Hidden Crisis: Homeless Emergency Department Visits and Unsheltered Rates

Abstract

This study is prompted by the California homelessness crisis and Emergency Departments (EDs) overcrowding; positing "What are the patterns of homeless ED visits with respect to county wealth and unsheltered population sizes?" This research hypothesizes that a higher proportion of unsheltered individuals would correspond to higher homeless ED usage rates. Conversely, wealthier counties would demonstrate lower ED usage by homeless individuals due to the availability of resources for needy groups. The study examines 33 counties over the single 2022 year period; the correlation between county wealth (as measured by median household income and poverty percentage) and homeless ED use, as well as the correlation between rates of unsheltered homelessness and homeless ED use; t-test between counties with high and low unsheltered rates, and a linear regression model for counties with small unsheltered rates are research methods employed. The findings revealed an unexpected lack of relationship between county wealth and homeless ED usage, a statistically significant difference between homeless ED rates in counties with low and high unsheltered population, and a statistically significant linear model for a surprising inverse relationship between unsheltered population size and homeless ED usage per county indicating as small unsheltered population incrementally increase, ED rates decrease. The findings have implications for future data collection methods and homeless healthcare transformations.

Introduction

Half of our entire nation’s unsheltered population resides in California (Senate Housing Committee). Terms like unsheltered, chronically homeless, temporarily unhoused, flutter under the same umbrella, and are often incorrectly used interchangeably. According to the U.S.

Department of Housing and Urban Development (HUD), “Unsheltered” refers to individuals or families who find their sleeping quarters in locations not intended for habitation, for example “abandoned buildings, cars, camping grounds, garages, parks, sidewalks, and train stations” ("Definition of Chronic Homelessness"). Numerous studies have associated the state of being homeless with higher ED visits (McConville; Routhier; Vohra; Yue). Moreover, recent studies have uncovered a stark disparity between California's healthiest and least healthy counties, where it has been observed that the healthiest counties often tend to be the wealthiest ("2019 County Health"). As such I pose the question, "What are the patterns of homeless ED visits with respect to county wealth and unsheltered population sizes?”

This paper begins by ED utilization rates and homelessness issues Significance to California. Then after synthesizing past research in the Background, Theory and Argument shall be explicated. Penultimately, research design and data will be discussed; where a t-test and a linear regression model are employed. Lastly, Implications will be presented.

Significance to California

California, known globally for its systematic and technological advancements, is facing a significant challenge regarding homelessness. This issue negatively impacts our reputation, likening us to nations with oppressive regimes. The financial implications of this crisis are enormous due to the substantial costs associated with emergency department visits by uninsured individuals. This research addresses two primary populations: the homeless, our most vulnerable, and healthcare workers, our most essential. The effects of their interactions extend from local communities to counties, the state, and beyond.

The unsheltered individuals carry the brunt of the harm, but the effects are not confined to them alone. According to CalMatters, "a single chronically homeless person can cost taxpayers up to $50,000 per year" (Walters). Addressing homelessness more efficiently could reduce these costs and free up resources for other needs. Recurring emergency department visits, especially by the uninsured, impose a significant financial burden on our state. According to the Public Policy Institute of California's 2023 report, homeless people use emergency departments four times more on average than the general population (McConville).

Understanding the patterns of emergency department usage can help counties focus their resources and provide better support for the homeless. This group not only affects our economy but also poses a potential risk to the real estate market. It is our moral duty as a nation to address the needs of specific communities that are disproportionately affected by the homelessness crisis. By reducing the number of homeless people and the utilization of emergency departments, we can provide more support for the non-homeless populations. Examining the statistics gives us a clearer understanding of the needs. For instance, in 2022, there were 123,423 unsheltered people in California (Senate Housing Committee). Understanding patterns of homeless emergency department utilization can help implement effective strategies at the county, state, national, and international levels.

The homelessness crisis in California is severe. Persons experiencing homelessness (PEH) often rely on hospital Emergency Departments (ED) as their primary source of healthcare (Vohra). The majority of street medicine programs are located in counties with a high density of homeless people (J. Feldman). California continues to lead the nation in homelessness, with data showing the state has the highest rate of unhoused people living outside, contributing to a worsening humanitarian crisis. California, the most populous state with the highest overall number of unhoused people, is a significant contributor to the homelessness surge. Experts and advocates attribute the primary cause of homelessness in the state to the lack of available affordable housing (Walters). This problem is worsened by the expiration of pandemic programs that had expanded shelter options and protected tenants from eviction (Walters).

A study published by Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute, shows that California's healthiest counties are also its wealthiest ("2019 County Health"). Poverty can limit access to fresh foods and other opportunities that can protect health and can also directly threaten health (McCullough). For example, low-income Californians are more likely to struggle to pay medical bills, leading them to cut back on other expenses, use savings, or borrow money. They may also face non-financial barriers to healthcare, such as long wait times for appointments. In contrast, families with higher incomes can more readily afford everyday supports that can reduce stress and mental health services.

Background

This project aims to explore relationships between homeless ED visits with primarily unsheltered rates, and on a lesser note measures of county wealth. Thus, a background on California homeless health-care mechanisms, previous research on ED recurrence and homelessness, and related legislative efforts will be discussed in this section.

Frequently, it's an individual's health that serves as the catalyst for their descent into homelessness, or the very element that keeps them entrenched in it. Among an array of charities, grassroots efforts, and academic studies like this one, two primary institutions grapple with this health-housing conundrum. These are shelters, the first line of defense against homelessness, and dedicated health care institutions that serve the homeless, emphasizing the reciprocal relationship between homelessness and health. California, consisting of 58 counties, has implemented 44 community-based Continuums of Care (CoCs) to address homelessness (Kennedy). Each CoC is responsible for managing the homeless shelters within its jurisdiction. Across the state, there are approximately 660 shelters. It's important to note that 33 counties have an individual CoC, while the rest share a CoC. Alongside the CoCs, California also supports 44 Health Care for Homeless (HCH) grantees ("California's Health Care"). These are federally funded institutions that provide essential health services to the homeless population. However, these HCH grantees aren't uniform in their operation, with many having subcontractors and offering various services ("California's Health Care").

The 2019 Senate Bill 1152 in California requires hospitals to create a discharge plan for homeless patients, ensuring they have food, shelter, medicine, and clothes post-discharge. Despite many homeless people being eligible for free health insurance, the application process can be challenging ("SB 1152"). The benefits for data analysis include understanding the impact of such policies on the health outcomes of the homeless population, and assessing the effectiveness of the health insurance application process for this demographic. Since then, another piece of legislation that affects the homeless was a law enacted in 2022 establishing county-level "CARE courts' ' in California ("GOVERNOR NEWSOM'S NEW PLAN").. CARE courts are different from the CARE Act, which can mandate housing and treatment for individuals with untreated schizophrenia or psychosis. Non-compliant countries face sanctions by December 2024. Another law, SB43, passed in 2023, makes it easier for the government to involuntarily hold and treat individuals with mental illnesses, including those with substance use disorders, reversing some restrictions from the 1967 Lanterman–Petris–Short Act ("Modernizing Conservatorship Law").

Despite efforts to alleviate poverty, California retains the highest poverty rate in the U.S., largely due to high living costs, particularly housing and utilities. Official poverty rates are considered misleading due to their simplistic factors, with the nationwide rate at 11.5% and California's at 11.4% (Walters). However, the supplemental rate, which considers living costs and other factors, places California at 13.2%, more than a third higher than the national rate (Walters).

A comprehensive study, published in the Journal of Health Care for the Poor and Underserved, thoroughly investigated the relationship between various types of housing insecurity and the use of emergency departments (EDs) for medical care. The study is titled "Associations Between Different Types of Housing Insecurity and Future Emergency Department Use Among a Cohort of Emergency Department Patients" written by Giselle Routhier , Tod Mijanovich , Maryanne Schretzman , Jessica Sell , Lillian Gelberg , Kelly M. Doran. Participants were recruited from an urban, public hospital in New York City between November 2016 and January 2018. The housing status was categorized into five major groups: homelessness (either sheltered or unsheltered in the past year), unaffordable housing (owed rent arrears or did not pay the full rent during the past year), overcrowded housing (living with more than two people per bedroom), forced move (experienced formal or informal eviction in the past year), and multiple moves (lived in three or more places in the past year). Those who reported being unsheltered for at least one night in the past year were nearly three times as likely to have an ED visit in the year after their baseline survey compared to those not experiencing homelessness. The researchers proposed several potential explanations for the relationship between unsheltered homelessness and increased ED use. They suggested that people experiencing unsheltered homelessness had a wide range of conditions that brought them to the emergency room, many of which were related to the challenges of living on the street, such as lack of access to hygiene resources. They also highlighted the fact that individuals remaining unsheltered may have more complex health and social needs that are not adequately addressed within the shelter system. The researchers concluded that their findings offer further evidence for the necessity of strengthening policies that prevent and alleviate homelessness, especially unsheltered homelessness. They emphasized that programs like Housing First have been proven to improve housing retention and stability among formerly homeless individuals. They also called for better state, local, and federal data on evictions, forced moves, and homelessness linked with health data to better understand the relationship between housing instability and health outcomes (Routhier).

Theory and Argument

Wholistically perceiving ED visits, meaning, rationalizing ED visits with respect to an entire counties unsheltered population has never been done before. Implications of county wealth is a trace confounding variable that is entrenched in all county discussions, and thereby is adopted into this research as a secondary hypothesis, as discussed in the previous section.

I hypothesize that as the unsheltered population of a county increases, the ED rates will be higher. This theory is based on the assumption that those without shelter will have greater incentive to seek emergency departments for shelter, and because health wise, they are at a much greater health risk because they are living outside; as discussed in the Background.

Conceptually, I propose that the increase of unsheltered people will cause the homeless ED rates to increase because their state of being in an unsheltered location will cause them to seek shelter in an emergency department hospital. Secondly, and parallel to the measures of unsheltered rates, I propose that a decrease in a county's wealth will make it more difficult to address the needs of the unsheltered population which will push the homeless population into finding refugee in emergency departments. The measures of wealth being utilized are median household income and poverty percent. A richer county with more resources will be able to cater to the homeless and unsheltered person more effectively, so unsheltered people will not need to rely on emergency departments at a greater level.

Operationally, two independent variables, x, to be measured; firstly is the county wealth and secondly is the unsheltered population. County wealth will be measured by median household income and poverty percent. The unsheltered population will be taken as a percentage of the total homeless population, and the total homeless population as a percent of county total population will also be measured.

The hypothesis initially created following the direction of these papers and this rationale therefore is that counties with higher unsheltered rates will have lower homeless ED visits, both by the homeless and non-homeless, and counties that are richer (lower poverty percent and higher median household income) will have lower ED visits, by the homeless and by the non-homeless. Discussing the non-homeless ED visits is integral to this study as it provides a comparative baseline, a "control" per se, that eliminates the state of being homeless from the equation. If the hypothesis for non-homeless ED visits follows the same hypothesis as the homeless ED visits, in relation to wealth increase of county wealth, as indicated by high median household income and low poverty percents, are hypothesized to be associated with low ED outcomes for the non-homeless.

Thus, this research focuses on one central hypothesis (pertaining to homeless ED usage) while focusing on two components, wealth and unsheltered population size, and an adjacent hypothesis, regarding the non-homeless, which serves to better inform about the homeless ED rates.

Research Design and Data

As explicated in Background, the year 2022 is the focus of this paper due to one, data prevalence, two, it's post-COVID-19, and three close proximity to our current year, 2024. The structure and strategy of this investigation are five total steps. 1. Data extraction, whereby I extracted data from publicly available state verified data-sets, 2. Data organization, whereby I organized the data into a single data set, 3. Descriptive statistics, 4. Exploratory data analysis, and 5. Inferential statistics. This section of this paper serves to detail my process of each of these five steps, and to provide clarity on the unit of analysis, operationalization of the hypothesis, measurements of dependent and independent variables, reliability, and validity.

The data sets I utilized come from 1. U.S. Housing and Urban Development (HUD), Continuum of Care Population and Subpopulation Reports, 2. U.S. Census Bureau, County Population Totals 2022, 3. Department of Health Care Access and Information (HCAI), 2022 Patient Origin/Market Share (Pivot Profile), 4. Department of Housing and Community Development, State Income Limits for 2022 Memorandum.

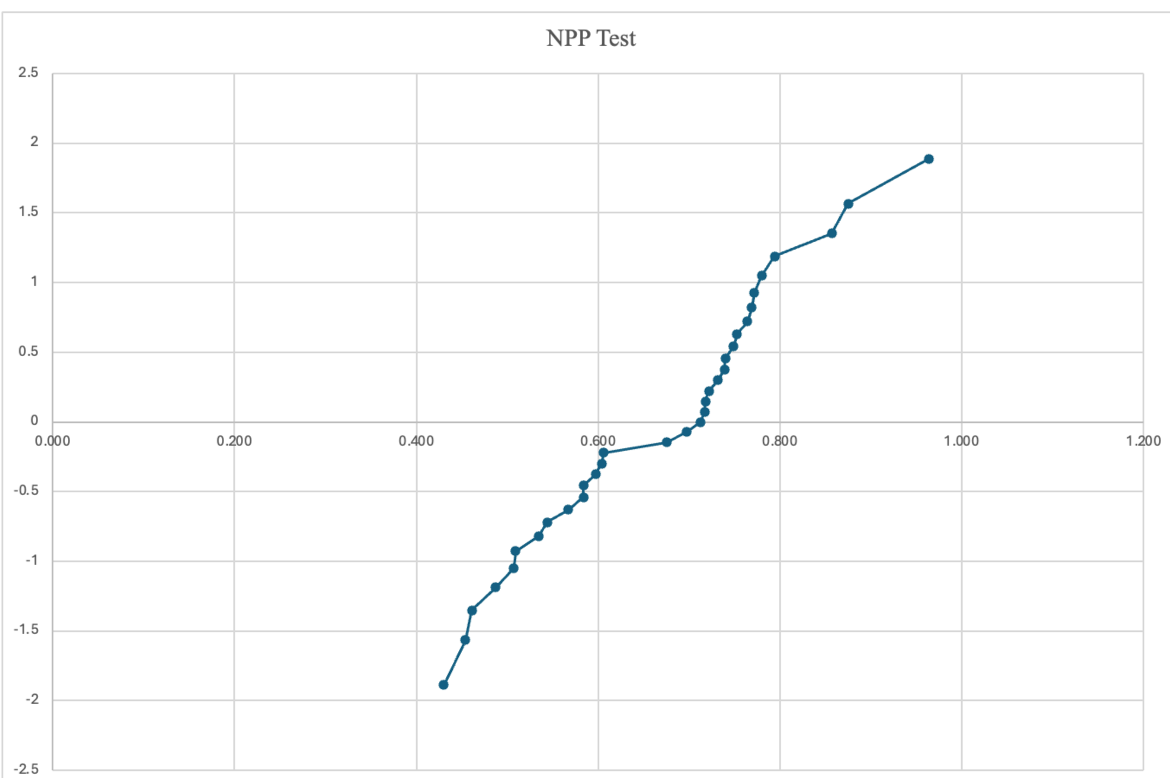
Not all of these data sets were downloadable .xlsl files, for example, U.S. Housing and Urban Development (HUD), Continuum of Care Population and Subpopulation Reports, are provided in a .pdf for each county. Therefore in order to maintain the one CoC to one homeless ED ratio, I had to first locate which CoCs were designated to a single county, and which counties were grouped together; this study excluded CoCs that included more than one county. For this reason, this study focuses on 33 counties, Alameda County, Butte County, Contra Costa County, El Dorado County, Humboldt County, Imperial County, Kern County, Lake County, Los Angeles

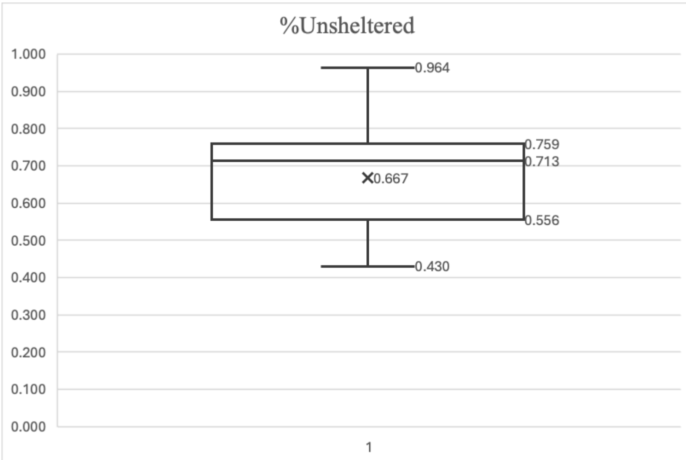
County, Marin County, Mendocino County, Merced County, Napa County, Nevada County, Orange County, Placer County, Riverside County, Sacramento County, San Bernardino County, San Diego County, San Francisco County, San Joaquin County, San Luis Obispo County, San Mateo County, Santa Barbara County, Santa Clara County, Santa Cruz County, Solano County, Sonoma County, Stanislaus County, Tehama County, Ventura County, and Yolo County. The implications of only utilizing 33/58 counties may be a point of future research; and the limitations it renders is explained in the Limitations section of this paper.

My list of variables by county included median household income, poverty percentage, unsheltered population, total homeless population, ED homeless, ED non-homeless, and total county population. To obtain data for ED homeless and ED non-homeless, I used the pivot table to deselect the HOMELESS category, and then select only the HOMELESS category. I also created additional variables that take population size into account. I calculated the ratio of ED homeless to total homeless population to determine the proportion of homeless individuals in each county who use the ED. Similarly, I calculated the ratio of ED non-homeless to total non-homeless population. Moreover, the percentage of unsheltered individuals within the total homeless population and the overall percentage of homelessness was also calculated for each county. The percentages were used in the correlation analysis, while all graphical analyses were conducted on a per 1,000 people scale.

This study's unit of analysis is the county level. The moving parts of the hypothesis; lower home research question; "What are the patterns of homeless ED visits with respect to county wealth and unsheltered population?" must first be identified. The dependent variable stands as ED visits; and the two independent variables are county wealth and unsheltered population. To assess county wealth, median household income and poverty percent will be utilized, and to assess unsheltered population, the POI counts from HUD for each county will be taken. As discussed in the Background section, homeless ED rates have been required of hospitals since 2019, and year 2022 Before further discussing the first step here is understanding the relationships between the different components of the research. These primary components, as explained in the previous section, are ED utilization rates per county, measures of county wealth, and measures of unsheltered population. To further analyze these variables, the emergency department utilization of those who are not homeless will be taken into consideration.

Analyzing homeless ED visits with respect to total homeless population sizes could have been a valuable point of research, but since total homeless population, even taken as a percent of total county population, did not follow a normal distribution. Therefore analysis was further pursued with the unsheltered variable, when taken as a percent of total homeless population can be approximated with a normal distribution curve. In order to justify utilizing a normal distribution curve, I employed three tests: descriptive statistics, box and whisker plot visual assessment, and finally a Normal Probability Plot (NPP) assessment.





Percent Unsheltered from Homeless	
Mean	0.66663636
Standard Error	0.02309458
Median	0.713
Mode	0.584
Standard Deviation	0.13266825
Sample Variance	0.01760086
Kurtosis	**-0.6233982**
Skewness	-0.0092291
Range	0.534
Minimum	0.43
Maximum	0.964
Sum	21.999
Count	33
Confidence Level(95.0%)	0.04704211

As indicated above, the mean and median are similar, the kurtosis is between -2 and +2, skewness is 0, the box and whisker plot does not show any outliers, and the NPP plot follows a linear path. (Assessing the median household income and poverty percent, per county proved to be difficult, as neither of these variables followed a normal distribution. However, through a log base 10 transformation median household income was able to pass two out of three normal distribution approximation tests, and marks a valuable point of future research.) Moreover, all confidence levels in this study are set at 95%.

The average proportion of unsheltered people out of homeless people in the 33 counties of analysis was 67%. The hypothesis test therefore asked "Is there a statistically significant difference in homeless ED visits between counties with above average and below average unsheltered rates?" In order to minimize skew, due to the odd number of 33 counties; I created a random sample, where I randomly assigned 20 counties into this hypothesis test using a simple random number generator with Excel and then arranging from least to greatest and choosing the top 20 counties. Before pursuing the t-test however, I ran an f-test to determine whether to use two sample equal variance or two sample unequal variance; the results of the f-test justified the utilization of an equal variance t-test, which is statistically significant.

F-Test Two-Sample for Variances		
	AboveAvg	*BelowAvg*
Mean	1.9321	2.9284
Variance	0.52665699	1.23010227
Observations	10	10
df	9	9
F	0.42814082	
P(F<=f) one-tail	0.11116742	
F Critical one-tail	0.31457491	
p > 0.05, reject null use equal variance t-test		

t-Test: Two-Sample Assuming Equal Variances		
	AboveAvg	*BelowAvg*
Mean	1.9321	2.9284
Variance	0.526657	1.2301023
Observations	10	10
Pooled Variance	0.8783796	
Hypothesized Mean Difference	0	
df	18	
t Stat	-2.3770264	
P(T<=t) one-tail	0.0143745	
t Critical one-tail	1.7340636	
P(T<=t) two-tail	0.028749	
t Critical two-tail	2.100922	
p > 0.05,		
cannot reject null hypothesis		
Statistically Signifigant		

The creation of multiple types of scatterplots and the assessment of the correlation heat-map matrix led to me pursuing the creation of a multi-series scatter plot with homeless ED visits graphed on the y-axis and unsheltered rates per 1,000 homeless people graphed on the x-axis. In order to better visualize the differences in county unsheltered rates, I decided to partition the counties into 3 groups based on the number of unsheltered individuals per 1,000 homeless people; the standards for creating this separations was based on descriptive statistic analysis, and the the maintenance of relatively similar sized groups. Additionally, this separation does not change any analysis that can be made as it is expressed through color code indication; Small; < 3 Unsheltered Individuals/1,000 Homeless; Medium; 3-5 Unsheltered Individuals/1,000 Homeless; Large; >5 Unsheltered Individuals/1,000 Homeless.

Results and Analysis

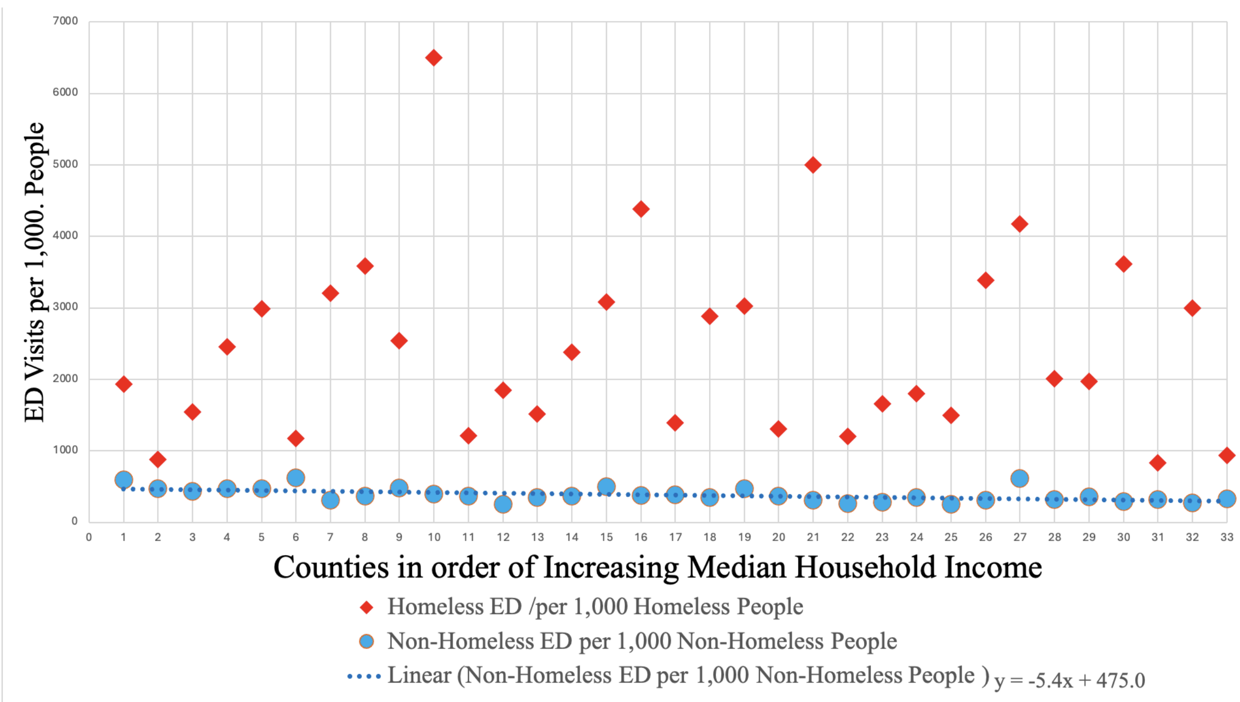


Figure 1. Homeless vs. Non-Homeless ED visits for every 1,000 residents Data Sources: HUD, HCAI , U.S. Census Bureau

The graph represents two populations, the homeless and the non-homeless, and their respective emergency department (ED) visits per 1,000 people, across 33 counties. These counties are arranged in increasing order of median household income from 1 to 33.

For non-homeless individuals, the trend shows that as the median household income of a county increases, the number of ED visits slightly decreases (correlation of -0.52). This is represented by the line of best fit equation y = -5.4x +475.0, suggesting a weak negative correlation.

However, for homeless individuals, no such trend is observed. The number of ED visits does not decrease with an increase in the county's median household income. This is represented by a correlation coefficient of 0, indicating no linear relationship between these two factors for the homeless population.

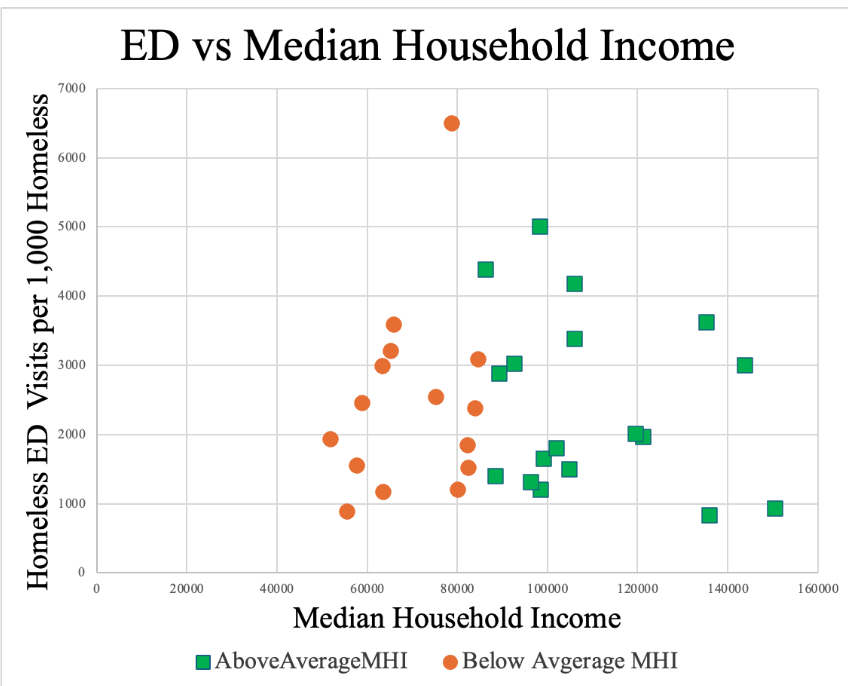


Figure 2. ED Visits by Homeless and Median Household Income (MHI) of a county Sources: HCAI, U.S. Census Bureau

This graph is a multi-series scatter plot that displays the relationship between the median household income (x-axis) and the count of emergency department (ED) visits by homeless individuals per 1,000 people (y-axis). The counties are categorized into two groups: those above the state average median household income (represented by blue dots) and those below the state average median household income (represented by orange dots). The scatter plot reveals that there is no observable linear relationship between the median household income and the rate of ED visits by homeless individuals, even when the counties are further categorized based on their median household income.

Median Household Income	-0.84			
Unsheltered Homeless	-0.07	0.05		
ED Visits NonHomeless	0.36	-0.52	0.07	
ED Visits Homeless	-0.01	-0.04	-0.51	0.06
	Poverty Percent	Median Household Income	Unsheltered Homeless	ED Total NonHomeless

Table 1. Correlations, Data Sources: HUD, HCAI, U.S. Census

This figure is a Correlation Heat Map that illustrates the relationships between several variables: median household income, unsheltered homeless count per 1,000 people, non-homeless ED visits per 1,000 people, homeless ED visits per 1,000 people, and the percentage of poverty.

As anticipated, there's a strong negative correlation (-0.84) between median household income and poverty percent. This means that as the median household income in a county increases, the poverty rate tends to decrease.

For non-homeless individuals, there's a moderately positive correlation (+0.36) between poverty percent and ED visits per 1,000. This implies that as the poverty rate rises, so does the number of ED visits. Conversely, there's a moderate negative correlation (-0.52) between a county's median household income and non-homeless ED visits per 1,000. This suggests that as a county becomes wealthier (i.e., its median household income increases), non-homeless ED visits tend to decrease.

Interestingly, for the homeless population, there's no correlation (0) between ED visits and either poverty percent or median household income. This suggests that for homeless individuals, the rate of ED visits doesn't seem to be affected by either the level of poverty or wealth in the county.

There's a moderately negative correlation (-0.51) between the unsheltered homeless population and ED visits for the homeless. This indicates that as the number of unsheltered homeless individuals decreases, ED visits from the homeless population appear to increase. This finding was unexpected and prompts further investigation, which is discussed in Figure 4.

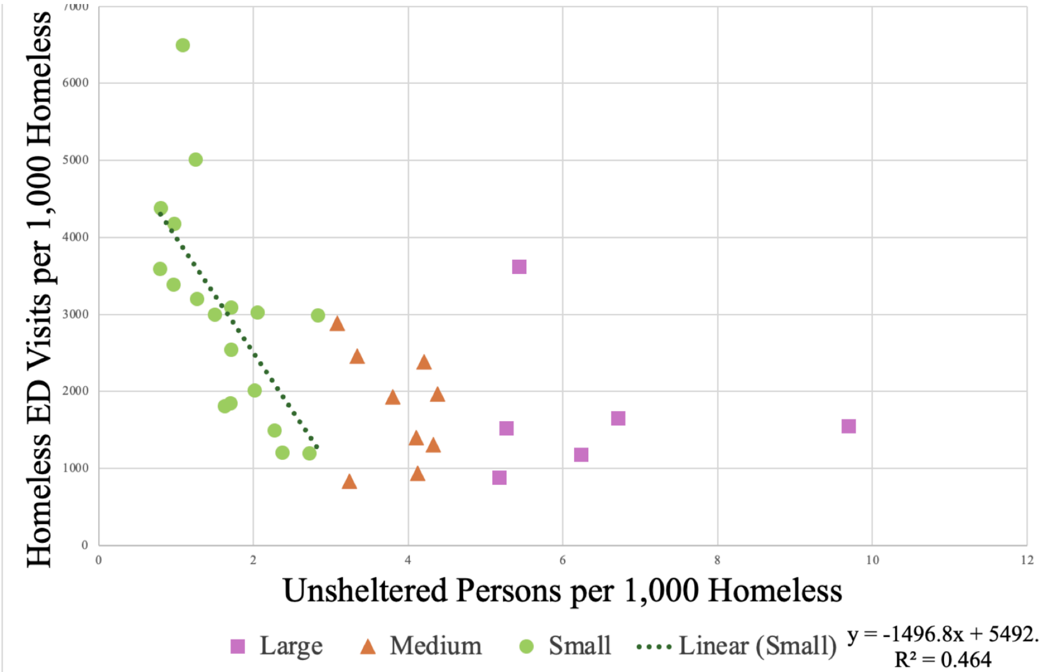


Figure 3. Homeless ED Visits vs Unsheltered Per 1,000 Homeless

Data Sources: HUD, HCAI

Figure 3 depicts the relationship between the count of emergency department (ED) visits by homeless people per 1,000 homeless individuals (y-axis) and the unsheltered homeless population per 1,000 homeless individuals (x-axis). The scatterplot is color-coded to differentiate between counties with various sizes of unsheltered homeless populations: large (blue), medium (orange), and small (green).

The graph shows a downward trend, almost negative exponential appearing trend, with moderate negative correlation of -0.51, indicating that as the unsheltered homeless population increases, the number of ED visits by the homeless population decreases. This relationship is further analyzed by dividing the unsheltered homeless population into three categories:

1. Small unsheltered count: less than 3 people per 1,000 homeless.
2. Medium: between 3-5 people per 1,000 homeless.

3. Large: greater than 5 people per 1,000 homeless.

This detailed view reveals that even within these categories, the same downward trend persists. This suggests that counties with a higher percentage of unsheltered homeless individuals have fewer ED visits from the homeless population. The linear trend for small unsheltered rates is graphically interesting, and prompted me to run a linear regression model:

SUMMARY OUTPUT								
				null				
Regression Statistics				no linear realtionship between the ED visits and unsheltered population				
Multiple R	0.681453564		p <= 0.05					
R Square	0.46437896			alternatie				
Adjusted R Square	0.430902645			fail to reject the null hypothesis				
Standard Error	1047.306603							
Observations	18			The linear regression model is signifigant.				
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	15215371.92	15215371.92	13.871866	0.00184445	p value for regression		
Residual	16	17549617.95	1096851.122					
Total	17	32764989.87						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	5492.212507	707.1156146	7.767064385	8.119E-07	3993.194368	6991.2306	3993.1944	6991.2306
Unsheltered Per Capita	-1496.779557	401.8744522	-3.72449542	0.0018445	-2348.715337	-644.8438	-2348.715	-644.8438

This linear regression model is statistically significant; indicating that as small unsheltered population sizes incrementally increase, homeless ED visits decrease.

Implications

Thus, this study reveals a notable and unexpected point, that, as unsheltered homelessness increases, ED visits by homeless people decrease, notably in counties with fewer unsheltered individuals, and counties with more unsheltered homeless individuals have fewer homeless ED visits. The statistical significance of ED rates between counties with high and low unsheltered populations was determined in Research Design and Data, but it is surprising to see the actual direction of trend of this statistical significance through the regression model. The hospital studies relating ED visits to homelessness that were mentioned in the Background focused on cohorts of patients in a specific hospital; however, analyzing overall county data and comparing counties to one another provides a new perspective to this discussion.

Through my investigation on this topic, I posit that this is likely due to better access to street medics and simply visible presence leading to increased community outreach for unsheltered people in highly populous unsheltered locations. Additionally, rural counties are the least populous, and the poorest counties of our state, and the grouping of these counties into CoCs makes it difficult to assess their performance on a county level, and retracts their ability to engage in studies like these. Assessing the effectiveness of street-medics and community outreach on a county level is a crucial point of future research.

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