment, greater percent male, higher percent Hispanic and Asian, lower percent non-Hispanic Black, higher retail sales density, lower manual labor density, higher off-premise alcohol outlet density, lower on-premise alcohol outlet density, and a lower overall hospitalization rate were all associated with decreased ZIP code-level risk of cannabis abuse/dependence hospitalization.

DISCUSSION

Similar to our prior cross-sectional analysis using 2012 data (16), we found that a greater density of medical cannabis densities in a ZIP code was associated with a greater number of cannabis abuse/dependence hospitalizations in California from 2013 through 2016. Conversely, a greater density of dispensaries in surrounding ZIP codes was associated with fewer cannabis abuse/dependence hospitalizations. These results indicate that there is a spatially localized impact of dispensaries on problematic use in a given location. Using multiple years of data (2013 through 2016) allowed us to look at whether the prior year's dispensary density impacted current hospitalizations. We found no such association, signifying a more temporally immediate impact of cannabis availability on abuse/dependence hospitalizations. Populations living in ZIP codes with greater availability of cannabis a have an increased risk of being hospitalized with cannabis abuse/dependence. Importantly, we find this relationship at a smaller unit of analysis than many previous studies (2,4,13).

Beyond the importance of cannabis availability through local dispensary density, several demographic and economic ZIP code-level factors were associated with cannabis hospitalizations. Both the main effect and the spatial lag of the poverty rate were associated with a greater number of cannabis hospitalizations, indicating that the association of poverty levels with cannabis hospitalizations operates at a larger spatial scale. Higher median household income was also associated with fewer cannabis hospitalizations. These relationships operate in the same direction as with individual-level income/poverty and cannabis use (28).

There are several important limitations to highlight. First, the analysis plan was not pre-registered so the findings must be considered to be exploratory. Second, the analyses focus only on hospitalizations with cannabis abuse/dependence codes (and do not differentiate between abuse and dependence); these represent only a subset of cannabis hospitalizations (e.g., use and poisonings were excluded), and an even smaller subset of cannabis use disorders in the general population. Individuals living in higher socio-economic status areas may be less likely to be hospitalized when they have a cannabis use disorder vs. in lower SES areas. The transition from ICD-9 to ICD-10 caused a shift in overall abuse/dependence codes (ICD-10 counts for abuse/dependence were smaller than ICD-9, but adding in cannabis use made the counts bigger). We do not differentiate between abuse and dependence codes, as we were trying to capture the breadth of cannabis use disorders. We do not account for whether dispensaries were open for all or only part of a given year; sensitivity analyses using only dispensaries open in January had comparable results.

These analyses highlight the population-level associations between local access to medical cannabis dispensaries and cannabis abuse/dependence, but do not investigate individual-level access and subsequent use patterns. Findings from this analysis are useful when generating local policies around the number/density of cannabis dispensaries or recreational sales outlets, or the locations where dispensaries are or are not allowed. Programs focused on prevention of cannabis use disorders should be targeted to areas with greater cannabis access and higher poverty.

Declarations of interest:

This project was supported by grant number P60-AA-006282 from the National Institute on Alcohol Abuse and Alcoholism and R01-DA-032715 from the National Institute on Drug Abuse, and the Clinical and Translational Science Institute (CTSI) at the University of Pittsburgh Virginia Kaufman Endowment Fund. The content is solely the responsibility of the authors and does not necessarily represent the National Institutes of Health.

References

1. Cerdá M, Wall M, Keyes KM, Galea S, Hasin D. Medical marijuana laws in 50 states: Investigating the relationship between state legalization of medical marijuana and marijuana use, abuse and dependence. Drug and Alcohol Dependence. 2012;120(1):22–27. [PubMed: 22099393]

2. Freisthler B, Gruenewald PJ. Examining the relationship between the physical availability of medical marijuana and marijuana use across fifty California cities. Drug and Alcohol Dependence. 2014;143:244–250. [PubMed: 25156224]

3. Harper S, Strumpf EC, Kaufman JS. Do medical marijuana laws increase marijuana use? Replication study and extension. Annals of Epidemiology. 2012;22(3):207–212. [PubMed: 22285867]

4. Pacula RL, Powell D, Heaton P, Sevigny EL. Assessing the effects of medical marijuana laws on marijuana use: The devil is in the details. Journal of Policy Analysis and Management. 2015;34(1):7–31. [PubMed: 25558490]

5. Wall MM, Poh E, Cerdá M, Keyes KM, Galea S, Hasin DS. Adolescent marijuana use from 2002 to 2008: Higher in states with medical marijuana laws, cause still unclear. Annals of Epidemiology. 2011;21(9):714–716. [PubMed: 21820632]

6. Wen H, Hockenberry JM, Cummings JR. The effect of medical marijuana laws on adolescent and adult use of marijuana, alcohol, and other substances. Journal of Health Economics. 2015;42:64–80. [PubMed: 25863001]

7. Choo EK, Benz M, Zaller N, Warren O, Rising KL, McConnell KJ. The impact of state medical marijuana legislation on adolescent marijuana use. Journal of Adolescent Health. 2014;55(2):160–166.

8. Khatapoush S, Hallfors D. “Sending the wrong message”: Did medical marijuana legalization in California change attitudes about and use of marijuana? Journal of Drug Issues. 2004;34(4):751–770.

9. Lankenau SE, Tabb LP, Kioumarsi A, Ataiants J, Iverson E, Wong CF. Density of medical marijuana dispensaries and current marijuana use among young adult marijuana users in Los Angeles. Substance Use & Misuse. 2019;54(11):1862–1874. [PubMed: 31154889]

10. Lynne-Landsman SD, Livingston MD, Wagenaar AC. Effects of State Medical Marijuana Laws on Adolescent Marijuana Use. Am J Public Health. 2013 Jun 13;103(8):1500–6. [PubMed: 23763418]

11. Sarvet AL, Wall MM, Fink DS, Greene E, Le A, Boustead AE, Pacula RL, Keyes KM, Cerdá M, Galea S, Hasin DS. Medical marijuana laws and adolescent marijuana use in the United States: A systematic review and meta-analysis. Addiction. 2018;113(6):1003–1016. [PubMed: 29468763]

12. Shi Y Medical marijuana policies and hospitalizations related to marijuana and opioid pain reliever. Drug and Alcohol Dependence. 2017;173:144–150. [PubMed: 28259087]

13. Chu Y-WL. The effects of medical marijuana laws on illegal marijuana use. Journal of Health Economics. 2014;38:43–61. [PubMed: 25205609]

14. Morrison C, Gruenewald PJ, Freisthler B, Ponicki WR, Remer LG. The economic geography of medical marijuana dispensaries in California. International Journal of Drug Policy. 2014;25(3):508–515. [PubMed: 24439710]

15. Wilkinson C Commentary on Shih et al. (2019): Lessons from alcohol outlet availability. Addiction. 2019;114(12):2171–2172. [PubMed: 31663192]

16. Mair C, Freisthler B, Ponicki WR, Gaidus A. The impacts of marijuana dispensary density and neighborhood ecology on marijuana abuse and dependence. Drug and Alcohol Dependence. 2015;154:111–116. [PubMed: 26154479]

17. California Office of Statewide Health Planning and Development (OSHPD). Patient Discharge Data File Documentation. 2013.

18. Pedersen ER, Zander-Cotugno M, Shih RA, Tucker JS, Dunbar MS, D’Amico EJ. Online methods for locating medical marijuana dispensaries: practical considerations for future research. Cannabis (Research Society on Marijuana). 2018;1(2):22.

19. California Department of Alcoholic Beverage Control. License Lookup | Alcoholic Beverage Control [Internet]. [cited 2018 May 7]. Available from: https://www.abc.ca.gov/licensing/license-lookup/

20. US Census Bureau. ZIP Codes Business Patterns (ZBP) [Internet]. The United States Census Bureau. [cited 2020 May 6]. Available from: https://www.census.gov/data/developers/data-sets/cbp-nonemp-zbp/zbp-api.html

21. Geolytics. Demographic Data, US Census & GIS Software | GeoLytics [Internet]. Available from: http://www.geolytics.com/
22. Besag J, York J, Mollié A. Bayesian image restoration, with two applications in spatial statistics. Annals of the Institute of Statistical Mathematics. 1991;43(1):1–20.
23. Zhu L, Waller LA, Ma J. Spatial-temporal disease mapping of illicit drug abuse or dependence in the presence of misaligned ZIP codes. GeoJournal. 2013;78(3):463–474. [PubMed: 23898219]
24. Rue H, Martino S, Chopin N. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. Journal of the Royal Statistical Society: Series B (Statistical Methodology). 2009;71(2):319–392.
25. Freisthler B, Kepple NJ, Sims R, Martin SE. Evaluating medical marijuana dispensary policies: Spatial methods for the study of environmentally-based interventions. American Journal of Community Psychology. 2013;51:278–288. [PubMed: 22821130]
26. Linthicum K, Blankenstein A. (September, 2012). The Los Angeles Times: A. U.S. raids L.A. marijuana shops http://articles.latimes.com/2012/sep/26/local/la-me-medical-marijuana-20120926. Accessed December 17, 2015.
27. Proposition D, City of Los Angeles. (May, 2013). http://clerk.lacity.org/stellent/groups/Departments/@CLERK_Elections_Contributor/documents/Contributor_Web_Content/LACITYP_024794.pdf. Accessed December 17, 2015.
28. Carliner H, Mauro PM, Brown QL, Shmulewitz D, Rahim-Juwel R, Sarvet AL, et al. The widening gender gap in marijuana use prevalence in the U.S. during a period of economic change, 2002–2014. Drug and Alcohol Dependence. 2017;170:51–58. [PubMed: 27875801]

Table 1.

Descriptive statistics, ZIP codes in California, 2013–2016 (*n* = 6,832 ZIP codes)

Covariate	Mean	Standard Deviation	Minimum	Maximum	Mean change, 2016 vs. 2013
Population size	22,679.34	22,575.76	5	120,917	421.32
Population density	3,395.18	5,516.10	0.004	55,606.95	110.92
Number of cannabis abuse/dependence hospitalizations	41.54	54.64	0	545	−5.00
Cannabis dispensary count	1.27	3.36	0	35	−0.70
Cannabis dispensary density, per mi^2	0.30	1.13	0	18.88	−0.19
Cannabis dispensary density, per mi^2, spatial lag	0.25	0.72	0	10.35	−0.14
Cannabis dispensary density, per mi^2, temporal lag	0.30	1.14	0	18.88	0.01
Retail sales, number of establishments per mi^2	25.37	97.00	0	1,981.99	0.58
Manual labor, number of establishments per mi^2	20.39	100.45	0	3,430.55	0.29
On-premise alcohol outlet density, per mi^2	6.13	24.86	0	409.45	0.16
Off-premise alcohol outlet density, per mi^2	2.60	6.19	0	105.66	−0.01
Demographic and environmental covariates					
Age					
0–19, %	25.74	7.39	0	52.38	−1.28
20–24, %	6.32	1.49	0	12.51	−0.22
25–44, %	24.50	5.88	0	79.01	−0.06
45–64, %	25.94	4.99	4.99	100	−0.58
Race/ethnicity, %					
Asian, %	8.54	12.81	0	100	0.02
Black, %	3.53	7.21	0	87.09	−0.16
Hispanic, %	30.15	25.46	0	98.51	1.92
Non-Hispanic White, %	48.21	25.05	0	98.24	2.33
Male, %	49.90	3.32	0	98.75	−0.68
Overall hospitalization rate, per 100 people	0.12	0.25	0	8.69	0.01
Economic conditions					
Med. household income ($10,000)	6.64	2.73	0	20.93	0.09
Population below 150% of poverty line, %	26.39	15.12	0	89.44	−0.09
Population below 150% of poverty line, %, spatial lag	26.25	11.50	0	70.30	−0.08
Unemployment rate	9.55	10.70	0	100	−7.01

Table 2.

Risk ratios (RRs) [95% credible intervals], cannabis abuse and/or dependence hospitalizations, Bayesian spatial misalignment models (n = 6,832 ZIP codes)

Variable	RR [95% credible interval]
Year 2014	1.003 [0.975, 1.031]
Year 2015	0.975 [0.945, 1.006]
Year 2016	0.963 [0.932, 0.996][b]
Cannabis dispensaries, per mi^2	1.021 [1.001, 1.041][b]
Cannabis dispensaries, per mi^2, spatial lag	0.946 [0.917, 0.976][b]
Cannabis dispensaries, per mi^2, temporal lag	1.006 [0.986, 1.026]
Manual labor, number of establishments per mi^2 (x10)	1.001 [1.001, 1.001][b]
Retail sales, number of establishments per mi^2 (x10)	0.999 [0.998, 0.999][b]
On-premise alcohol outlet density, per mi^2	1.008 [1.006, 1.009][b]
Off-premise alcohol outlet density, per mi^2	0.989 [0.985, 0.994][b]
Demographic and environmental covariates	
Overall hospitalization rate, per 100 people	2.258 [2.121, 2.401][b]
Age, %	
0–19	0.995 [0.989, 1.000]
20–24	1.092 [1.067, 1.117][b]
25–44	0.985 [0.981, 0.988][b]
45–64	1.040 [1.034, 1.046][b]
Race/ethnicity, %	
Asian	0.986 [0.985, 0.988][b]
Non-Hispanic Black	1.013 [1.011, 1.015][b]
Hispanic	0.993 [0.992, 0.995][b]
Male, %	0.986 [0.981, 0.992][b]
Population density, per mi2 [a]	
Quartile 2	1.065 [1.014, 1.118][b]
Quartile 3	1.176 [1.107, 1.249][b]
Quartile 4	1.149 [1.072, 1.232][b]
Economic conditions	
Below 150% of poverty level, %	1.019 [1.017, 1.020][b]
Below 150% of poverty level, %, spatial lag	1.004 [1.001, 1.006][b]
Median household income, per $10,000	0.918 [0.910, 0.927][b]
Unemployment, %	0.988 [0.986, 0.990][b]
Misalignment effects	
ZIP code instability	1.001 [0.991, 1.011]
Random effects	

Variable	RR [95% credible interval]
Spatial random effects (s.d. CAR[c] process)	0.441 [0.435, 0.447]
ZIP-code-level random effects (s.d.)	0.147 [0.122, 0.173]
Spatial to total random variability ratio[d]	0.900 [0.866, 0.928]

[a] Population density was divided into equal quartiles as follows: 1 (referent; 41.52 < people / mi^2), 2 (41.52–732.10), 3 (732.11–5053.76), and 4 (> 5053.76);

[b] Indicates findings that are well-supported by the data as evidenced by credible intervals that exclude one for relative risks;

[c] CAR = conditional autoregressive;

[d] calculated as the variance ratio of spatial to spatial and non-spatial random effects.