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Socioeconomic Status, Air Quality and Geographic Variation in Emergency Room Visits for Acute Bronchitis on the California Central Coast

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Abstract

Importance

Analysis of geospatial variation in acute bronchitis due to socioeconomic and environmental factors can allow the efficient delivery of resources to populations most at risk.

Objective

We sought to determine if small-scale variation in socioeconomic factors and emergency room (ER) visits for acute bronchitis are associated with small cities or rural communities. We also modeled the effects of air quality on daily rates of ER visits for acute bronchitis in the context of socioeconomic factors to investigate modifying relationships.

Design, Setting, and Participants

We examined ER visits for acute bronchitis in San Luis Obispo and Santa Barbara counties from 2009 through 2012. The study area included 49 ZIP codes with a total population of 765,836 residents.

Exposures

Socioeconomic exposures included ZIP code level socioeconomic indicators collected for the 2010 American Community Survey. Environmental exposures included PM10, PM2.5, Ozone and temperature.

Main Outcomes and Measures

The rate of ER visits was calculated for each ZIP code. Spatial clustering (hotspots) of ER visits for acute bronchitis was examined using the local Getis-Ord Gi* statistic. Differences between the distribution of socioeconomic variables across ER visit rate quintiles was assessed using the nonparametric Kruskal-Wallis test. Four Generalized Linear Mixed Models (GLMMs) were used to examine the association between lagged air quality, socioeconomic status and daily rates of ER visits for acute bronchitis in each ZIP code.

Results

5,620 ER visits for acute bronchitis were reported during the study period. The four-year rate of ER visits was between 2 and 17 visits per 1,000 residents for all ZIP codes. Two hotspots of ER visits were observed around the communities of Templeton and Lompoc, CA. Significant differences in home value and rent were observed across ER visit rate quintiles ($p = .003$ and $p < .001$, respectively). PM10 was found to be a significant predictor of daily ER visits in a GLMM including only environmental exposures. No exposures were found to be significant in a GLMM with both environmental and socioeconomic exposures. No clear evidence of socioeconomic factors modifying the effect of air quality on ER visits for acute bronchitis was found.

Conclusions

We found clear evidence of significant variation in ER visit rates for acute bronchitis at a small geographic scale in rural counties with small to medium size cities. Variation in ER visit rates across ZIP codes was associated with significant differences in socioeconomic factors including home value and rent.

Introduction

Socioeconomic status has been linked to the prevalence of respiratory infections on a small geographic scale. Recent work by Beck et al. has discovered high variation in the rate of pediatric emergency room visits for acute bronchitis and pneumonia across census tracts in one urban county near Cincinnati, Ohio, correlated with differences in socioeconomic status indicators.[1] The methods of Beck et al. have not been replicated in a rural area, and it is not reasonable to generalize these associations to communities that have different economic conditions from major cities, such as small cities, suburban and rural areas.

Air quality has been associated with respiratory infections and mortality in urban and rural communities.[2–15] Daily air quality has been shown to predict emergency room visits days to weeks later for conditions including respiratory infections such as pneumonia and acute bronchitis, and air quality has been shown to affect mortality rates up to two months later.[15–21]

Evidence exists that socioeconomic factors are related to air quality effects on respiratory illness. Socioeconomic status has been found to modify the effect of air quality on respiratory mortality.[22–24] However, little work has been done to observe socioeconomic effects in the context of daily emergency room visits for respiratory infections, especially in rural areas. It is unknown if socioeconomic factors modify the effect of air quality on respiratory infections (slope), or change the background rate of disease (intercept). To increase our understanding of the effects of socioeconomic factors on respiratory infections, we performed two analyses in a rural area with small cities. We sought to determine if evidence of relationships between local variation in socioeconomic factors and emergency room visits for acute bronchitis can be found in small cities or rural communities. We also investigated the effects of air quality on emergency room visits for acute bronchitis in the context of local variation in socioeconomic factors to describe evidence of a modifying relationship. The California Polytechnic State University Institutional Review Board approved this study.

Methods

Study Location and Population

We examined the rates of emergency room visits for acute bronchitis in San Luis Obispo and Santa Barbara counties from 2009 through 2012. These counties are located on California's central coast. Land use is primarily agricultural with small towns to medium cities located along US Highway 101 and California Highway 1. We chose ZIP codes as the geographic unit of analysis to explore small-scale spatial variation in emergency room visit rates because the low population density in rural areas could confound finer spatial analysis. The study area included 49 ZIP codes with a total population of 765,836 residents after excluding three ZIP codes with less than 75 residents. Demographic characteristics of the study population can be seen in **Table 1**.

Emergency Room Visit Data

Acute bronchitis emergency room visits were defined using the International Classification of Diseases, Ninth Revision (ICD-9) code 4660.[25] Emergency room visit data was acquired from the California Office of State Health Planning and Development (OSHPD).[26] The dataset included emergency room visits with a primary diagnosis of acute bronchitis for residents of San Luis Obispo and Santa Barbara counties. The dataset was limited to date of emergency room visit, patient ZIP code of residence, age group, gender, secondary diagnosis and ethnicity (Hispanic or non-Hispanic) to protect patient privacy.

Environmental and Socioeconomic Data

Population size and socioeconomic data collected for the 2010 American Community Survey was downloaded from the US Census Bureau FactFinder Website.[27] Hourly air quality data was downloaded from the US EPA Air Quality System Data Mart.[28] Temperature data was downloaded from the California Agricultural Resources Board Meteorology Data Query Tool.[29] Air quality and temperature were sampled at 22 monitoring stations between 12:00 a.m. January 1, 2008 and 11:00 p.m. December 31, 2012, for more than 38,000 observations.[30,31] Ozone was sampled at 19 of the stations and particulate matter was sampled at 6 of the stations.

Statistical Analysis

Hotspot Analysis

Spatial clustering of emergency room visits for acute bronchitis was examined using the local Getis-Ord Gi* statistic, similarly to Beck et al.[1] The Gi* statistic was used to identify ZIP codes with higher than expected rates of emergency room visits, assuming a random spatial distribution. Analysis was performed using Esri ArcGIS.[32,33]

Analysis of Socioeconomic Factors and Emergency Room Visit Rate Variation

ZIP codes were categorized by quintile of emergency room visit rate, and differences in socioeconomic status (SES) variables were analyzed following the procedure described by Beck et al. Differences between the distribution of SES variable medians across emergency room visit rate quintiles were assessed using the nonparametric Kruskal-Wallis test.[34] Variables were selected from the 2010 American Community Survey (ACS 2010) to allow comparison to previous studies and to highlight vulnerable populations. Variables selected included: adults with less than a high school education, unemployment, median annual household income, vacant homes, renter-occupied homes, households without a vehicle, median home value, median rent, residents never married, disabled residents and households with gross rent greater than 35% of income. We calculated the percent of older adults and children with no health insurance as the proportion of children ages 0–19 and adults 65 and older with no insurance using ACS 2010 data. To allow comparison of our findings to Beck et al., we performed a sensitivity analysis that found that the results of our analysis of SES effects do not differ when the analysis is limited to emergency room visits by patients age 21 years or younger.

Independence of Air Quality and SES Predictors

To assess the independence of air quality and SES for confounding relationships, average air quality for the study period was compared between socioeconomic quintiles using a Kruskall-Wallis test. We also calculated the correlation between daily air quality predictors and SES quintile as well as the correlation among air quality predictors.

Mixed Effects Modeling

We created four Generalized Linear Mixed Models (GLMMs) with Poisson log-link functions to examine the association between air quality, socioeconomic status and emergency room visits for acute bronchitis. The response variable was the daily rate of emergency room visits per 100,000 residents in each of 32 ZIP codes. ZIP codes with no emergency room visits during the study period were excluded. Similarly to Berhane et al. our models incorporate a hierarchical structure of predictors at the day and ZIP code level.[35] Fixed effects for air quality predictors were included in all GLMMs. The air quality predictors included lagged daily mean PM10, PM2.5, Ozone and Temperature for each ZIP code. ZIP code level predictors included random spatial effects and socioeconomic effects.

Fixed Effects

Air quality and temperature were interpolated at the geographic center of each ZIP code using covariance kriging.[36–38] Empirical variograms were calculated using hourly observations. Seven potential models were fit to select the most appropriate kriging functions. A Gaussian model was selected for zone and PM2.5, a Cauchy model was selected for PM10 and an exponential model was selected for temperature. The kriging functions were applied to interpolate hourly estimates of air quality for each ZIP code. The hourly estimates were aggregated into time series of 24-hour mean measurements.[39]

Methods described by Schwartz and others were used for seasonal trend adjustment and smoothing.[40–42] In order to correct for dominance of seasonal trends in the GLMM and focus the analysis on changes in daily air quality, harmonic models were fit to de-trend air quality and temperature predictors and emergency room visits in each ZIP code.[40,43] Gaussian Kernel smoothing (window width of ten days) was applied to the emergency room visit series. To determine the appropriate lag periods for predictors, we adapted methods described by Katsouyanni et al. to account for variation between ZIP codes.[42] Cross Correlation Functions (CCFs) were fit to determine the lag period with strongest correlation between each predictor variable and emergency room visits for acute bronchitis in each ZIP code.[39] A histogram of strongest correlation lags from all ZIP codes, weighted by emergency room visits in each ZIP code, was used to choose a single lag period for each variable to be used in regression modeling. We performed a sensitivity analysis that found little difference in the conclusions of models fitted with the same lag period for all ZIP codes and a lag period individualized for each ZIP code. Lagged time series were created for Ozone ($k = 3$ days), PM10 ($k = 10$ days), PM2.5 ($k = 4$ days) and Temperature ($k = 5$ days).[44]

Random Effects

A base GLMM was created to model the effects of air quality on emergency room visits for acute bronchitis. Random effects were included to account for potential spatial correlation and observation imbalance between ZIP codes.[45] Random intercepts and slopes for lagged PM10, PM2.5, Ozone and Temperature were fit by ZIP code.

Three additional GLMMs were fit by adding effects for ZIP code socioeconomic status to the base model. Factor analysis was used to classify ZIP codes in socioeconomic quintiles.[46] A single socioeconomic factor was created by incorporating the most significant variables from the emergency room visit quintile analysis, which included: vacant homes, median home value, median rent and adults and children with no health insurance. The second and third GLMMs were fit by subsequently adding random intercepts by socioeconomic quintile and random slopes for air quality predictors by socioeconomic quintile. A fourth GLMM was fit by adding fixed effect for socioeconomic quintile to the base model of air quality predictors.

Computation of GLMMs

Markov-Chain Monte Carlo (MCMC) estimation was used to fit the mixed effects Poisson GLMs because of possible zero inflation or spatial autocorrelation in the emergency room visit rate distribution.[45] Three MCMC chains were computed for each model, using a parameter expanded proper Cauchy prior.[47,48] The base air quality model was run for 80,000 iterations with a burn-in of 30,000 and a step of 50. The socioeconomic status models were run for 120,000 iterations with the same burn-in and step. Convergence was tested using the Gelman-Rubin statistic.[49,50] Gelman-Rubin statistic values less than 1.02 are considered indicative of good convergence as a test for model reliability. Models were assessed by comparing the variances of the random effects and quantifying fit with the Deviance Information Criterion, a measure similar to the AIC for Bayesian mixed models.[45,51]

Results

Emergency Room Visits for Acute Bronchitis

5,620 emergency room visits with a primary ICD-9 diagnosis of 4660 by residents of San Luis Obispo and Santa Barbara counties were reported during the study period. 1,352 cases were residents over age 55; 1,667 cases were residents age 22–54; 2,601 cases were residents age 0–21 and 3,305 cases were women. Women 21 and older visited the emergency room more frequently than men (2,487 men vs. 1,466 women). The total daily emergency room visits for acute bronchitis for the study area had a mean of 3.84 and followed a Poisson distribution, with 0–16 total visits per day and 0–2 visits per day in any single ZIP code. At least one emergency room visit was reported on more than 96% of days in the study period. The rate of acute bronchitis emergency room visits showed strong seasonal periodicity. Visits peaked in the late winter between December and February. The lowest rates of admission were seen in midsummer.

Hotspot Analysis

Geographic variation was observed in emergency room visit rates. The emergency room visits included residents of 32 of the 49 ZIP codes in the study area. The four-year rate of emergency room visits for acute bronchitis is between 2 and 17 visits per 1,000 residents for all ZIP codes. Two clusters of ZIP codes with high emergency room visit rates were observed around the communities of Templeton and Lompoc, CA (**Figure 1**). ZIP codes 93465, 93432 and 93454 in these clusters were found to be hotspots by the Gi* analysis at 90% significance (**Figure 2**). No significant cold spots were found, but lower emergency room visit rates were observed in San Luis Obispo County along the coast.

Socioeconomic Differences across Emergency Room Visit Rate Quintiles

The median rate for acute bronchitis emergency room visits varied significantly across quintiles. 0.0, 0.0, 4.28, 8.07 and 13.5 emergency room visits were reported per 1,000 residents over four years in the lowest to highest quintiles, respectively ($p < .001$). The lowest and low medium quintiles were combined during analysis because of indistinguishable rates of 0.0 emergency room visits during the study period. Significant differences in socioeconomic measures were observed among quintiles (**Table 2**). Median home value and median rent were significant ($p = .003$ and $p < .001$, respectively) with similar trends of lower home values and rent in higher quintiles of emergency room visit rates, with the exception of the lowest median home values and rent being in the combined low and low medium emergency room visit quintiles. The percentage of vacant homes and the percentage of older adults and children without health insurance were close to significant ($p = .036$ and $p = .083$, respectively).

Generalized Linear Mixed Models

The MCMC estimates for the mixed effects models showed strong convergence with a Gelman-Rubin statistic of less than 1.01 and low autocorrelation. Posterior predictive tests for model misspecification found only slight zero-inflation.

No significant difference was found in the distribution of air quality between socioeconomic quintiles (KW p-values ≥ 0.20). No meaningful correlations between predictor variables were found. Air quality predictors were found to be correlated with SES quintile with Pearson's R coefficients less than 0.0001. Air quality predictors were found to be correlated with other air quality predictors with a Pearson's R coefficient less than 0.32.

Lagged daily mean PM10 concentration was found to be a significant predictor of emergency room visits in models including only air quality predictors and random effects for spatial autocorrelation (see model A in **Table 3**).

The addition of a fixed affect for SES quintile was not found to improve the fit of the model (see model D in **Table 3**). The DIC did not decrease meaningfully (5%) compared to the base model, and the credible interval of the SES quintile effect was wide and correlation was observed in most posterior distributions, indicating poor fit.

The addition of random intercepts for SES quintile improved the fit of the model leading to a large reduction of the DIC (41%) compared to the base model (see model B in **Table 3**). SES quintiles 1–3 generally have larger intercepts than SES quintiles 4–5, suggesting that lower SES may be associated with higher rates of emergency room visits. Lagged daily average temperature was a significant predictor in the random intercepts model.

The addition of random slopes for SES quintile resulted in a minimal decrease of the DIC (<1%) compared to the random intercepts model (see model C in **Table 3**). This model was considered to be a better fit because there were only minor changes in ZIP code random effect variances from the random intercepts model, and the most of the variance in the SES quintile random intercepts was partitioned into the SES quintile random slopes. No air quality fixed effects were found to be significant predictors of emergency room visits. While the variances of the SES quintile random slopes are objectively close to zero, the interquartile range size of the effects is 2% to 96% of the size of the average slopes. There is no consistent association between SES quintile and the size of the random slope for individual quintiles, but the mean effect of quintiles 1 and 2 is larger than the mean effect of quintiles 4 and 5 for all variables. However, the 95% credible intervals from the posterior distributions for all SES quintile random slopes overlap zero. This suggests that there may be an association between low SES and increased effect of air quality that this sample does not have enough power to identify.

Discussion

Findings

Our Hotspot analysis provides clear evidence that significant variation exists in emergency room visit rates for acute bronchitis across ZIP codes in rural counties with small to medium size cities. There is also clear evidence that variation in emergency room visit rates is associated with significant differences in ZIP code level socioeconomic factors, including median home value and median rent.

Relationship to Previous Literature

However, we did not find significant differences for all socioeconomic factors found to be associated with emergency room visit rates by Beck et al. in Cincinnati, OH. We are unable to conclude that SES modifies the short-term effect of air quality on emergency room visit rates for acute bronchitis. Although we observe differences in the random coefficients of air quality predictors on emergency room visit rates that suggest lower SES is associated with greater effects of air quality, these differences do not appear large enough to be statistically meaningful.

Limitations

Since our emergency room visit dataset time series are very sparse, we believe this study is underpowered for the effect sizes of air quality and SES. We anticipate that a longer study period or a similar investigation of a more prevalent respiratory illness, such as asthma, would result in more conclusive results. Previous research has found significant short term effects of air quality during summer months only.[2,9] Our analysis included data from all seasons, and it is not known how seasonal limitations (such as limiting the analysis to flu season, when acute bronchitis is most prevalent) could have affected the conclusions. Like all ecological studies, our analysis is limited by the lack of individual level data about emergency room visits, including patient identity, socioeconomic status and confounding health factors.[52] As noted previously, emergency room visits do not capture the full burden of acute bronchitis, especially cases that result in private medical care.[1] Observational studies of emergency room visits may also be confounded by varying rates of emergency room utilization, which have been shown to be higher among individuals with lower SES.

Significance

These results show significant variation in the epidemiology of respiratory infection rates at a small geographic scale in rural areas and small cities, with implications for health care, policy and research. While counties with low overall rates of respiratory infections may not appear to require control efforts, hotspots of disease can exist, potentially in places where vulnerable low socioeconomic status populations live. Therefore, public health agencies should consider small-scale geospatial analysis as one method to identify disparities in health and efficiently deliver resources to the populations most at risk.

We found strong evidence that socioeconomic factors at a small geographic scale should be considered important in epidemiological studies of respiratory infections in small cities and rural communities. While socioeconomic factors are associated with differences in rate of emergency room visits for respiratory infections in both large urban cities and rural areas, a different set of socioeconomic factors may be important in rural areas, and the relationships with disease may be different. Similarly, the effect of air quality on emergency room visits for respiratory infections may vary considerably between nearby communities and may be modified by socioeconomic factors. Analyses that ignore these relationships risk biased conclusions. Our suggestions for research and health policy for small cities and rural areas reinforce existing recommendations developed using data from large metropolitan areas.[53]

Conclusion

We found clear evidence of significant variation in emergency room visit rates for acute bronchitis at a small geographic scale in rural counties with small to medium size cities. Variation in emergency room visit rates was associated with significant differences in socioeconomic factors including median home value and median rent.

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Tables and Figures

Name	Total	ZIP Codes in Study Area (n=49)		
		Mean	Median	SD
Population	765836	15316.72	9971	15635.31
Male	392662 (51.6%)	7853.24 (51.6%)	4806 (50.41%)	8055.47 (5.68%)
White	564137 (76.13%)	11282.74 (76.13%)	7593.5 (78.63%)	10961.04 (15.16%)
Black/ African American	16638 (1.74%)	332.76 (1.74%)	78.5 (1.02%)	609.94 (2.21%)
Asian	30077 (2.77%)	601.54 (2.77%)	205.5 (2.34%)	1013.22 (2.11%)
Two or more races	32448 (3.85%)	648.96 (3.85%)	317 (3.66%)	777.48 (1.49%)
Other	113410 (14.31%)	2268.2 (14.31%)	664 (9.64%)	3558.22 (14.81%)
Hispanic or Latino	271721 (32.28%)	5434.42 (32.28%)	1977.5 (27.82%)	8149.06 (21.13%)
0-19	200532 (25.18%)	4010.64 (25.18%)	573.5 (21.11%)	4725.76 (6.95%)
65+	108997 (15.75%)	2179.94 (15.75%)	276.25 (12.18%)	2042.35 (6.64%)
Population Density (n/ sqmi)	748.99	748.99	22.49	1665.88

Table 1: Sample Characteristics

Name	Q1 & Q2	Q3	Q4	Q5	P
ER visits per 1,000 (n/year)	0.0	4.28	8.07	13.85	<0.001***
Adults with less than a high school education (%)	0.85	0.90	0.87	0.87	0.192
Unemployment Rate (%)	0.05	0.03	0.04	0.04	0.219
Median Annual Household Income ($)	55574.50	71357.50	61074.50	58670.00	0.123
Vacant Homes (%)	17.90	10.20	6.20	9.00	0.036*
Renter Occupied Homes (%)	37.85	41.20	47.45	37.75	0.834
Households that do not own a vehicle (%)	3.40	4.60	5.80	4.65	0.367
Median Home Value ($)	243500.00	665000.00	662750.00	371500.00	0.003**
Median Rent ($)	1033.50	1407.00	1364.50	1102.50	<0.001***
Residents Never Married (%)	34.65	38.35	33.90	29.20	0.338
Disabled Residents (%)	0.97	0.99	1.00	0.97	0.798
Gross Rent greater than 35% household income (%)	48.00	49.30	46.35	46.75	0.731
Percentage of older (65+) adults and children (0-19) with no health insurance (%)	1.18	0.97	0.97	1.27	0.083*

Legend: * p < .10 (close to significant), ** p < .01 (significant), *** p< .001 (significant)

Table 2: Socioeconomic Factors in Emergency Room Visit Rate Quintiles

Model	A. Base Model	B. Random Intercepts by SES Quintile	C. Random Slopes by SES Quintile	D. SES Quintile Fixed Effect
DIC	679769.5	403512.9	403457.7	644410.7

Fixed Effects	Posterior Mode	Coefficient Percentile		Posterior Mode	Coefficient Percentile		Posterior Mode	Coefficient Percentile		Posterior Mode	Coefficient Percentile	
		2.50%	97.50%		2.50%	97.50%		2.50%	97.50%		2.50%	97.50%
Intercept	-0.1055	-0.7181	0.6042	-2.0545	-3.4346	-0.8493	-2.2485	-3.4929	-1.0117	0.8471	-1.3503	2.7012
Lag_Temp	-0.0487	-0.1251	0.0695	-0.0654	-0.0934	-0.0359	-0.0667	-0.1740	0.0556	-0.0315	-0.1987	0.1715
Lag_PMten	0.0036	0.0006	0.0076	0.0110	-0.0149	0.0293	-0.0092	-0.1065	0.1328	0.0040	-0.0002	0.0084
Lag_PMtwo	-0.0068	-0.0223	0.0093	-0.0013	-0.0420	0.0250	-0.0136	-0.1333	0.1042	-0.0044	-0.0261	0.0158
Lag_Ozone	0.7611	-12.3018	9.1841	-5.6422	-23.0301	14.9378	-1.8456	-21.3271	14.5221	-2.9438	-12.6263	9.9823
SES quintile										-0.1937	-0.7679	0.4520

Random Effects	Posterior Variance	Coefficient Percentile		Posterior Variance	Coefficient Percentile		Posterior Variance	Coefficient Percentile		Posterior Variance	Coefficient Percentile	
		2.50%	97.50%		97.50%	2.50%		2.50%	97.50%		2.50%	97.50%
units	1.0115	1.0115	1.0115	12.5055	12.3306	12.6762	12.4984	12.3157	12.6795	0.9028	0.9028	0.9028
By ZIP Code:												
Intercept	3.4584	2.0362	5.1463	11.3518	6.4266	17.4310	11.2774	6.3908	17.6967	3.6377	1.8666	5.6191
Lag_Temp	0.0510	0.0056	0.1445	0.0062	0.0035	0.0094	0.0066	0.0036	0.0102	0.1207	0.0096	0.2768
Lag_PMten	0.0001	0.0000	0.0001	0.0039	0.0023	0.0058	0.0043	0.0024	0.0067	0.0006	0.0000	0.0002
Lag_PMtwo	0.0022	0.0011	0.0033	0.0082	0.0047	0.0125	0.0091	0.0046	0.0137	0.0040	0.0010	0.0051
Lag_Ozone	913.0605	549.6501	1392.8088	2471.8034	1343.4210	3846.1064	2481.2271	1331.7519	3785.6584	933.0524	525.1977	1412.2857
By SES Quintile:												
Intercept				0.0980	0.0024	0.3586	0.0293	0.0057	0.0730			
Lag_Temp							0.0156	0.0052	0.0315			
Lag_PMten							0.0156	0.0046	0.0323			
Lag_PMtwo							0.0160	0.0042	0.0322			
Lag_Ozone							0.0306	0.0047	0.0829			

Table 3: Generalized Linear Mixed Effects Models

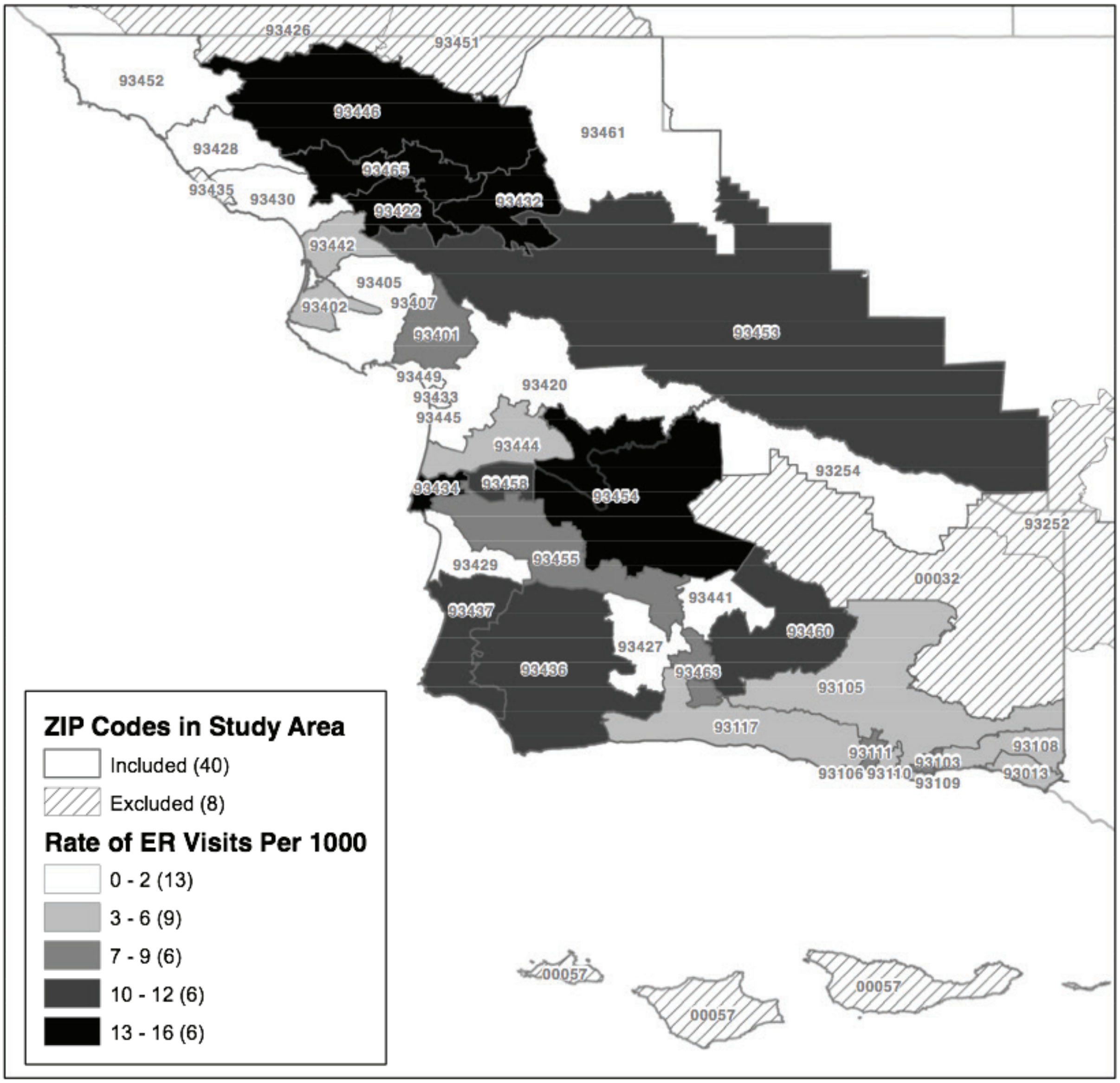

Figure 1: Emergency Room Visits for Acute Bronchitis

Map of San Luis Obispo and Santa Barbara counties with a chloropleth of 4-year rate (2009–2012) of ER visits for acute bronchitis. ZIP codes not fully contained in San Luis Obispo or Santa Barbara county or with a population less than 75 were exluded from the study area.

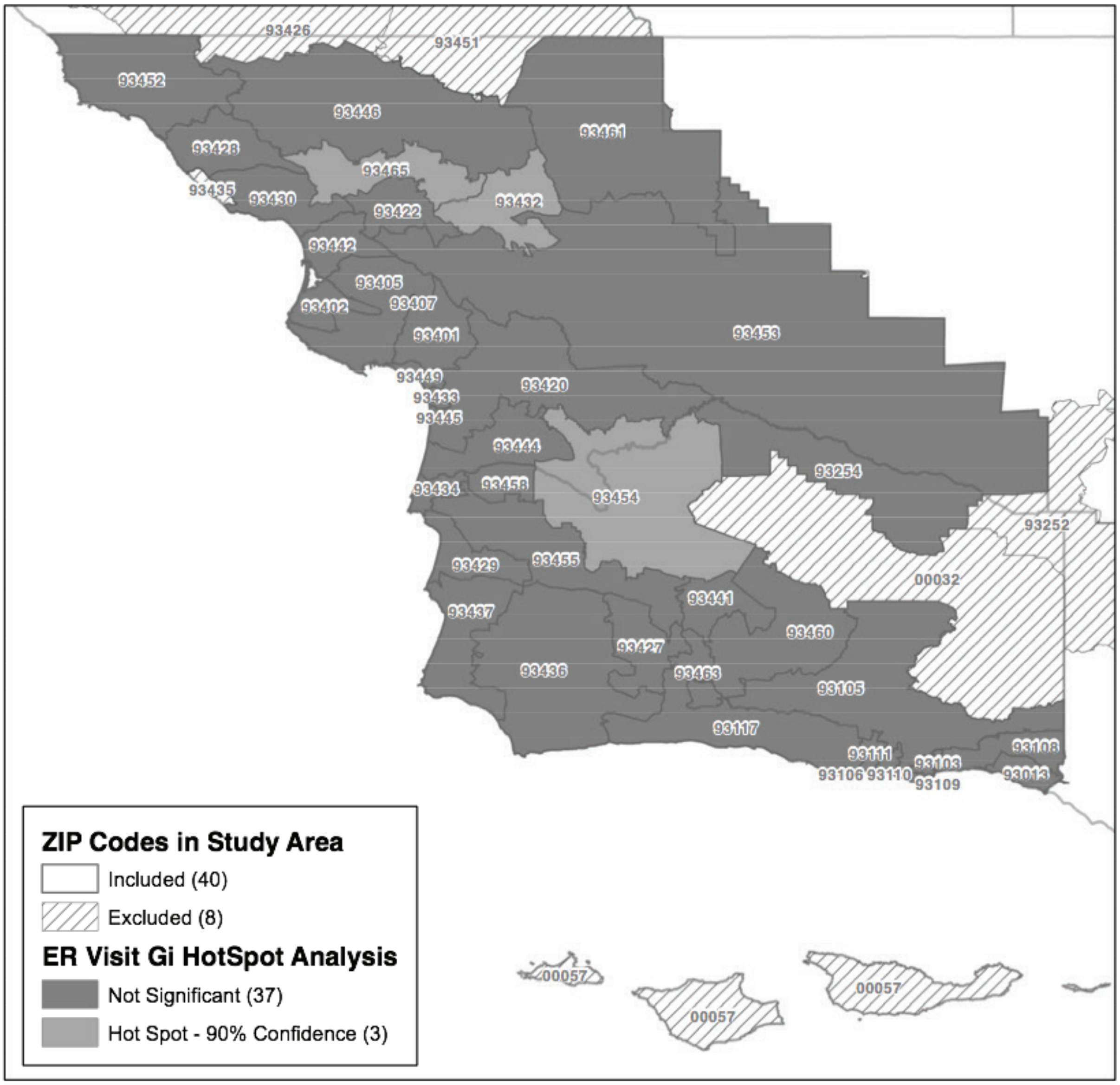

Figure 2: Hotspot Analysis

Map of San Luis Obispo and Santa Barbara counties with Hotspots of ER visits for acute bronchitis highlighted. Hotspots were identified using the Getis-Ord Gi statistic calculated using the four-year rate of ER visits with Esri ArcGIS software.*

About the Author

Sean Lang-Brown graduated from California Polytechnic State University, San Luis Obispo in 2016 with a B.S. in Biology and a minor in Statistics. Sean was a participant in the Cal Poly Honors Program, an intern at the San Luis Obispo County Public Health Department Tobacco Control Program, and a founding member of the Cal Poly Public Health Club. He was also treasurer of Yo Tango (the Cal Poly Argentine Tango Club) and involved in the Cal Poly Ballroom Dance Club. Sean is now a Clinical Research Coordinator in the Division of Geriatrics at The University of California, San Francisco.

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