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A Disparity Analysis of Health Determinants and Outcomes in 500 Cities in the United States

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By

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ABSTRACT

Health disparity is an issue of global concern necessitating diverse studies. This study thus, investigated intra city and inter-city health disparity for the 500 largest cities in the United States using the health determinant and outcome data at census tract level from the Centers for Disease Control and Prevention. The Urban Health Index (UHI) approach for small area assessment was used to compute for the UHI and disparity ratios for all 500 cities. Data for socioeconomic status was obtained from 2013-2017 American Community Survey 5-year estimate data. Urban sprawl data was collected from National Cancer Institute. Cities were ranked based on their disparity ratios from best to worst. OLS regression analysis was employed to research the driving factors of disparities. This research found that larger cities recorded higher health disparities than smaller cities. Greater disparities were present in cities in higher residential segregation for African Americans and less availability of cars, but in lower residential segregation for Hispanics. Because the regression residuals in the OLS model were not independent, more advanced models such as spatial regression models are necessary to investigate the influential factors.

INDEX WORDS: Health disparities, GIS, Cities, Census Tracts

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DEDICATION

I dedicate this thesis to my mum and brother; Patience and Isaac, who have been my backbone and support throughout my education. I would also like to thank the Adarkwa family for their love and support throughout my graduate school years, that meant a lot. Finally, to my family and friends; thank you for being on my team and cheering me on.

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LIST OF ABBREVIATIONS

UHI – Urban Health Index

GIS- Geographical Information Systems

GWR - Geographically Weighted Regression

FA - Factor Analysis

SES – Socioeconomic Status

1 INTRODUCTION

1.1 Background

The health outcomes of cities differ from one geographical region to another both locally and globally. The health of cities is described by complex and interconnected health indicators and health determinants (Rothenberg et al, 2014). Some key questions arise as to how some cities have better health outcomes than others and vice versa. It is also important to know what factors drive the better health outcomes in some regions than others.

Many health disparities in the United States are associated with inequalities in education and income (Drewnowski et al, 2004). In its broadest sense, the term “health disparities” can be explained as preventable differences in the indicators of health of different population groups, often defined by race, ethnicity, sex, educational level, socioeconomic status, and geographic location of residences (Mensah et al, 2005). Health disparities are largely attributed to social determinants of health, the conditions where people are born, grow, live, work, and age (World Health Organization, 2010; Dai et al, 2017).

Understanding health disparities is crucial for improving health and averting social inequality (Gordon-Larsen et al, 2005). Examining intra-urban disparities in health determinants and health outcomes at small-area levels is not only of value in understanding of such inequality but also may guide resource allocation to disadvantaged communities (Amey, et al, 1997). Moreover, analyzing urban health disparities is important for cities to understand how to make their cities better. The task of eliminating health disparities seems overwhelming, since minorities and the less educated have higher mortality rates for a wide range of diseases (Mitchel et al, 2002), however, it may become achievable by targeting the problems that have the greatest influence on disparities.

Generally, researchers have used three different comparisons to assess the association between cities and health (Galea, Freudenberg, & Vlahov, 2005). The first and most common approach compares and contrasts urban to non-urban areas (Chen, Chen, & Cheng, 2017; Eberhardt & Pamuk, 2004; Fotso, 2006; Hartley et al., 1994). Second line of research focuses on cross-urban studies mostly highlighting the differences across cities within a country or across countries (Brown et el., 2000; Davydova, 2005; Hunt et el., 2014; Yerger et al., 2007). The third group of studies seek to investigate intra-urban differences or variability of health within cities or smaller geographical regions (Dai, 2010; Krieger, 2002; Pardo-Crespo et al., 2013).

1.2 Assessing Health Disparities

Disparities in health in the United States has been a subject of major concern. Most research work has focused on how both ethnic/racial backgrounds or social class and socioeconomic resources jointly affect health (Adler & Rehkopf, 2008). Multiple investigations have drawn attention to substantial variations of health outcomes across geographical areas particularly between non-Hispanic whites and minority populations (Murray, Kulkarni, & Ezzati, 2005). Other researchers focused on the social determinants of health that may influence a region's population. According to WHO's Health Impact Assessment, commonly considered factors such as access and use of healthcare have fewer impacts on health, as compared to socioeconomic factors: the environment in which we live, income and educational levels and even our relationship with friends and family (WHO, 2013). These determining factors of health are also affected by a pernicious combination of unfair economic and social policies which results in unequal allocation of social and financial resources (Marmot & Friel, 2008). Assessing the spatial pattern of health can help to provide responsive measures and action on specific health determinants and population groups to reduce disparity in health outcomes and improve overall level of health (Parrish, 2010).

According to Center for Disease Control and Prevention, "an ideal population outcome metric should reflect a population's dynamic state of physical, mental, and social well-being. Positive health outcomes include being alive; functioning well mentally, physically, and socially; and having a sense of well-being. Negative outcomes include death, loss of function, and lack of well-being". The Center for Disease Control and Prevention designed a causal web that illustrates relationships among contributing factors that generate health outcomes in a simplified model in figure 1. These factors may contribute to health disparity as different populations exhibit characteristics distinct to their livelihood status.

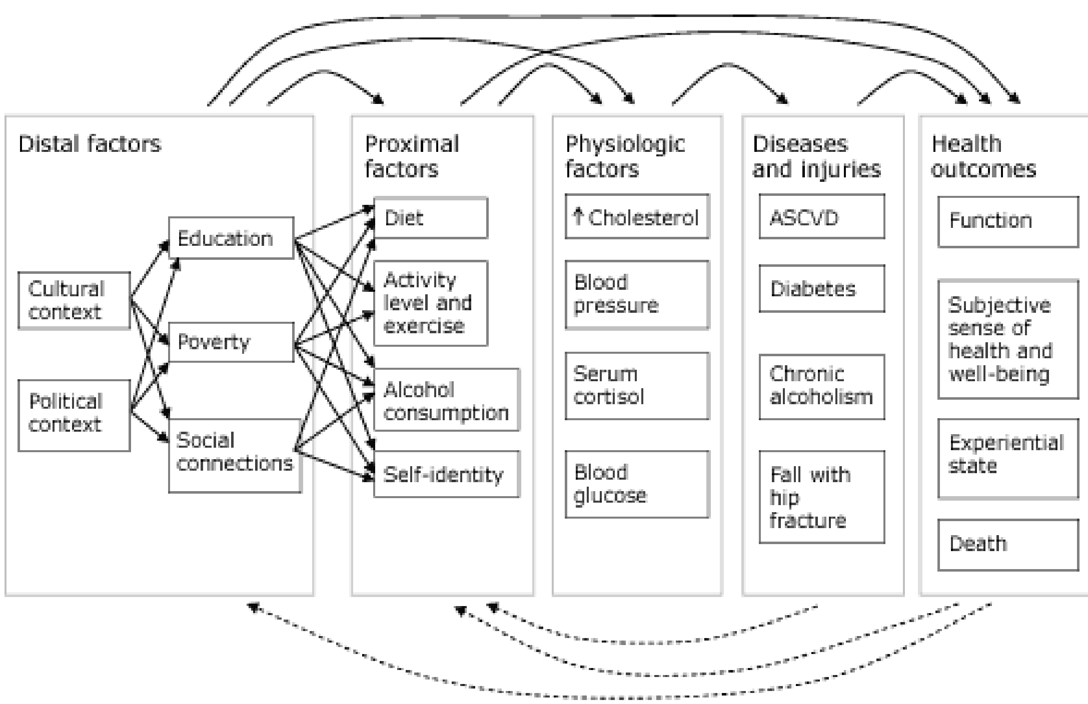

Figure 1 Causal Web of Health Outcomes
(www.cdc.gov)Note ASCVD- atherosclerotic cardiovascular disease

Figure1 demonstrates a causal web that illustrates various factors influencing health outcomes and interactions among them. Solid arrows represent potential causal relationships between factors, diseases, and outcomes. Dashed arrows represent potential feedback from outcomes and diseases on proximal and distal factors. Distal and proximal factors operate through both intermediate factors and directly on health outcomes. For example, a person's level of education can directly influence his or her subjective sense of health and level of social function and also influence intermediate factors, such as diet and exercise. Similarly, the understanding that death or loss of function may occur as a result of a person's lifestyle or social and economic factors, such as education and poverty, may influence those factors through either behavior change or changes in social or economic policy.

1.3 The Influence of Socioeconomic Status (SES) on Health Disparities

An individual's health is undoubtedly affected by socioeconomic factors, the social determinants of health. These socioeconomic factors have been measured based on three indicators, alone or in combination to assess a person's socioeconomic status. These include an individual's educational level, income, and occupation (Katz, 2006). Socioeconomic factors are well-recognized to be associated with health disparities within the United States (Spatz, Beckman, Wang, Desai, & Krumholz, 2016) and internationally (Vafaei, Rosenberg, & Pickett3, 2010). Previous researchers have investigated the associations between SES and health disparities within the country by focusing on individual socioeconomic factors simultaneously or individually by focusing on how a population's income, educational level or occupation trends can affect their health outcomes and consequently lead to health disparities.

Populations living in low-income areas tend to have limited resources to implement policies and fewer opportunities to practice healthy behaviors (Spatz et al., 2016). Those with the lowest income and who are least educated are consistently least healthy than wealthiest and most educated groups (Braveman, Cubbin, Egerter, Williams, & Pamuk, 2010). In response to investigating existing relationships between socioeconomic factors and health disparity, researchers have conducted a wide range of study with supporting findings. A study has found that the association between income and premature mortality was stronger among low-income counties than high-income counties (Cheng & Kindig, 2012). A similar study found mean hospitalization rates to be significantly higher among low-income areas compared with high income areas (Spatz et al., 2016). Further, some researchers have conducted empirical analysis quantifying the relative impact of each socioeconomic measure (income, education and occupation) to assess the strongest predictor of health outcomes. According to Davis et al. (1995), education rather than income or occupation may be the strongest predictor of health outcomes. Ross and Wu (1995), support this by establishing that high educational attainments directly improves health, and also indirectly improves health through work, economic conditions, social-psychological resources, and healthy behaviors.

1.4 Impacts of Residential Segregation and Urban Sprawl on Health

Racial residential segregation, which is explained as the physical separation of races, is one of the fundamental causes of health disparities (Williams and Collins, 2001). In the United States, rates of economic disadvantages vary among racial and ethnic groups, which is a spatial manifestation of residential segregation (Roberts & Wilson, 2009). Racial health disparities of health outcomes and socioeconomic status in the US have remained unchanged for the past 50 years despite efforts to minimize them (Landrine & Corra, 2009). Several studies have mapped out a spatial trend of health disparities that exists among racial and ethnic groups who live in segregated neighborhoods. Given the history of racial segregation in the US, a majority of the research in the past decade have been focused on white/black segregation and health disparities as compared to whites and other minority groups (Yang, Zhao, & Song, 2017). One such study suggested that blacks living in metropolitan areas characterized by high black residential isolation have a higher likelihood of reporting poor health than blacks living in low black isolation neighborhoods (Subramanian, Acevedo-Garcia, & Osypuk, 2005). Similarly, Yang et al (2017) found that blacks who lived in segregated neighborhoods had poor Self-Rated Health than their counterparts in neighborhoods that are more diverse.

A considerable evidence also shows that residential segregation is deleterious to the health of Hispanics. Lee (2009) found positive associations between Hispanic segregation, depression and anxiety and established that living in a Mexican American-dominated neighborhood is detrimental to mental health. Hispanics living in isolation are more exposed to risk factors that facilitates tuberculosis transmission than non-Hispanic Whites (Acevedo-Garcia, 2001). Thus, residential segregation needs to be accounted for, to determine its influence on health disparities among cities in the US.

Urban sprawl can be defined as an overall pattern of development across a metropolitan area where greater proportions of the population live in lower-density residential areas (Lopez, 2004). The association between sprawl and health have already been established by investigators who often linked urban form to physical inactivity. The physical design of many US suburbs contribute to growing prevalence of overweight and obesity among both children and adults (Lopez & Hynes, 2006). People living in high-sprawled vicinities have lower propensity to walk, bike or be physically active and higher likelihood to drive (Lopez, 2004). Living in more sprawling suburbs increases the risk of overweight or obesity and inadequate physical activity (Garden & Jalaludin, 2008).

1.5 Research Question and Objectives

There is no systematic research at a national scale to study both intra city and inter-city disparities in health in the United States. To fill in this research gap, this thesis, using the 500 cities project from the Centers for Disease Control and Prevention (CDC), raises two research questions: (1) are there any health disparities among these largest 500 cities? (2), if so, what are the possible factors explaining these disparities? These questions led to two primary objectives: (1) assessing the level of health and health disparity of each city by comparative ranking, and (2) examine the factors that influence the disparities in health these cities may demonstrate.

1.6 Significance of this Study

Previous studies have focused on measuring health disparities within the United States on various levels (Adler & Rehkopf, 2008; Braveman et al., 2010; Chu et al., 1996; DeChello & Sheehan, 2007; Farmer & Ferraro, 2005; LI, Malone, & Daling, 2003). However, none of them has focused on investigating the level of health disparities that exist within and among the largest 500 cities in the country. The UHI approach has been used by researchers to measure intra-urban disparities on local levels. For instance, Dai et al. (2017) adopted the UHI to examine the change of geographic disparities in social determinants of health within the city of Atlanta over a period of ten years. This approach, however, has not been used to measure disparities among cities and compare their degree of disparities. Such inter-urban disparity assessment is needed to understand the underlying causes or factors and to provide appropriate intervention measures to minimize disparities.

2 STUDY AREA AND DATA SOURCES

2.1 Study Area

The study area of this thesis focused on the 500 major cities in the United States. The Robert Wood Johnson Foundation and the CDC Foundation launched the 500 Cities Project in partnership with the CDC in 2015. The 500 cities project contains data for the 497 largest American cities using the 2010 population and including data from the largest cities in Vermont (Burlington – population: 42,417), West Virginia (Charleston – population: 51,400) and Wyoming (Cheyenne – population: 59,466) to ensure inclusion of cities from all the states; bringing the total to 500 cities. The number of cities per state ranges from 1 to 121. The cities range in population from 42,417 in Burlington, Vermont to 8,175,133 in New York City, New York. Among these 500 cities, there are approximately 28,000 census tracts, for which data are provided. The tracts range in population from less than 50 to 28,960, and in size from less than 1 square mile to more than 642 square miles. The number of tracts per city ranges from 8 to 2,140. The project includes a total population of 103,020,808, which represents 33.4% of the total United States census 2010 population of 308,745,538. (www.cdc.gov/500cities)

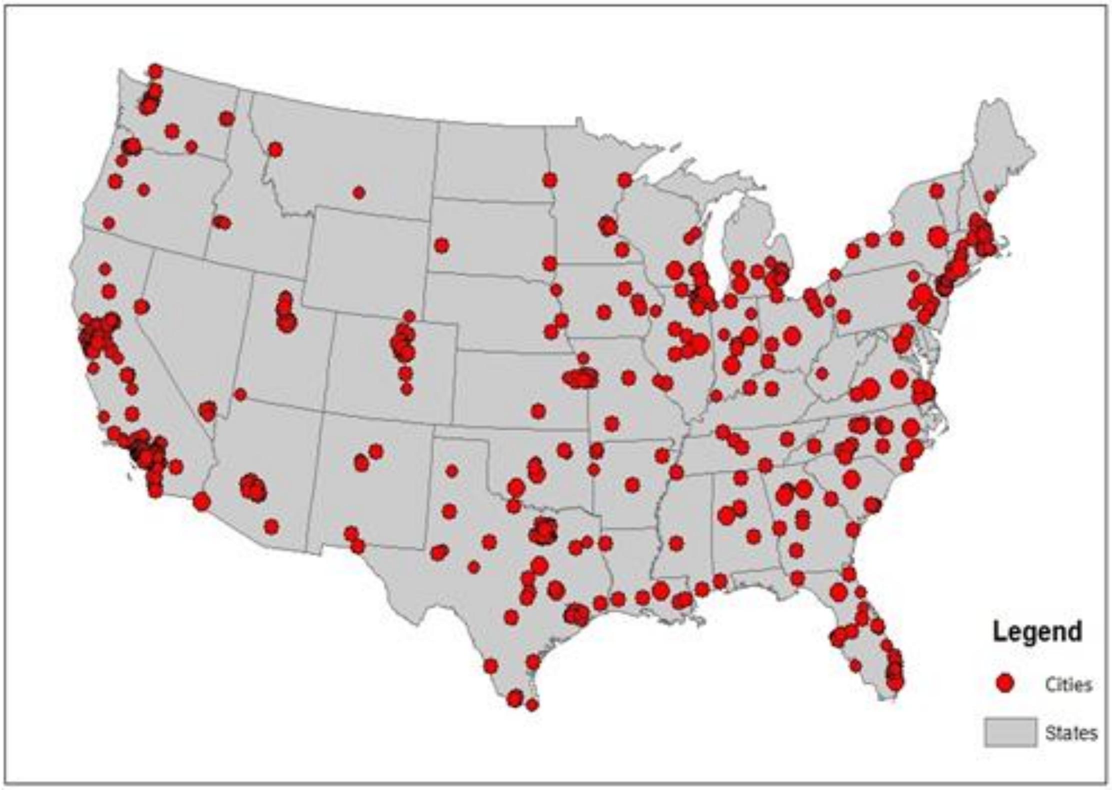

Figure 2 the 500 Largest Cities in the US

2.2 500 Cities Data

This 500 cities data reports city and census tract-level data obtained using small area estimation methods (Wang et al., 2018). These data sets were generated to fully understand the health issues affecting residents at census tract level. The data can also be used to better understand the geographic distribution of health-related variables across cities that would be useful for planning public health interventions and improve the health of residents (CDC, 2015). The data encompasses measures for 28 chronic disease risk factors, 13 health outcomes, 5 unhealthy behaviors and 10 clinical preventive service-use (Table 1). The group field “PREVENTIVE” consists of variables of clinical care services provided to avert diseases and poor health outcomes. Values for the “preventive” factors have been inverted to ensure consistency with the rest of the data where “the higher the value, the worse the measure”. This was done by subtracting the original value from 100.

Table 1 the 28 Measures of Health Factors

Group field	Variables
Preventive Care(10)	
	Taking medicine for high blood pressure control among adults aged > = 18 Years with high blood pressure
	Visits to doctor for routine checkup within the past Year among adults aged > = 18 Years
	Cholesterol screening among adults aged > = 18 Years
	Fecal occult blood test, sigmoidoscopy, or colonoscopy among adults aged 50-75 Years
	Older adult men ages > = 65 Years who are up to date on a core set of clinical preventive services: Flu shot past Year, PPV shot ever, Colorectal cancer screening.
	Older adult women ages > = 65 Years who are up to date on a core set of clinical preventive services: Flu shot past Year, PPV shot ever, Colorectal cancer screening, and Mammogram past 2 Years
	Visits to dentist or dental clinic among adults aged > = 18 Years
	Mammography use among women aged 50-70 Years
	Papanicolaou smear use among adult women aged 21-65 Years
	Current lack of health insurance among adults aged 18-64
Health Outcomes(13)	
	Arthritis among adults aged > = 18 Years
	High blood pressure among adults aged > = 18 Years
	Cancer excluding skin cancer) among adults aged > = 18 Years
	Current asthma among adults aged > = 18 Years
	Coronary heart disease among adults aged > = 18 Years

	Chronic obstructive pulmonary disease among adults aged > = 18
	Diagnosed diabetes among adults aged > = 18 Years
	High cholesterol among adults aged > = 18 Years who have been screened in the past 5 Years
	Chronic kidney disease among adults aged > = 18 Years
	Mental health not good for > = 14 days among adults aged > = 18 Years
	Physical health not good for > = 14 days among adults aged > = 18 Years
	Stroke among adults aged > = 18 Years
	All teeth lost among adults aged > = 65 Years
Unhealthy Behavior (5)	
	Binge drinking among adults aged > = 18 Years
	Current smoking among adults aged > = 18 Years
	No leisure-time physical activity among adults aged > = 18 Years
	Obesity among adults aged > = 18 Years
	Sleeping less than 7 hours' adults aged > = 18 Years

2.3 Census Data

This thesis research collected census data to examine the residential segregation and socioeconomic status of the cities' population and to understand how that influences their disparities. Race and socioeconomic variables from the 2013-2017 American Community Survey data were downloaded from the US census bureau website to assess the socioeconomic status of cities. These data have estimates of urban and rural population, housing units and characteristics that reflect boundaries based on Census 2010 data. In addition, for Black and Hispanic population, nine additional variables were collected: language (speak English less than very well), education (less than high school graduate), median income(dollars), poverty status (below 100 percent of the poverty level), mean travel time to work (minutes), no vehicle available, owner-occupied housing units, percent uninsured and Management, business and financial occupation.

Table 2 Socioeconomic Variables

Socioeconomic Variables
Less than high school graduate
Speak English less than very well
Median income(dollars)
Poverty status (below 100 percent of the poverty level)
Mean travel time to work (minutes)
No vehicle available
Public transportation
Owner-occupied housing units
Percent uninsured
Management, business and financial occupation

2.4 Urban Sprawl Data

Data for urban sprawl was obtained from the database of National Cancer Institute (https://gis.cancer.gov/tools/urban-sprawl/). These data were based on urban sprawl indices that was developed by Dr. Reid Ewing and his team at the University of Utah. The urban sprawl indices were computed using longitudinal analysis to assess which geographical regions are sprawling less or becoming more compact and which are sprawling more over time. Sprawl occurs mainly as previously rural counties outside metropolitan areas become low-density suburbs and exurbs of metropolitan areas. (Ewing and Hamidi, 2010). Sprawling is a significant phenomenon and key to this research because it alters the physical plan of a geographical area.

Sprawling cities threatens the quality of drinking water sources and the availability of green spaces, which may affect the network of social interactions and even mental health (Frumkin, H., Frank, L., & Jackson, R. J., 2004). Understanding the physical attributes of sprawl within the 500 cities was therefore important to assess its health implications and to aid in developing better future public health policies. The excel data obtained from the sprawl indices on census tracts level had values that ranged between 40-120 where lower values signified less sprawling and more geographical compactness and higher values interprets more urban sprawling. The sprawl data were included in subsequent analysis to assess the impact of urban sprawling on health disparities.

2.5 Methods

2.5.1 UHI Ranking

To be able to assess health disparities for these 500 cities, WHO's Urban Health Index was used. The Urban Health Index (UHI) method developed by the World Health Organization Centre for Health Development (WHO Kobe Centre) provides a flexible approach for identifying intra-urban disparities for small geographic areas (Rothenberg et al., 2014).

To calculate for the UHI, values for each indicator is standardized. For each indicator, which in this case is a variable at each census tract, for example cancer rates among adults aged > = 18 Years, the actual value is transformed into a dimensionless proportion: the distance of the value from minimum, divided by the range:

$$I^S = \frac{I_i - min{*}(I)}{\max(I) - min{*}(I)}$$

I^S is the standardized indicator, I_i is the observation, e.g., cancer rate in a census tract, "max (I)" is the maximum value for that indicator, e.g., the highest cancer rate of a census tract in the country, and "min*(I)" is the minimal value, e.g., lowest cancer rate of a census tract in the country altered by a very small amount, which in this case is 10% of the standard deviation, to avoid zero values in the numerator. In small areas for which Ii is the minimum value, the numerator would be zero without this small alteration, rendering the UHI for that area zero. After standardizing the indicators that were used in the index, the indicators then become the same logical type in terms of the proportions of the range. These indicators are then combined using the geometric mean approach:

$$G = \left(\prod_{i=1}^{m} I_i^S \right)^{\frac{1}{m}}$$

where I_i^S is the ith standardized indicator.

Assessing Disparities: To assess the disparity of the distribution in a city, the ratio of the mean of the upper 10 % of the distribution to the mean of the lower 10 % of the distribution is a marker of the overall disparity ratio between the best-off and the worst-off area units. The ratio of means rather than the ratio of medians is used (which would be equivalent to the ratio of the 95th to the 5th percentiles) in order to accentuate the difference between the two extremes (Rothenberg et al., 2014). To compare the disparities between the 500 cities, their disparity ratios were ranked, and their rank orders were also recorded. A scatter plot was generated using the log transformation of cities' population with their disparity ratio to assess whether there exists any relationship between them.

2.5.2 Residential Segregation

Segregation has been measured along five distinct dimensions: clustering, isolation, centralization, concentration and unevenness (Chang, 2006; Massey & Denton 1988). This research focused on the isolation aspect, which is a common practice to investigate the extent to which Black and Hispanic groups were isolated from other groups in geographical settings. The isolation index is calculated as follows; assuming finding the black isolation index for city *j* which consists of n census tracts, the formula is explained as follows:

$$R_j = \sum_{i=1}^{n} \frac{b_i}{b_{total}} \times \frac{b_i}{T_i}$$

where i is the i^{th} census tract in the city j, b_i is the black population in i, b_{total} is the total black population in j, and T_i is the total population in census tract i. The isolation index ranges between 0 and 1 where 0 interprets no segregation and 1, maximal segregation (Massey and Denton, 1988) The resulting values of the index can be interpreted as the chance of having blacks as neighbors. (Dai, 2010; Hass et al., 2008). For instance, a black residential segregation index of 0.65 means that, on average, a Black person lives in a neighborhood where 65% of his or her co-residents are also Black. This study considered residential segregation for Blacks and Hispanics separately.

2.5.3 Relationship between Health Disparities and Socioeconomic Status in Cities

To prepare for the analysis of health disparities in relationship to socioeconomic factors, segregation and urban sprawl, natural log transformation was taken to normalize the distribution of health disparities, because of highly skewed distribution in the raw data (Figure 3). Then bivariate correlation was conducted on segregation, sprawl and all ten socioeconomic factors to test for the significance of their relationships with health disparities. Using OLS regression model, the association between urban health disparities and socioeconomic status was evaluated. Model selection is an important component of any regression model construction. It involves identifying which predictor variables to include and/or techniques for transforming and reducing the predictor subset (Comber & Harris, 2018). Factor analysis (FA) approach was used mainly for data reduction to uncover latent variables for easy interpretation and to remove multicollinearity for subsequent regression analysis. Multicollinearity may exist in the socioeconomic variables. For example, median income level is highly correlated with poverty level Collinearity occurs when pairs of predictor variables have a strong positive or negative relationship with each other and is typically considered a potential problem when these data pairs have correlations of less than − 0.8 or greater than + 0.8, (Comber & Harris, 2018). The FA extraction criterion retains factors with eigenvalues greater than one (Griffith and Amrhein, 1997). The highest loaded variables for each factor were selected as independent variables for OLS analysis. The dependent variable is the health disparity ratios generated from the Urban Health Index. Failure to correctly specify a model when collinearity is present can result in a loss of precision and power in the coefficient estimates-leading to poor inferences (Comber & Harris, 2018).

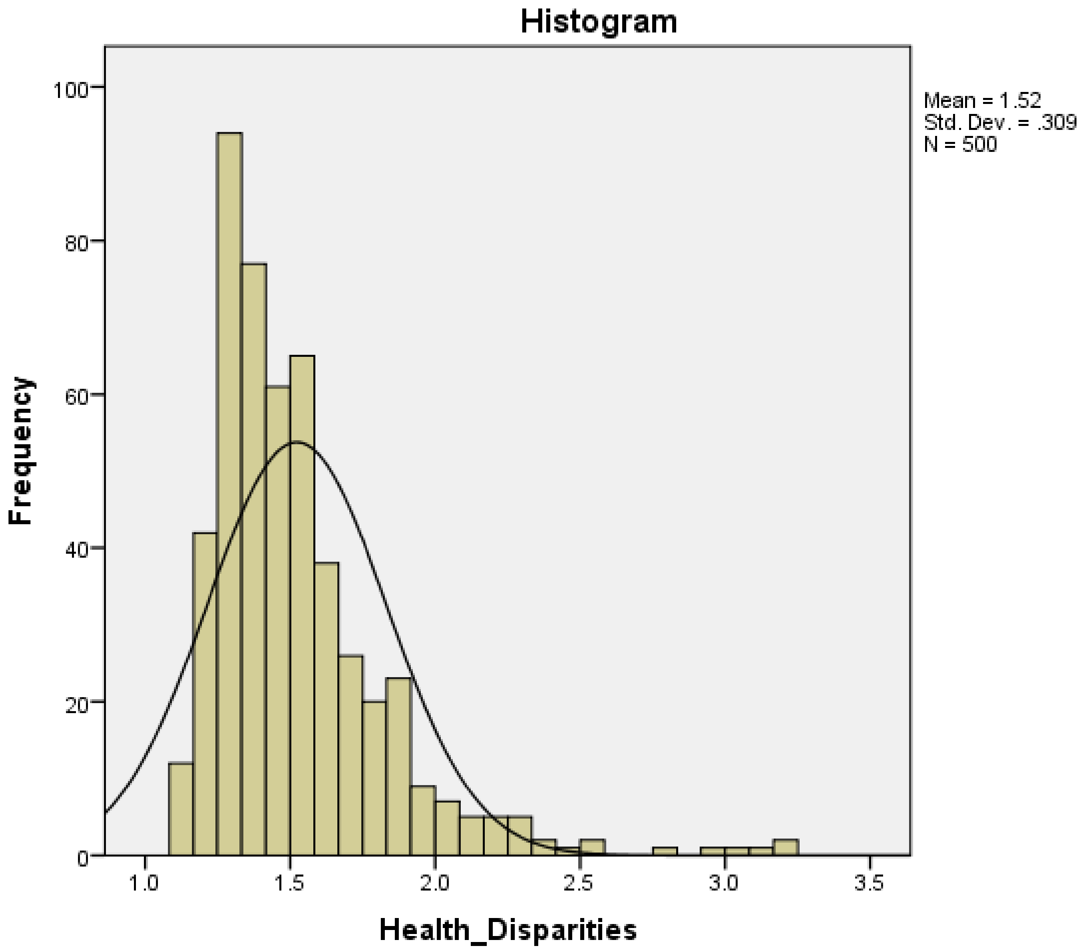

Figure 3 Histogram of Health Disparities

3 RESULTS

3.1 UHI

The results of disparity ratios generated values ranging from 1.098 to 3.22. Lower values explain low disparity ratios and higher values denotes high disparity ratios. Cities were ranked based on their disparity ratios from 1 to 500, one being the “best” city with lowest health disparity and 500 being the “worst” city with very high disparity. The best-off city—Cicero, Illinois--recorded the lowest disparity of 1.098. It suggests the best part of the area in Cicero is 1.098 times better off than the worst part of Cicero. In contrast, Champagne Illinois was found to be the worst-off city with a disparity ratio of 3.22 (Table 3), suggesting the best area of Champagne is 3.22 times better than the worst area of Champagne.

Graphing the natural log of disparity ratio of the cities against the rank order generated from their disparity ratios (Figure 4) suggests that, smaller cities have better ranks or low disparity ratios. On the other hand, larger cities have the worst disparity ratios. (Figure 5) represents a visualization of the ranks of the 500 cities ranging from 1 to 500. These ranks were categorized into 5 classes; 1-100, 101-200, 201- 300, 301-400 and 401- 500 as displayed in the legend. Cities within the first 100 range were observed to have low health disparity comparatively to the other cities within subsequent range groups. Cities among the last 100 ranking (401-500) are recorded to have the highest rates of disparities in the country. Clusters of poorly ranked cities tend to be predominant along the eastern United States as compared to the rest of the country with a few clusters in California.

Table 3 Summary Statistics of Disparity Ratio

Min(Cicero, IL)	Max(Champagne, IL)	Mean	Standard Deviation
1.098	3.22	1.52	0.31

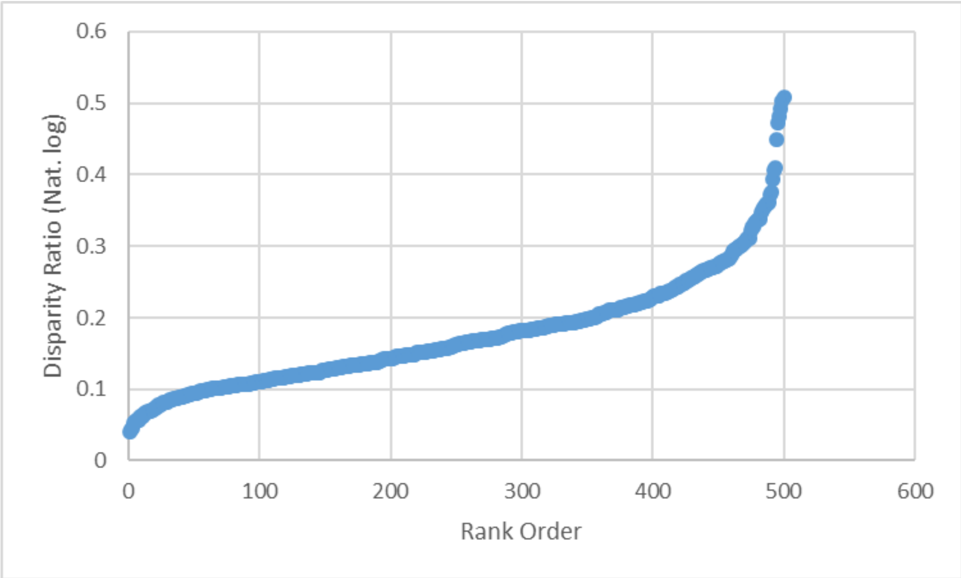

Figure 4 Disparity Ratio and Rank Order

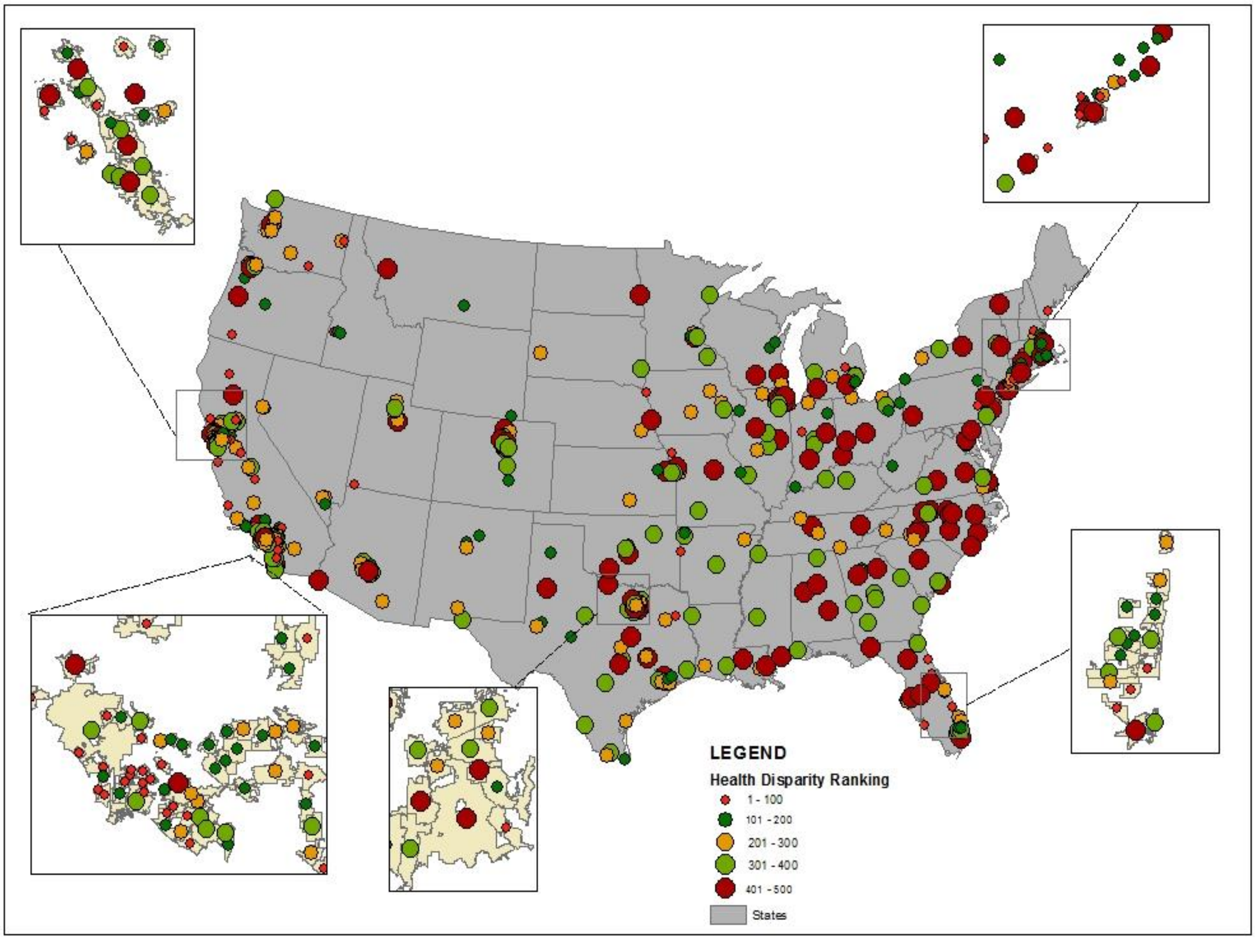

Figure 5 Disparity Ratio Ranking for 500 Cities

3.2 Minority Residential Segregation and Urban Sprawl

The residential segregation indices generated output values ranging between 0-1 where values closer to zero suggests less segregation and values closer to one indicate high rates of residential segregation. Black residential segregation was high around eastern areas of the United States with observed clustered patterns throughout the north eastern to south eastern areas (Figure 5). On the other hand, Hispanic segregation was clustered on the south western areas of the country with a few clustered observations on the extreme north eastern region (Figure 6). Both Hispanic and Black segregation are concentrated in the states located at the extreme north eastern areas such as New Jersey, New York, Connecticut and Massachusetts.

Urban sprawl is observed among cities throughout the country. High concentrations of sprawl is found around north eastern United States and a few around the western states such as California, Oregon and Washington. States such as North Carolina, Alabama, Tennessee and Kentucky recorded less urban sprawl within their cities (Figure 6).

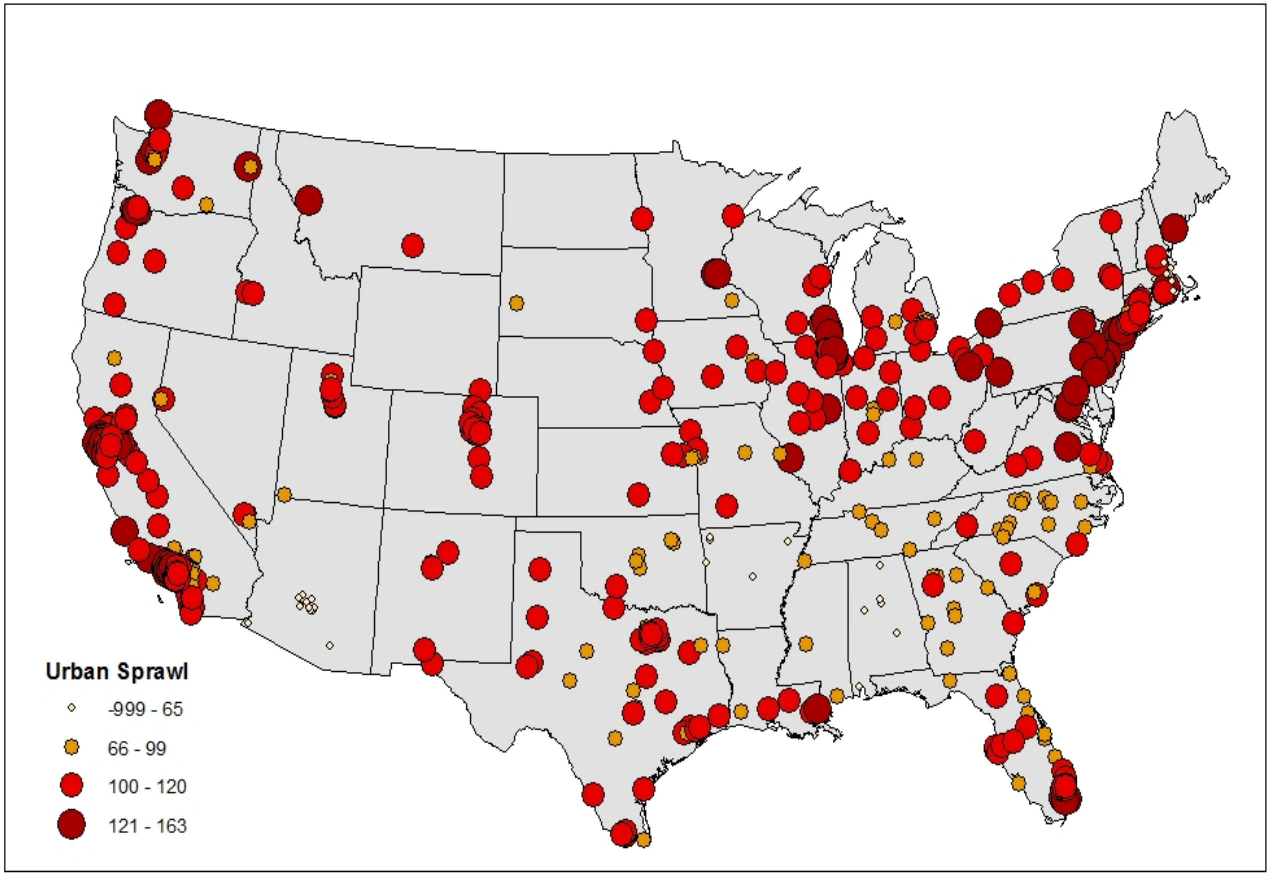

Figure 6 Level of Sprawl among Cities

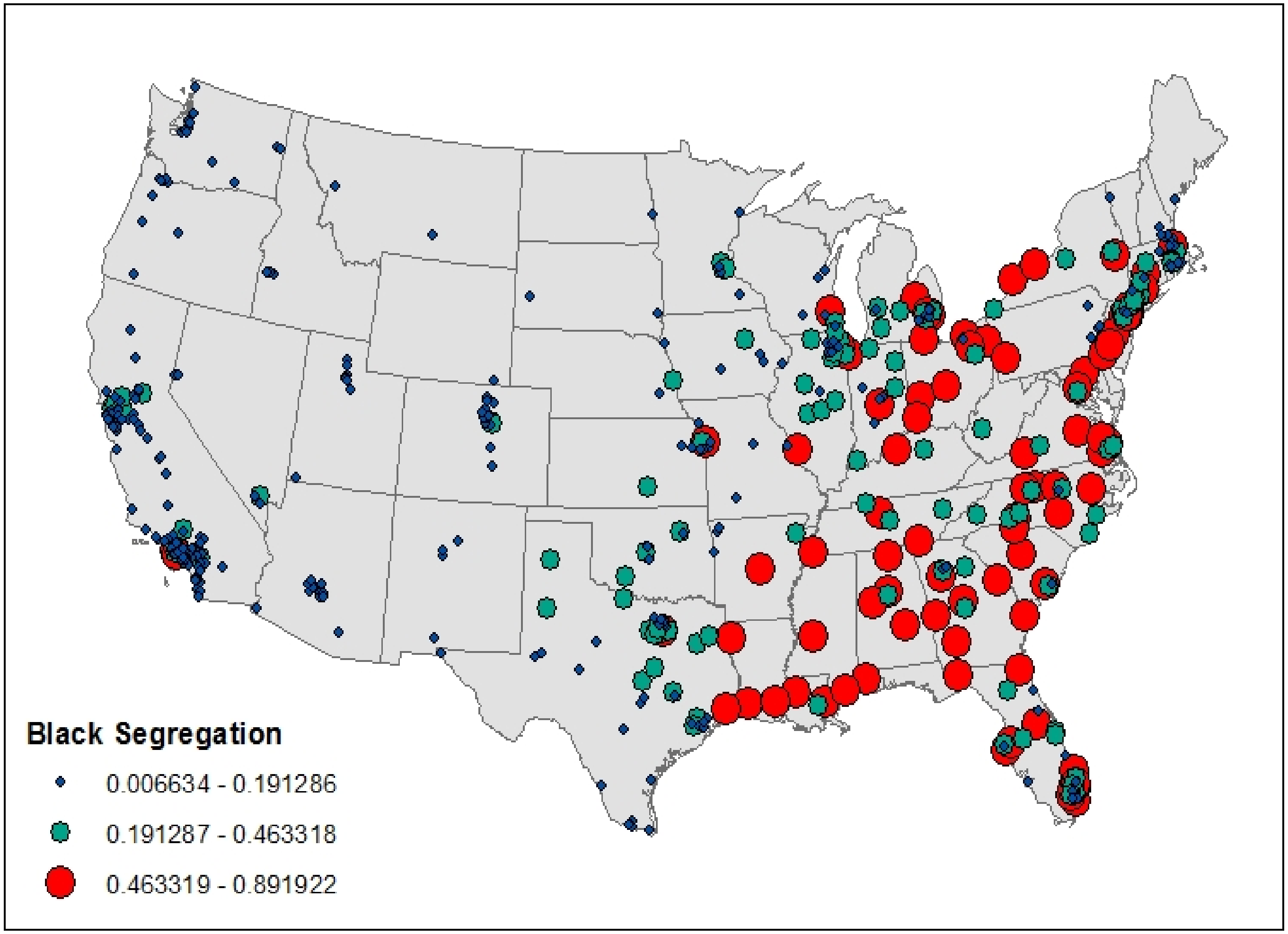

Figure 7 Black Residential Segregation

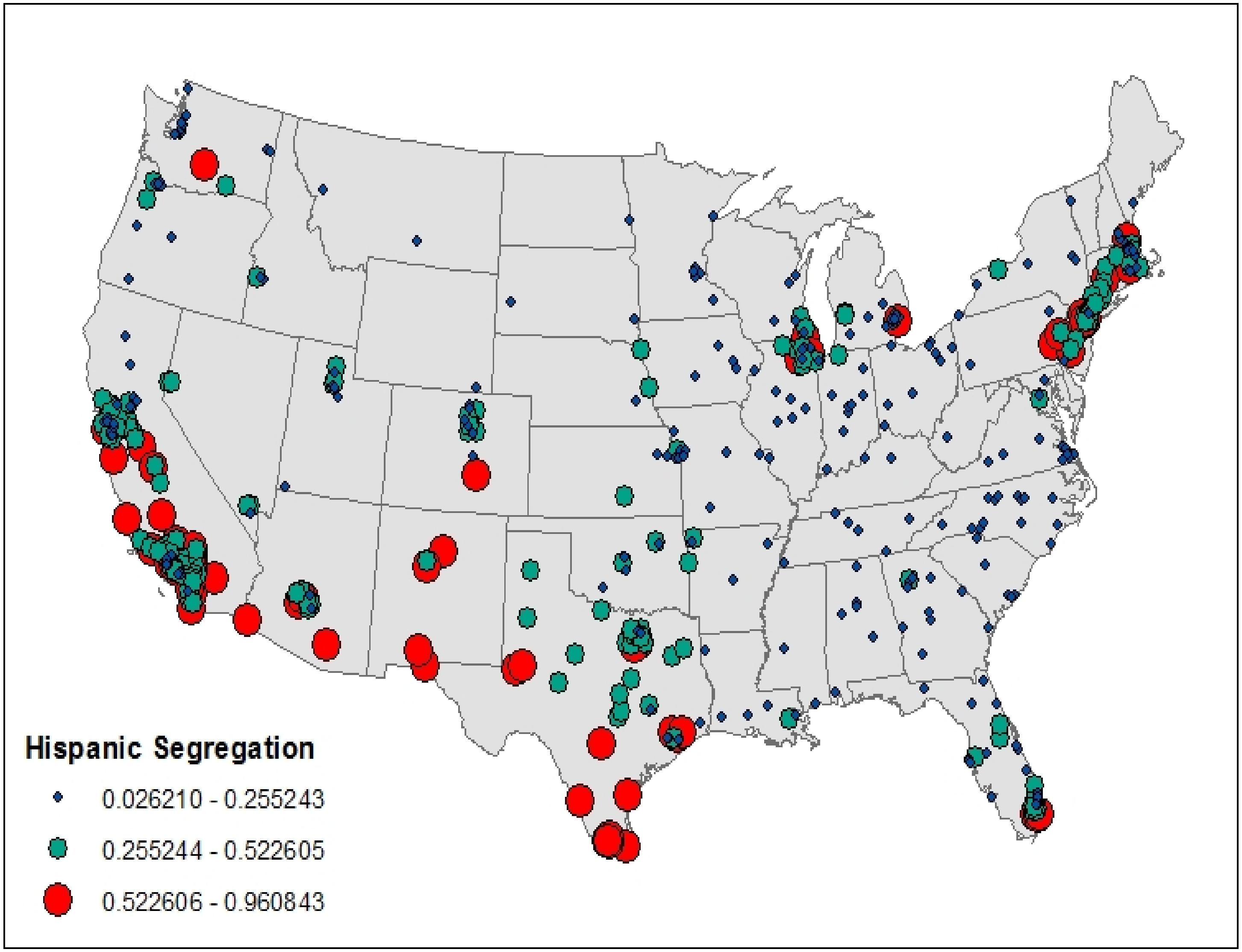

Figure 8 Hispanic Residential Segregation

3.3 Correlation and Regression Results

As shown in Table 4, health disparities are significantly correlated ($p < 0.05$) with segregation and socioeconomic factors except for income and sprawl. Language is strongly correlated with education and Hispanic segregation. Income has a strong positive association with financial occupation and poverty. In addition, there is a strong positive relationship between no vehicle available and public transport. However, there are significantly negative associations between poverty status and financial occupation including owner-occupied housing units. Multicollinearity exists among these variables especially among the socioeconomic variables which may affect interpretation of the results.

The factor analysis method was used to remove multicollinearity to ensure that observations are independent to avoid violating that regression assumption. Four factors were generated from the factor analysis. These four factors explain 80% of the total variance in the original dataset, reducing its complexity. Factor 1 loads three main variables which include median income, poverty status and financial occupations. Factor 2 loaded mainly four variables. These include educational level, language, uninsured persons and Hispanics residential segregation. A high factor 2 implies high suggests high levels of uneducated persons, persons that speak English less than very well, uninsured persons and high Hispanic segregation. Factor 3 characterizes three main factors reflecting transportation challenges and owner-occupied housing units. The transportation challenges include no vehicle available and public transportation. Factor 4 positively loads one main variable which is average urban sprawl (Table 5).

The variables that loaded highest on each factor were adopted for OLS analysis. Income from factor 1, Hispanic segregation from factor 2, no vehicle available from factor 3 and urban sprawl from factor 4. Black segregation was not strongly loaded on any of the factors and was therefore added to the four factors to make a total of five independent variables for regression analysis. The OLS regression model suggested that the five factors explained 14.9% of variance of the dependent variables that is the health disparity ratios. An R value of .386 suggests a low correlation between dependent and independent variables used for the regression (Table 6). Significance values generated from ANOVA <.05 suggests that that there is a statistically significant relationship between the dependent variable and Black segregation, Hispanic segregation and no vehicle available. However, Hispanic segregation presents a negative correlation, which suggests greater values of Hispanic segregation were associated with decreased disparity ratios. There was no statistically significant associations between health disparities and median income as well as urban sprawl (Table 7).

To ensure that none of the assumptions of linear regression is violated, spatial autocorrelation was tested. Moran's I was used to investigate the spatial pattern of the regression residuals to check for spatial autocorrelation. The Moran's index was 0.053 with a z-score of 4.78 which suggests a clustered pattern. Meaning that the residuals of the regression model are not normally distributed, violating that regression assumption. Therefore, interpreting the results may take caution as the residuals of the OLS model were not independent. Also, the mean of the residuals is zero, which means that the assumption was not violated.

Table 4 Associations between Health Disparities, Segregation, Sprawl and Socioeconomic Characteristics

Sprawl	1														
Lang	0.051	1													
Educ	0.012	.732**	1												
Income	-0.002	.117**	.549**	1											
Poverty	-0.021	0.062	.492**	.820**	1										
Travel	0.039	.422**	.192**	.321**	-.340**	1									
No_veh	-0.059	.172**	.211**	.194**	.401**	.113*	1								
Public_tra	-0.022	.236**	.092*	0.079	.118**	.356**	.846**	1							
Own_occu	0.05	.272**	.360**	.418**	-.609**	.145**	-.599**	-.455**	1						
Uninsured	.166**	.504**	.666**	.500**	.394**	-0.008	0.052	-0.077	-.237**	1					
Financial	-0.017	.243**	.681**	.866**	-.690**	.176**	-.147**	.090*	.339**	-.484**	1				
BlackSeg	0.015	.252**	0.069	.317**	.479**	-.091*	.375**	.225**	-.303**	.163**	-.197**	1			
HispSegh	0.058	.781**	.776**	.245**	.162**	.324**	0.083	0.069	-.189**	.625**	-.366**	-.240**	1		
Disparity	-0.011	.269**	.273**	-0.053	.224**	.255**	.224**	.209**	-.306**	-.128**	.155**	.312**	-.239**	1	
	Sprawl	Lang	Educ	Income	Poverty	Travel	No_veh	Public_tra	Own_occu	Uninsured	Financial	BlackSeg	HispSeg	Disparity	

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 5 Rotated Factor Structure of Independent Variables

Variables	Factor 1	Factor 2	Factor 3	Factor 4
Urban sprawl	0.027	0.05505	-0.05255	0.94266
Less than high school graduate	0.036	0.91568	0.14923	-0.0292
Speak English less than very well	-0.475	0.80932	0.11239	-0.00235
Median income(dollars)	0.918	-0.1736	-0.04782	-0.0054
Poverty status (below 100 percent of the poverty level)	-0.877	0.05034	0.31847	-0.00219
Mean travel time to work (minutes)	0.552	0.49642	0.25773	0.10635
No vehicle available	-0.139	0.0614	0.92639	-0.03776
Public transportation	0.196	0.11547	0.92391	-0.01031
Owner-occupied housing units	0.464	-0.1437	-0.64077	0.10550
Percent uninsured	-0.491	0.61267	-0.05816	0.27038
Management, business and financial occupation	0.820	-0.3420	0.01117	0.00956
Black segregation	-0.442	-0.3236	0.46409	0.26103
Hispanic segregation	-0.1214	0.92146	-0.01267	0.00059

Note: The highlighted variables are those that are mainly loaded on a factor

Table 6 OLS Model Summary

R	R Square	Adjusted R Square	Std. Error
.386[a]	0.149	0.140	0.16575

Table 7 Coefficients of OLS

	Unstandardized	Coefficients	Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig
(constant)	.390	.017		23.455	.000
Black Segregation	.166	.038	.203	4.332	.000
Hispanic Segregation	-.167	.036	-.202	-4.646	.000
No vehicle available	.006	.002	.165	3.621	.000

4 DISCUSSION AND CONCLUSION

4.1 UHI and Health disparities

This thesis research sought to investigate the spatial distribution of health disparities among the 500 largest cities in the United States and the driving factors of the disparities. The UHI approach was used as a small area disparity assessment tool which recorded both intra city and intercity disparities among the cities. To achieve the second objective, socioeconomic factors were employed to examine their extent of influence on the recorded disparities by adopting OLS regression. Both bivariate correlation and OLS were used to analyze relationships between dependent and independent variables. Black and Hispanic segregation as well as unavailability of personal vehicles had a significant influence on health disparities among cities.

Furthermore, this research revealed that larger cities have higher health disparities as compared to smaller cities as shown in Figure 4. However, a few larger cities were found to be among the first 100 cities with low health disparities while some smaller cities were ranked among the last 100 cities with the largest disparities. Past studies have also found that substantial inequalities among urban population is partly due to common spatial and socioeconomic factors (Chandola, 2012). Living in cities or urban areas is accompanied by both pros and cons. The concept of “urban health advantage” comes into play here, which explains that people living in cities enjoy better health care access as opposed to rural areas and is therefore a driving force to better health outcomes of cities (Vlahov, Galea, & Freudenberg, 2005). That could explain the reason why certain larger cities among the 500 cities ranked among the first 100 with low health disparities and lower UHI values within its census tracts.

On the other hand, other researchers argue that big cities are characterized by replacement of green space with urban construction, industrial pollution and population growth which hinder healthy behaviors and influence the quality of health in such areas (Koplan and Fleming, 2000). That notwithstanding, cities also have many other built social and physical environmental features that might have an influence on population health (Richardson et al., 2012). Health levels of cities are largely dependent on residents' conditions and lifestyle which results from a complicated interaction of health determinants; physical, economic and social, in residential environments (Takano T & K, 2001).

4.2 Health Disparities and Socioeconomic Factors

This study identified a positive correlation between spatial variation of health disparities and some existing socioeconomic systems and factors, mainly segregation and unavailability of personal vehicle which supports previous studies. It is evident that living in areas higher socioeconomic disadvantages and higher socio- cultural barriers is associated with a higher likelihood of greater disparities in breast cancer access in Detroit (Dai, 2010). According to previous studies, populations with socioeconomic disadvantages become marginalized and increasingly have trouble meeting basic needs such as housing, education, and health care that improves well-being (Galea et al., 2005 ;Wilson, 1996; Katz 1989). Socioeconomic disadvantages typical of deprived neighborhoods such as economic hardships are assumed to be correlated to health status (Laxy, Malecki, Givens, Walsh, & Nieto, 2015). Although rates of health disparities on average are influenced by socioeconomic factors, it is insufficient to say health disparities will improve with economic growth or demographic change. Rather, there should be a conscious effort to actively create and maintain healthy living conditions of urban areas through policy interventions (Rydin et al., 2012). Decisions about housing, food, energy, transport services and health care profoundly affect health, wellbeing and safety of growing urban populations (Badland et al., 2014).

4.3 Residential segregation and Urban Sprawl

Segregation of minority population influences health disparities of cities. Clustering of minority populations allows for characteristics of racial traits to be centered on specific geographical areas, which in turn results in disparities. The persistence of racial/ethnic disparities, particularly black health disparities, is measured across multiple mortality and morbidity outcomes (White & Borrell, 2011). The OLS regression model as well as bivariate correlation in this research found a significant correlation between black residential segregation and health disparities, which is in line with past studies.

There are multiple ways segregation and clusters of socioeconomic disadvantages could affect overall health and wellbeing. Residential segregation leads to institutional discrimination which severely limits minority populations from accessing quality educational institutions and high-paying jobs which also results in low income (Williams & Collins, 2001). Such residents that fall within the low-income belt may not be able to afford basic health care, which intensifies the overall poor health in neighborhoods. Past studies have pointed to the role of increased obesity associated with segregated neighborhoods contributing to health disparities. Highly segregated neighborhoods are usually isolated from healthy foods and with a rather higher number of fast food restaurants within easy access (Logan & Parman, 2018; Zenk et al., 2005; Morland and Filomena, 2007; Powell et al., 2007). Researchers have also associated physical inactivity to segregation resulting in obesity and poor health outcomes (Logan & Parman, 2018; Corral et al., 2012; Wilson-Frederick et al., 2014). This thesis contributes to this line of research by showing that residing in highly segregated areas for minorities' impacts overall disparities of a city's population.

Urban sprawl did not present any significant relationship with the disparities among cities. This is different compared to previous literature that have established associations between these two factors (Ewing et al., 2006; Garden & Jalaludin, 2009). However, such studies assessed urban sprawl's influence on specific health indicators such as obesity and diseases associated with physical inactivity (Lopez & Hynes, 2006; Ewing et al., 2003; Zhao & Kaestner, 2010; Plantinga & Bernell, 2007). Health disparity as computed in this research is a compound of several health indicator variables without focusing on specific diseases, as such a combination might affect the strength of correlation with urban sprawl.

4.4 Conclusion and Limitations

The ultimate goal of population health study is to improve the health of individuals and populations by investing in policies and interventions that influence determinants of health (Kindig, Asada, & Booske, 2008). Employing a standard approach to investigate small-area level disparities allows for the assessment of local disparities (Rothenberg et al., 2014), which can be used by decision makers and public health workers to trace the source of disparity specific to each local area and respond accordingly. Using the 500 cities as an example, this study investigated health disparities at census tract and city levels by focusing on the assessment of disparities based on socioeconomic variables and geographical settlement characteristics. It is clear that minority segregation and some socioeconomic factors have a strong influence on cities' health. The UHI approach was used as the primary index in identifying disparities among cities. Findings of worst-off localities can be used by policy makers to create intervention programs and helps to channel resources at required locations for improvements

There may be a few aspects of limitations to this study. First, more advanced models shall be used to explore the relationships. The OLS model requires the residential to be independent, which were violated in this case. In future studies, spatial regression models may be better choices to account for the clustering of errors. Second, data obtained from the CDC as well as census data from American Community Survey for socioeconomic factors and minority population had some missing data. Some census tracts were completely deleted due to data unavailability. Others were missing data for a number of variables but were included in the data analysis. Third, small population issue may play a role in calculating disparity ratios. Fewer census tracts in a small city will exaggerate the disparity ratio compared to large cities. This could affect the result of the study. This research however may be used by future researchers to assess whether there has been a change among these cities' health disparities.

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APPENDICES

Appendix A: The First 100 Cities and Disparity Ranks

City name	Rank	City name	Rank	City name	Rank	City name	Rank
Cicero	1	Clifton	29	Santa Maria	57	West Jordan	85
Lakewood	2	Bellflower	30	Burbank	58	Manchester	86
Parma	3	Paterson	31	Salinas	59	Concord	87
South Gate	4	Westminster	32	Escondido	60	Pawtucket	88
Pharr	5	Napa	33	Livonia	61	Camden	89
Ogden	6	Deltona	34	Flint	62	Trenton	90
Redondo Beach	7	Miami Gardens	35	Hollywood	63	Independence	91
Downey	8	Manteca	36	St. George	64	Allentown	92
Lynwood	9	Sioux City	37	Bloomington	65	Inglewood	93
Warren	10	Warwick	38	Compton	66	Lowell	94
Kennewick	11	Citrus Heights	39	Palmdale	67	Mesquite	95
Fishers	12	Port St. Lucie	40	Portland	68	Santa Monica	96
Brockton	13	Whittier	41	Longview	69	Mount Vernon	97
Norwalk	14	Westland	42	Simi Valley	70	Nampa	98
Union City	15	Springfield	43	Clearwater	71	Roswell	99
Garden Grove	16	Modesto	44	Cape Coral	72	Perris	100
Alhambra	17	Torrance	45	Daly City	73		

Gary	18	Moreno Valley	46	Santa Ana	74		
Medford	19	Sandy	47	Merced	75		
Elizabeth	20	Broken Arrow	48	Hemet	76		
New Bedford	21	Gresham	49	Lafayette	77		
Palm Coast	22	Reading	50	San Mateo	78		
Norwalk	23	Redding	51	Waukesha	79		
Hialeah	24	Temecula	52	Tracy	80		
Fort Smith	25	St. Joseph	53	Arlington Heights	81		
Sterling Heights	26	Santa Rosa	54	Newport Beach	82		
Southfield	27	Spokane Valley	55	Wyoming	83		
Apple Valley	28	San Leandro	56	Visalia	84		