The Park Place Economist

Volume 28 | Issue 1 Article 11

September 2021

The Intersectionality of Socioeconomic Status, Socioeconomic Status, Air Pollution Exposure, and Negative Health Outcomes in Chicago

Tera Wilson
Illinois Wesleyan University

The Intersectionality of Socioeconomic Status, Socioeconomic Status, Air Pollution Exposure, and Negative Health Outcomes in Chicago

Abstract

In recent decades, there's been growing awareness surrounding the environmental justice movement, in which historically marginalized groups are bringing attention to their unequal exposure to environmental hazards and unequal access to environmental benefits. This paper ties together environmental injustice and economic theories by drawing from the economic concept of negative externalities to explore the experience of a marginalized group in Chicago. The marginalized group and the environmental hazards they face as a result of consumptive externalities is those of a lower socioeconomic status facing exposure to poor air quality. Using geographic distributions, scatterplots, and OLS regressions, this paper found that socioeconomic status and O_3 exposure have some explanatory weight in understanding the average annual deaths from heart disease and chronic lower respiratory disease, respectively, for residents of different communities in Chicago. Other variables were of little statistical significance, which may be due to flaws in data collection, examined variables, and project design. In the future, other researchers should consider more air quality data on a smaller time frame, with a more robust measurement of negative health outcomes.

The Intersectionality of Socioeconomic Status, Socioeconomic Status, Air Pollution Exposure, and Negative Health Outcomes in Chicago

By: Tera Wilson

Introduction

Unhealthy exposure to environmental hazards can happen in a broad variety of ways- whether it be emissions from a nearby coal-fired power plant causing asthma or toxic chemicals in municipal water systems causing child leukemia (Coal and Air Pollution 2008, Case Summary 2016). With the negative impacts that environmental hazards can cause, it is important to examine who they impact, and why. There is much evidence that shows that some groups are more impacted by environmental hazards than others, revealing injustices in our system that should be understood and remedied (Environmental Protection Agency 2019). The groups that are exposed to environmental hazards at higher rates typically include racial/ethnic minorities, and people of a lower socioeconomic status.

Research has shown that lower levels of socioeconomic status (SES) are correlated with greater levels of air pollution exposure on nearly every continent, likely due to exposure and proximity to roadways (Hajat 2015). There has also been extensive research on air pollution exposure and how it influences negative health outcomes within the cardiovascular and respiratory systems (American Health Association 2019). Within the city of Chicago, there are neighborhoods extremely stratified by wealth, and many people that live in the city are exposed to different levels of air pollution throughout their day (United Way of Illinois 2019, Chicago Health Atlas 2019). Therefore, the research question explored in this paper examines the difference between people of different SES in Chicago and their experiences as it relates to air pollution exposure and negative health outcomes.

The types of air pollution that will be examined are particulate matter 2.5 ($PM_{2.5}$), also known as fine particulate pollution, and ozone (O_3). $PM_{2.5}$ are particles and droplets smaller than 2.5 micrometers in diameter, often consisting of components of fossil fuels that were not entirely combusted, commonly black carbon and other chemicals. Therefore, the most common source of $PM_{2.5}$ in residential areas is traffic emissions, often with high rates of $PM_{2.5}$ near major roadways (Wilson 2019). The reason that $PM_{2.5}$ is so concerning for residents' health is because it is small enough to be inhaled deep into the lungs, which can then deliver it to the bloodstream (American Health Association 2019). Once inside the respiratory and cardiovascular system, $PM_{2.5}$ can cause blockages that lead to health issues such as cardiovascular disease, heart attacks, asthma, and other respiratory diseases (American Health Association 2019).

Ozone is a component of photochemical smog in cities. Like $PM_{2.5}$, the original source of most ozone is from fossil fuel combustion, typically in the form of traffic emissions. Ozone is produced when nitrogen dioxide, a byproduct of fossil fuel combustion, reacts with oxygen due to the energy emitted from ultraviolet rays. Ozone is rarer in nature, because NO_2 is typically dispersed by wind. In cities, however, the NO_2 tends to stay near where it was emitted because buildings "trap" it. When NO_2 is "trapped," the sun can heat it up with ultraviolet rays, causing it to react with oxygen (O_2). The result of this reaction is O_3, which can make it more difficult to breathe for vulnerable populations, especially on hot, sunny days (Wilson 2019). Vulnerable populations, which include the children and elderly, may experience decreased lung function and higher rates of asthma morbidity and mortality. Therefore, this paper will examine $PM_{2.5}$ levels, ozone levels, and reported rates of morbidity and mortality related to air pollution.

Literature Review and Hypothesis

There has been a growing body of research surrounding the health impacts of air pollution and the disproportionate exposure to environmental harm of those of lower socioeconomic status (SES). The term “environmental justice” gained popularity in the United States during the 1980’s as a response to the unfair treatment and exposure to environmental hazards experienced by marginalized people (Environmental Protection Agency 2019). This movement has inspired a body of research that focuses on marginalized people and their experience with the environment. Marginalized groups that are commonly studied include populations of women, racial minorities, ethnic minorities, rural residents, and those of low SES.

When it comes to environmental justice, the category of environmental factors can cover a broad range, but most commonly studies will research a group’s exposure to pollutants in the air, land, or water. In cities, “environmental problems…of greatest concern are the state of air quality, noise, and congestion” (Ksenija 2016). Air quality is an area of great concern because it is one of the most common types of pollution in cities, often due to motorized traffic (Ksenija 2016). Air quality is also worrisome because it has been well-established that it has a significant impact on health (Anderson 2011).

Since the United States is relatively wealthy and less polluted than other countries, differences in exposure to different air pollutants may be small when examining exposure differentials of different populations (Evans 2002). However, people of a lower SES are considered a vulnerable population because they often cannot afford to protect themselves from exposure to air pollutants in the same ways that those with wealth are able to. One study in Rome found that while residents of a higher SES were exposed to greater levels of air pollution, those of a lower SES showed greater impacts to health from air pollution exposure (Forastiere 2007). This difference in air quality exposure may have been due to the way the city developed, as more wealthy residents were able to afford housing in city centers while lower SES populations had to find housing farther away. It was concluded that air pollution exposure had greater impacts on those of a lower SES, making them a more susceptible population to changes in air quality (Forastiere 2007). This susceptibility may stem from a lack of access to health insurance, or inability to pay for healthcare.

However, in the United States, it has been found that people of a lower SES are more likely to be exposed to greater amounts of air pollutants than their wealthy counterparts. One study has shown "evidence of inverse relations between income… with environmental risk factors including hazardous wastes and other toxins, ambient and indoor air pollutants, water quality, [etc]" (Evans 2002). This phenomenon has been shown to be widespread, occurring in many different areas of the United States across time (Evans 2002). This relationship, however, may be dependent on the size of the geographic area examined, since some cities showed that higher SES was correlated with higher rates of exposure, and dependent on the specific pollutant being studied, due to the inherently geographically spatial structure of air pollution (Evans 2002).

The literature on the health impacts of poor air quality is well-established, particularly regarding particulate matter. A literature review of the health effects of different pollutants on the cardiovascular, respiratory, and cerebrovascular systems in humans provides many valuable insights and summaries about the available data (Anderson 2011). One such insight is the list of health outcomes that particulate matter has been linked to, which includes: heart attacks, chronic obstructive pulmonary disease, asthma, decreased lung function, lung cancer and cardiopulmonary disease (Anderson 2011). Particulate matter does this by entering the lungs, and sometimes translocating into the bloodstream, where it can cause chronic inflammation and clotting issues (Anderson 2011).

Ozone has been found to be correlated with asthma incidence and mortality due to asthma (World Health Organization 2018). However, the mechanisms of how O_3 interacts with the body are less understood than the interactions of $PM_{2.5}$. Regardless, both pollutants cause issues for vital functions of the human body. This issue is particularly important because Chicago's air pollution continues to be problematic. WTTW reported that in 2015, Chicago experienced 151 "dirty air days," which puts vulnerable populations at risk for negative health outcomes (Ruppenthal 2017).

While differences in air quality may be smaller within a small geographic area, there is evidence to support the conclusion that those of a lower SES are more likely to be exposed to higher rates of air pollution and be more vulnerable to the negative health impacts of poor air quality. Therefore, based on the available literature, my hypothesis is that populations of a lower SES in Chicago will experience higher rates of air pollution exposure, and have higher rates of related negative health outcomes.

Theoretical Model

My hypothesis draws mainly from the economic theory of consumption externalities. "Externality" refers to something produced as a result of economic activity, that has a consequence on a third party who is not part of that market transaction. This reflects a market failure, since the costs of a good or service fall on a third party and are not accurately reflected in the final price, demonstrated by Figure 1 below.

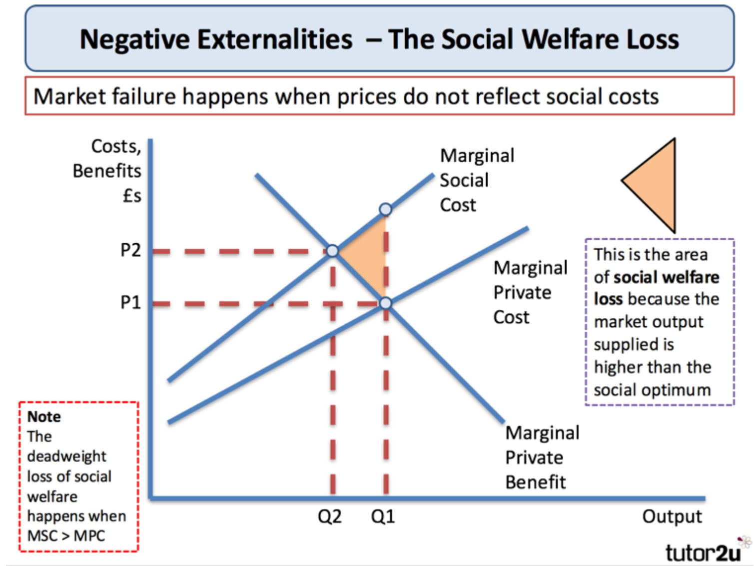

Figure 1: *Graphical representation of market failure due to negative externalities (Externalities 2016).*

The concept of externality is often applied to pollution, where pollution is the negative externality that has consequences on a third party, which in this case arises as the health costs to society. In Figure 1 above, the health costs would be part of the "social welfare cost" triangle that appears when there is a higher supply of a good than what is socially optimal. When an externality is not socially desirable, it is called a "negative externality," because it causes a negative impact to society. Examining pollution as a negative externality implies that the price of the activity that causes pollution is not high enough, which causes an excess supply of that activity. Therefore, there is an excess supply of polluting activity, which then contributes negative impacts to society.

"Consumption externalities" are externalities that are produced when a good is consumed. In this case, the main source of $PM_{2.5}$ and ozone pollution comes from traffic emissions. When gas is consumed, the consumption externalities that are created as a result are the $PM_{2.5}$ and ozone emissions. This consumption externality then impacts whoever happens to be nearby, often in the form of negative impacts to the cardiovascular and respiratory systems.

This impacts lower income people in particular, as they have a lower purchasing power when it comes to paying for medical care. Therefore, this paper explores air pollution as a negative consumption externality on susceptible populations.

Data and Empirical Model

The first data source that I plan to use to establish stratifications in SES in neighborhoods in Chicago is from the unpublished 2019 ALICE Report (United Way of Illinois 2019). "ALICE" stands for "Asset Limited, Income Constrained, Employed," and is a more comprehensive measurement of SES than the federal poverty line. This is because ALICE measurements establish a minimum threshold, which is above the federal poverty line, which is a "bare-minimum" budget that considers the cost of basic necessities such as health, housing, food, transportation, taxes, and technology for a particular area (United Way of Illinois 2019). Any family living below this line is, at best, living paycheck-to-paycheck with little to no assets or savings. Those living below this line include families that are currently living below federal poverty line, who may have little or no income and no financial stability. The dataset is geographically organized by neighborhood, which will make calculations more feasible and revealing. I plan to use this measure because it creates a locally informed measure of where lower SES families reside, rather than relying on a single number that is nationally defined, such as the federal poverty line.

The second set of data that is used originally comes from United States Environmental Protection Agency (US EPA) air quality monitors. The US EPA monitoring system reports daily averages from more than 20 monitors for $PM_{2.5}$ and more than eight monitors for O_3. The data is limited, as not all monitors were in working condition for the entire year. The daily averages have been averaged for the year of 2017. After the averages are calculated for each monitor, the Chicago Health Atlas conducted inverse distance weighting calculations to report one annual average for each pollution measure for each community area in Chicago in 2017.

The third set of data I will be working with is also reported by Chicago Health Atlas, which sources data from the Illinois Department of Public Health and the Chicago Department of Public Health. The specific data sets I will be using report crude death rates from cardiovascular disease, deaths from coronary heart disease, and deaths from chronic lower respiratory disease. These are reported both in nominal numbers and rates according to neighborhood in Chicago. Specifically, I will examine pooled data of the average annual number of incidences per 100,000 people for each health measure from the years 2013-2017. One shortcoming of this dataset, however, is that it does not report on health data that may be more directly linked to air pollution, such as emergency room visits due to asthma. Additionally, since health events are often linked to acute air quality, using this data does not allow me to examine the timing of air quality, since I will be using data that is reported on an annual basis.

The software I intend to use is ArcGIS, a system that allows a user to map out and perform calculations on their data. “GIS” stands for “Geographic Information Systems,” and is mainly used by environmental agents to map out endangered populations, areas of pollution, watersheds, etc. I intend to use ArcGIS to map the neighborhoods of Chicago, and then construct new “layers” of data for each variable I examine. By layering the data in a map, I will then be able to examine the relationship between SES, air pollution, and health outcomes for each neighborhood.

The first step in this process will be to assign each neighborhood an “ALICE value,” which will be the percentage of households living below the ALICE threshold for that neighborhood, and average annual rates of $PM_{2.5}$ and O_3. For the final layers, I will be assigning the average annual rate of negative health outcomes per 100,000 people to each neighborhood. These negative health outcomes will include deaths due to cardiovascular disease, coronary heart disease, and chronic lower respiratory disease. Therefore, I will have one baseline layer of solely neighborhood borders, one layer for SES, two layers for air pollution exposure, and three layers for health outcomes, which brings me to a total of five layers of data to work with within ArcGIS.

Once the layers are constructed, it will be possible to examine the dataset for correlations and perform regressions. I will also map the geographic distribution of each variable, to examine if each variable has a geographic pattern. Additionally, I will run a Moran I analysis to test for possible clusters of the data, to further understand possible geographic patterns of each variable. Moran I analysis shows where certain values are grouped together, and provides evidence for "clusters" and "outliers" in the geographic data. To examine correlations, I will construct scatterplots of the relationship between the ALICE values and every other variable for each neighborhood, using the ALICE value as the independent variable each time. I will also use GIS to run multivariate ordinary least squared (OLS) regressions on the data. The regressions will look like the following equations:

$$\text{Average Annual Deaths due to Heart Attack/100,000 people} = B_0 + B_1(\text{ALICE}) + B_2(PM_{2.5}) + B_3(O_3)$$

$$\text{Average Annual Deaths due to Chronic Lower Respiratory Disease/100,000 people} = B_0 + B_1(\text{ALICE}) + B_2(PM_{2.5}) + B_3(O_3)$$

$$\text{Average Annual Deaths due to Coronary Heart Disease/100,000 people} = B_0 + B_1(\text{ALICE}) + B_2(PM_{2.5}) + B_3(O_3)$$

Results and Analysis

To test the hypothesis that that populations of a lower SES in Chicago will experience higher rates of air pollution exposure and related negative health outcomes, I explored the various relationships between $PM_{2.5}$, ozone, heart disease deaths, coronary heart disease deaths, and chronic lower respiratory disease deaths in community neighborhoods in the Chicago area.

The following sections illustrate my results in a series of maps, scatterplots, and regression results tables. The sections include results of geographic distributions, ALICE and single variable relationships, and regressions. Following each results section is analysis of results for that corresponding section.

<u>Geographic Distribution Results</u>

The following maps demonstrate the geographic distribution of each variable, with an additional Moran cluster analysis of the ALICE and pollutant variables.

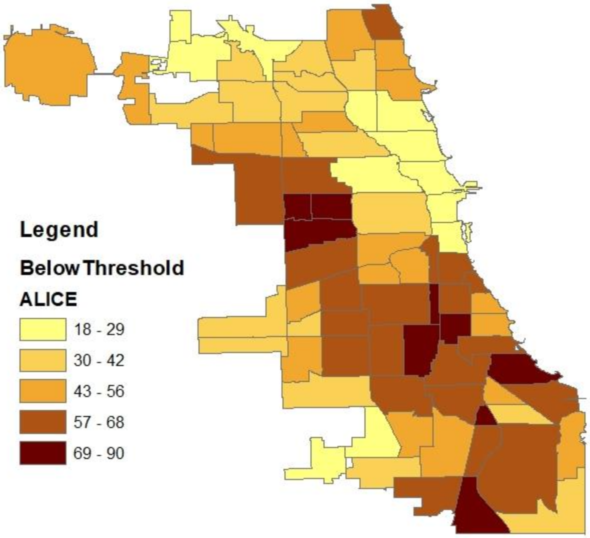

Figure 2: Map of Community Areas of Chicago. "BelowThreshold: ALICE" represents percentage of population living below ALICE's minimum budget threshold in 2017. (United Way Illinois 2019)

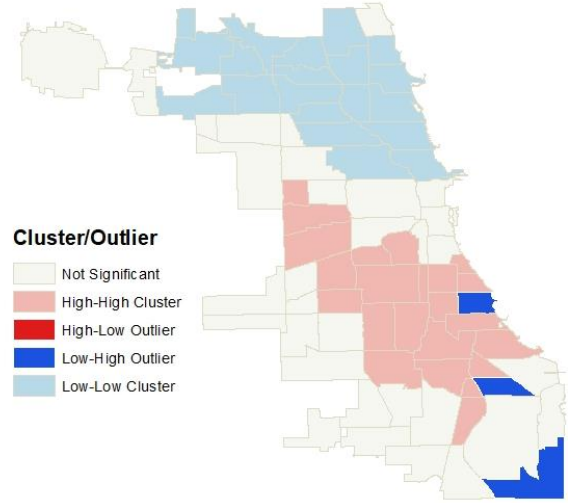

Figure 3: Map of Moran's cluster analysis for ALICE rates (see: Figure 2) for Community Areas of Chicago. "High-High cluster" represents areas of high ALICE rates, surrounded by more high ALICE rate areas, indicative of low SES clustering. "Low-Low cluster" represents areas of low ALICE rates, surrounded by more low ALICE rate areas, indicative of high SES clustering. "Low-High outlier" indicates community areas with low ALICE thresholds, surrounded by areas of high ALICE percentages (United Way Illinois 2019).

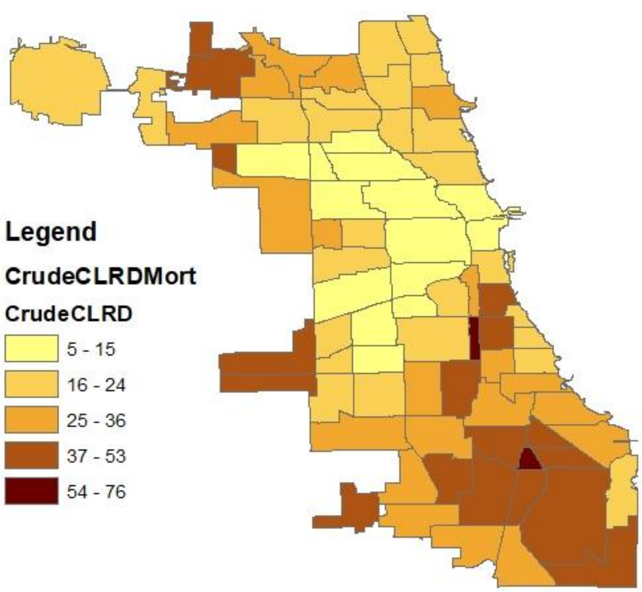

Figure 4: Map of Community Areas of Chicago. "CLRD" represents average number of chronic lower respiratory disease deaths per 100,000 people per community area from 2013-2017. (Chicago Health Atlas 2019)

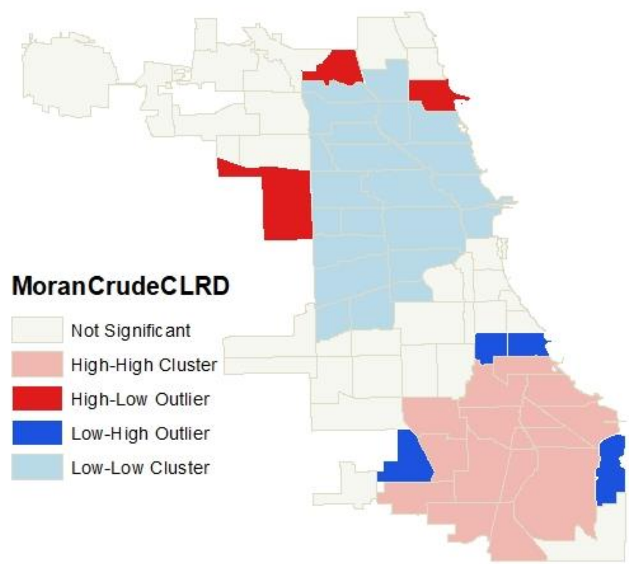

Figure 5: Map of Moran's cluster analysis for CLRD rates (see: Figure 4) for Community Areas of Chicago. "High-High cluster" represents areas of high rates, surrounded by more high rate areas, indicative of clustering. "Low-Low cluster" represents clusters of low death rates. "Low-High outlier" indicates community areas with low deaths, surrounded by areas of high death rates. "High-Low outlier" represents the opposite (Chicago Health Atlas 2019).

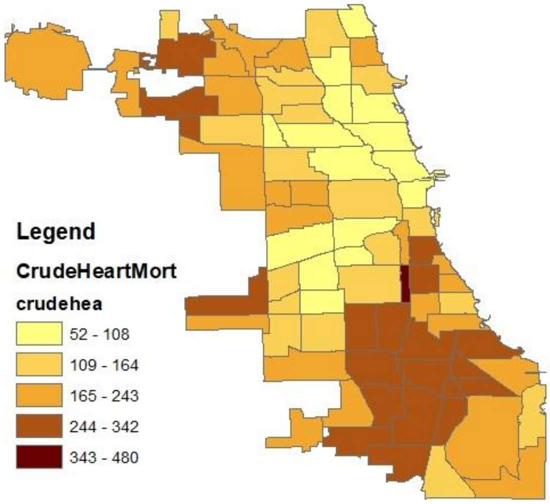

Figure 6*: Map of Community Areas of Chicago. "CrudeHeartMort" represents average number of heart disease deaths per 100,000 people per community area from 2014-2017. (Chicago Health Atlas 2019)*

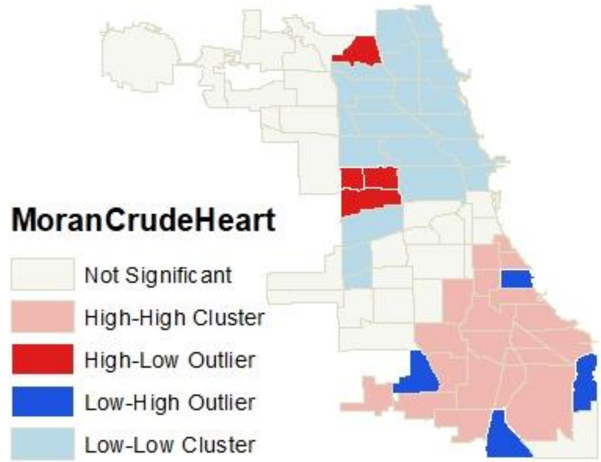

Figure 7*: Map of Moran's cluster analysis for heart disease death rates (see: Figure 4) for Community Areas of Chicago. "High-High cluster" represents areas of high rates, surrounded by more high rate areas, indicative of clustering. "Low-Low cluster" represents clusters of low death rates. "Low-High outlier" indicates community areas with low deaths, surrounded by areas of high death rates. "High-Low outlier" represents the opposite (Chicago Health Atlas 2019).*

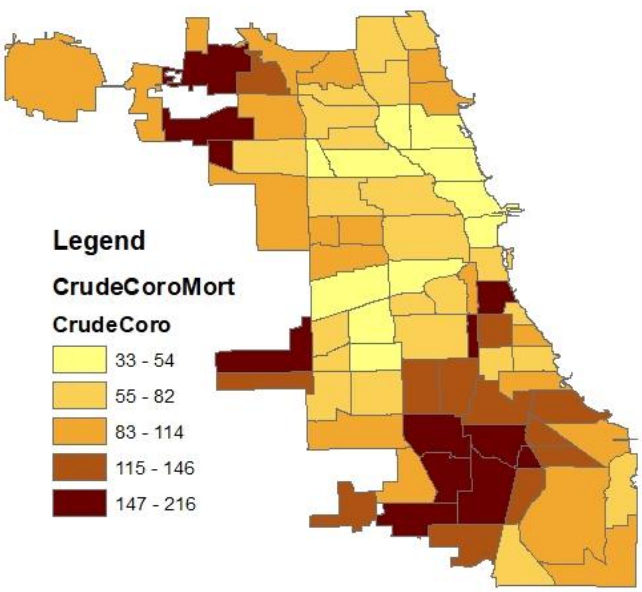

Figure 8*: Map of Community Areas of Chicago. "CrudeCoroMort" represents average number of coronary heart disease deaths per 100,000 people per community area from 2014-2017. (Chicago Health Atlas 2019)*

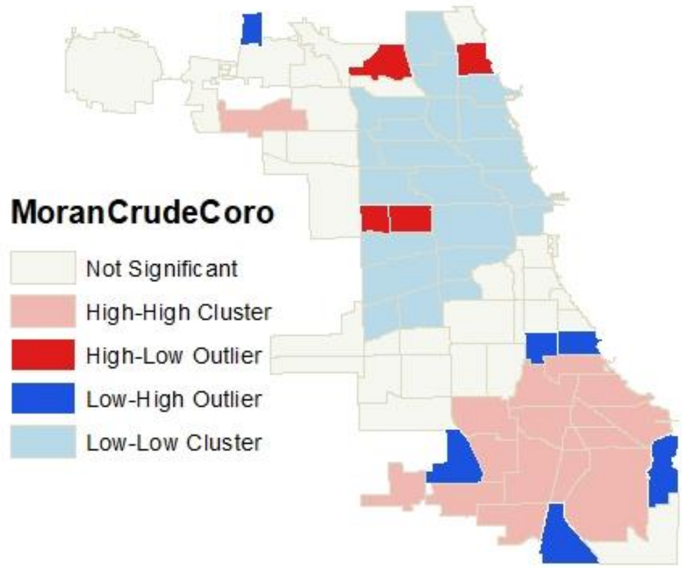

Figure 9*: Map of Moran's cluster analysis for coronary heart disease death rates (see: Figure 8) for Community Areas of Chicago. "High-High cluster" represents areas of high rates, surrounded by more high rate areas, indicative of clustering. "Low-Low cluster" represents clusters of low death rates. "Low-High outlier" indicates community areas with low deaths, surrounded by areas of high death rates. "High-Low outlier" represents the opposite (Chicago Health Atlas 2019).*

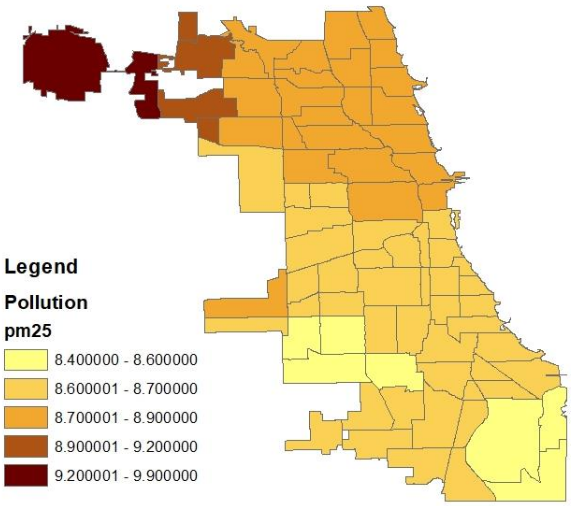

Figure 10: *Map of Community Areas of Chicago. "pm25" represents average number of PM2.5/micrometer^3 per community area from 2014-2017. (Chicago Health Atlas 2019 US EPA 2019)*

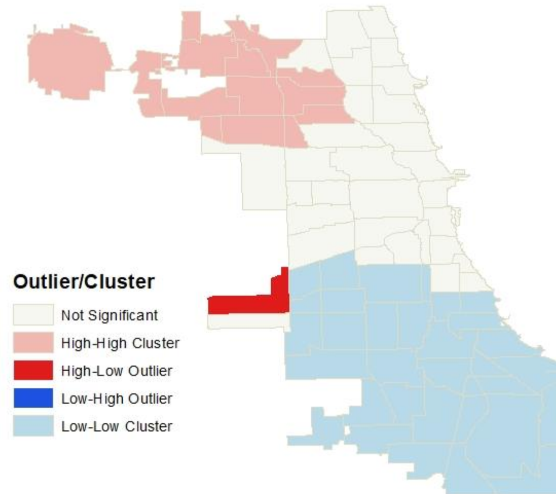

Figure 11: *Map of Moran's cluster analysis for PM2.5 rates (see: Figure 10) for Community Areas of Chicago. "High-High cluster" represents areas of high ALICE rates, surrounded by more high ALICE rate areas, indicative of low SES clustering. "Low-Low cluster" represents areas of low ALICE rates, surrounded by more low ALICE rate areas, indicative of high SES clustering. "Low-High outlier" indicates community areas with low ALICE thresholds, surrounded by areas of high ALICE percentages (Chicago Health Atlas, US EPA 2019).*

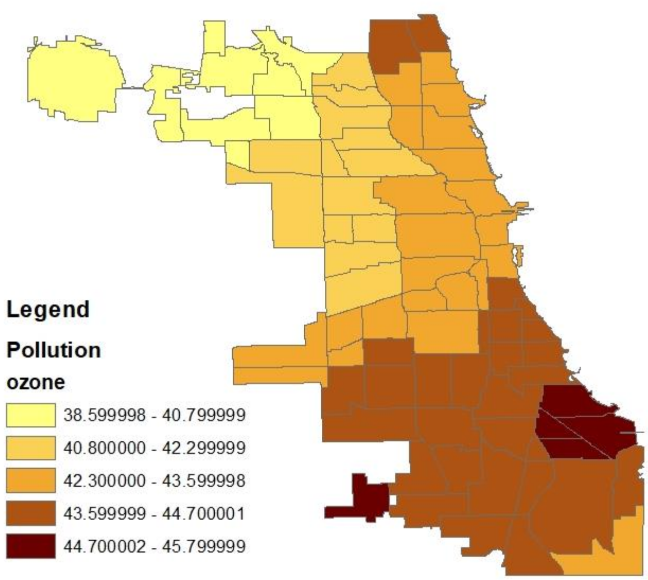

Figure 12: *Map of Community Areas of Chicago. "ozone" represents average number of PM2.5/micrometercubed per community area from 2014-2017 (Chicago Health Atlas 2019, US EPA 2019).*

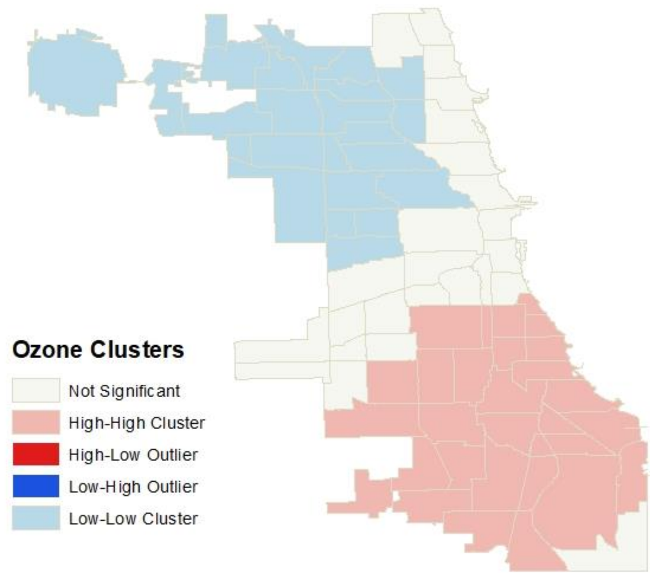

Figure 13: *Map of Moran's cluster analysis for PM2.5 rates (see: Figure 12) for Community Areas of Chicago. "High-High cluster" represents areas of high ALICE rates, surrounded by more high ALICE rate areas, indicative of low SES clustering. "Low-Low cluster" represents areas of low ALICE rates, surrounded by more low ALICE rate areas, indicative of high SES clustering. "Low-High outlier" indicates community areas with low ALICE thresholds, surrounded by areas of high ALICE percentages (Chicago Health Atlas, US EPA 2019).*

Geographic Distributions Analysis

ALICE data shows that there is a wide range of socioeconomic statuses in Chicago, with some communities having rates as low as 19 percent of the population of the respective community area fall below the ALICE threshold, where other communities have rates as high as 90 percent (Figure 2). Moran cluster analysis is designed to reveal patterns and clusters within geographic data, and the Moran analysis shows that there is some clustering of the ALICE data. In the central eastern portion of the city, there is a cluster of low SES communities, while there is a cluster of high SES communities further north in the city (Figure 3).

For each of the health indicators, there appears to be some evidence of clustering (Figures 4 through 9). All the health indicators show some clusters within the southeast area, somewhat near the cluster of lower SES areas. This would suggest that there is a correlation between SES and health indicators. However, there are many outliers within the health graphs, with at least seven outliers per health indicator. The high number of outliers suggests there is not as strong a geographic component as the original graphs might suggest. Therefore, while there does appear to be a relationship between health and geography, the relationship does not appear to be very strong.

$PM_{2.5}$ shows strong evidence of clustering, with high rates of $PM_{2.5}$ pollution in the northwest section of the city, and lower rates in the southeast (Figures 10 and 11). The high rates of $PM_{2.5}$ in the northwest section are likely due to emissions from airplanes, as the community area furthest west contains O'Hare airport, which is a busy international airport. These patterns suggest $PM_{2.5}$ has a strong relationship to geographic distributions, which matches current literature about the spatial structure of air pollution. The "high-low" outlier is likely due to the location of the Midway airport, a smaller airport, whose airplanes would emit high amounts of $PM_{2.5}$.

Ozone also shows strong evidence of clusters, although the patterns are nearly opposite of $PM_{2.5}$ patterns, because there are relatively higher rates of O_3 in the southeast section of the city, and lower rates in the northeast section (see Figure 12 and 13). This may be due to higher traffic density and a higher building density in the southeast, which would create the “trapping” effect explained previously. The opposite of this, greater open space and lower traffic density, may explain the low levels of O_3 in the northeast. However, since both of these data measures reflect averaged annual numbers, each pollutant level is affected by seasonality, and therefore the day-to-day lived experience of air pollution exposure may not be reflected accurately by annual averages.

The geographic distribution of each variable shows strong evidence of a strong geospatial relationship for both air pollutants. There is a weaker, but visible, geospatial relationship for the SES measure, suggesting there is some clustering of people of a similar SES. However, there is little evidence to suggest a strong geographic relationship for the examined health measures.

ALICE and Single Variable Relationship Results

The following graphs demonstrate the relationship between ALICE and every other variable, for each neighborhood, to examine the potential relationship between SES with health outcomes and air pollution exposure.

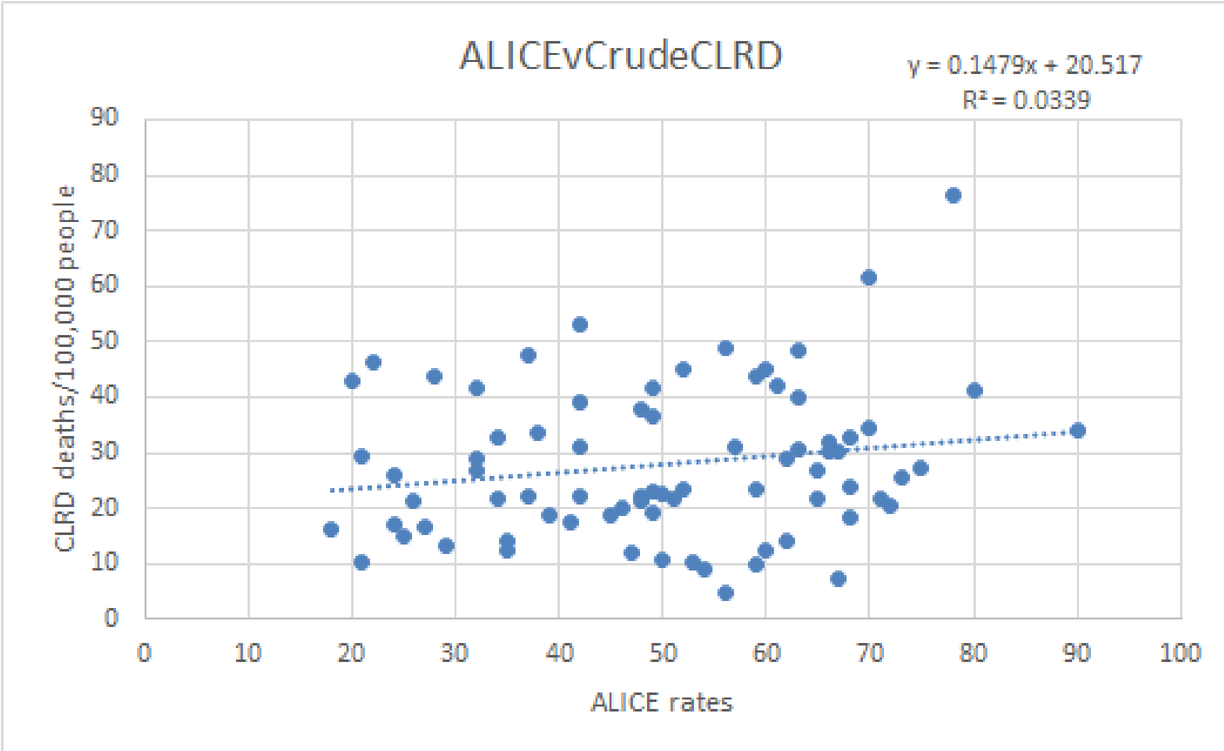

Figure 14: *The relationship between 2019 ALICE rates and average deaths due to chronic lower respiratory disease per 100,000 people for each neighborhood in Chicago (United Way of Illinois 2019, Chicago Health Atlas 2019).*

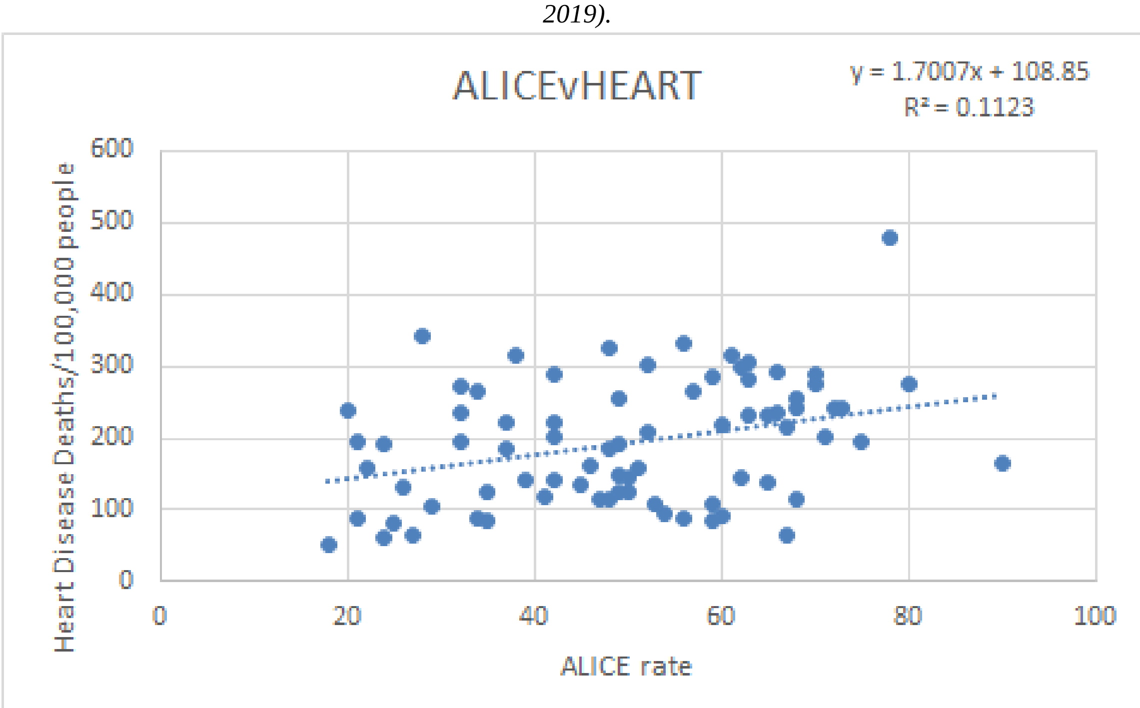

Figure 15: *The relationship between ALICE rates and average deaths due to heart disease per 100,000 people for each neighborhood in Chicago (United Way of Illinois 2019, Chicago Health Atlas 2019).*

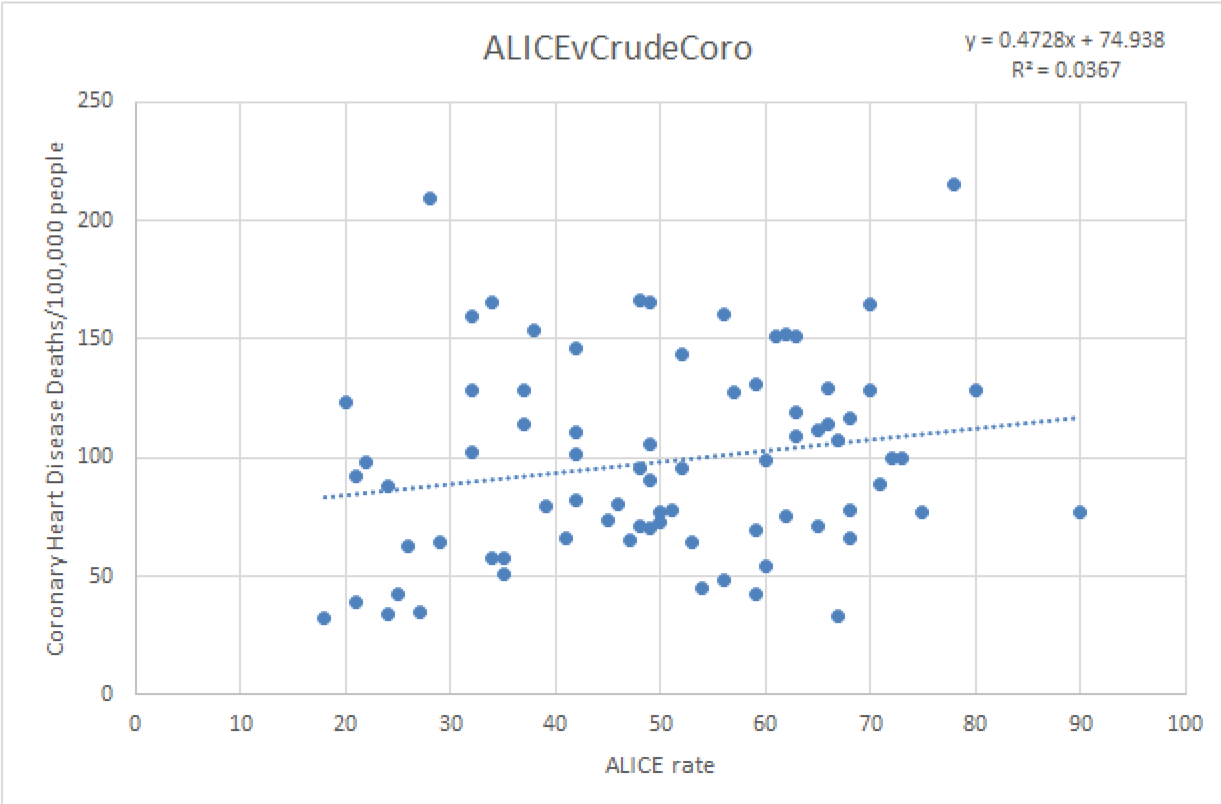

Figure 16*: The relationship between ALICE rates and average deaths due to coronary heart disease per 100,000 people for each neighborhood in Chicago (United Way of Illinois 2019, Chicago Health Atlas 2019).*

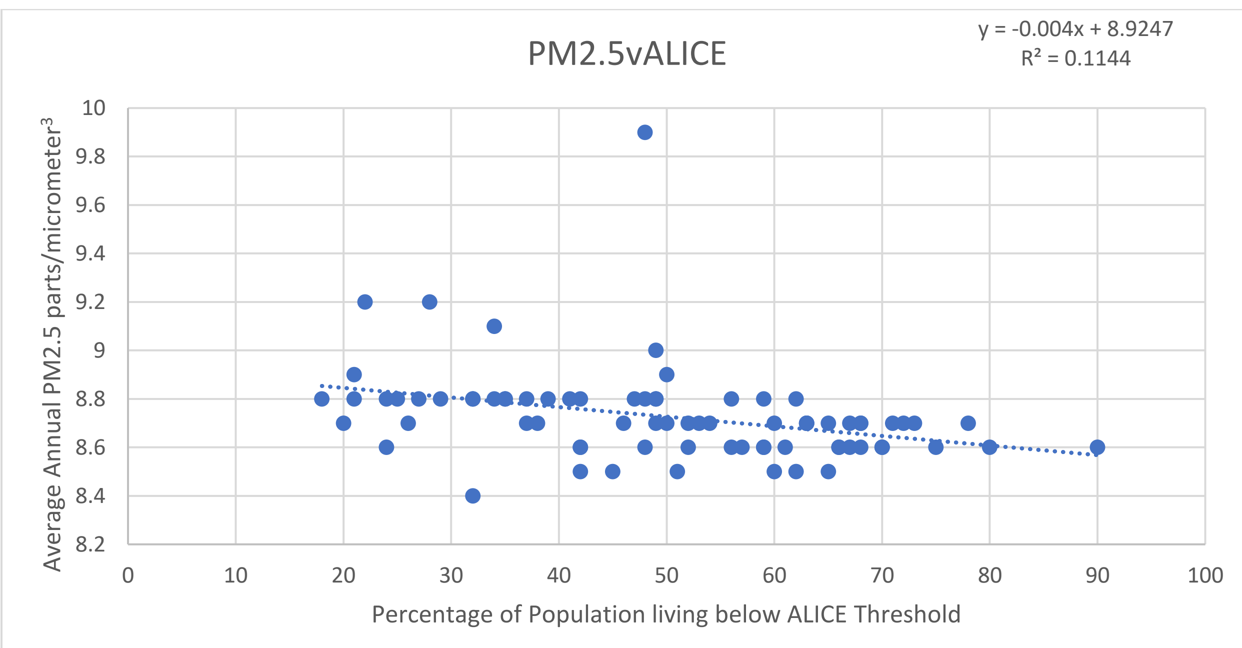

Figure 17*: The relationship between ALICE rates and average rates of $PM_{2.5}$ pollution for each neighborhood in Chicago (United Way of Illinois 2019, Chicago Health Atlas 2019).*

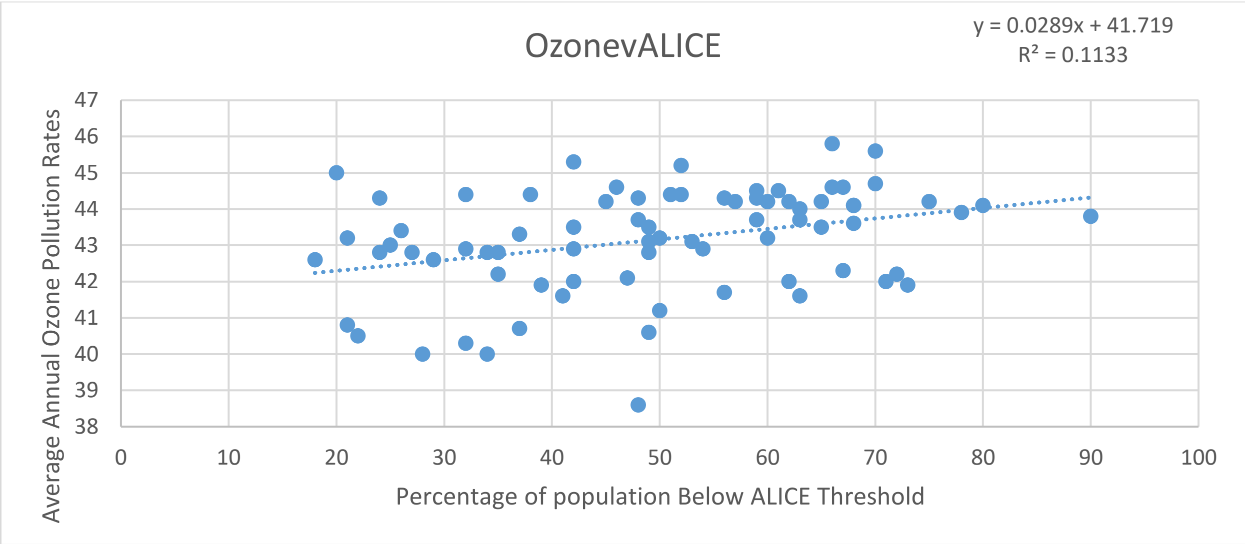

Figure 18*: The relationship between ALICE rates and average rates of ozone pollution for each neighborhood in Chicago (United Way of Illinois 2019, Chicago Health Atlas 2019).*

ALICE and Single Variable Relationship Analysis

These graphs begin to represent the relationship between the measure for SES (the ALICE rates per population) and health outcomes, as well as SES and exposure to air pollution. In the first three scatterplots for health, there is evidence to suggest a relationship between SES and health outcomes, particularly in the case of heart disease (Figure 15). For the other two outcomes, there is less evidence of a relationship (Figures 14, 16). The R^2 values, which represent how well the estimated linear equation explains variations in the data, are promising for heart disease, but not as much for the other two. The R^2 value for heart disease is .1123, which represents that variations in SES explain just over 11 percent of the variation in the crude heart disease death rate. The other two health outcomes, deaths due to chronic lower respiratory disease and coronary heart disease, have R^2 values of 0.0339 and 0.0367, respectively. Translated into percentages, the estimated equations account for about 3 percent of the variation of the health outcome data for both chronic lower respiratory disease deaths and coronary heart disease deaths. Therefore, this data would suggest that there is a possible relationship between heart disease mortality rates and SES, but not a strong relationship between SES and chronic lower respiratory disease mortality or coronary heart disease mortality.

The final two scatterplots represent the relationship between SES and air pollution exposure. For the first graph, it appears that there is a negative relationship between SES and $PM_{2.5}$ exposure (Figure 15). As the percentage of the population living below the ALICE threshold rises, the average $PM_{2.5}$ pollution rate decreases. For the final graph, there appears to be a positive relationship between ozone and SES. As the percentage of the population living below the ALICE threshold increases, the average ozone pollution rate rises (Figure 18). However, the R^2 values for these trendlines is relatively low as well, explaining just over 11 percent of the variation in the data for each trendline. These relationships can also be inferred by closer examination of the geographic distributions for the ALICE, $PM_{2.5}$, and O_3 variables, as seen in Figures 2, 10, and 12, respectively. However, these graphs only represent correlation, not causation, and thus I will turn to regression analysis to determine if ALICE rates can serve as one of multiple explanatory variables for variance in air quality.

Regression Results

The following results demonstrate the results of the regressions outlined in the “Data and Empirical Model” section. The three different health outcomes serve as the dependent variables, which are the mortality rates per 100,000 people per community area for 2013-2017. The air pollution rates and ALICE rates serve as the explanatory variables for each recession. “*” denotes statistically significant results.

Chronic Lower Respiratory Disease Regression

CLRD = -255.61 + 14.76($PM_{2.5}$) + 3.46(O_3) + 0.11(ALICE)

Overall R^2 value: 0.0536

Variable	Intercept	$PM_{2.5}$	O_3	ALICE
p-value	0.129	0.229	0.041*	0.274
T statistic	-1.534	1.213	2.086	1.102

Heart Disease Deaths Regression

Equation: CrudeHeartDis = -1411.36 + 87.31($PM_{2.5}$) + 17.76(O_3) + 1.53(ALICE)

Overall R^2 value: 0.113

Variable	Intercept	$PM_{2.5}$	O_3	ALICE
p-value	0.170	0.244	0.084	0.011*
T statistic	-1.386	1.175	1.752	2.609

Coronary Heart Disease Deaths Regression

Equation: Coro = -623.92 + 48.61($PM_{2.5}$) + 6.357(O_3) + 0.48(ALICE)

Overall R^2 value: 0.021

Variable	Intercept	$PM_{2.5}$	O_3	ALICE
p-value	0.234	0.204	0.224	0.115
T statistic	-1.200	1.281	1.227	1.597

Regression Analysis

In regression equations, the ideal value for the p-value is less than 0.05, and the ideal value for the t-statistic is greater than two. If those two things are true, then the coefficients in a regression equation are of significance. In the preceding equations, two independent variables are highlighted as being statistically significant. For the CLRD regression, the R^2 value is 0.0536, which means that the independent variables can explain about 5 percent of the CLRD mortality rate. Additionally, ozone is the only statistically significant variable, which means that variations in ozone levels are the strongest indicators for variations in the crude CLRD mortality rate in this regression. Further, the coefficient for the ozone variable is 3.46, which means that for every increase in ozone by 1 microgram/meters^3, there is a corresponding increase in the CLRD mortality rate by 3.46 deaths per 100,000 people per year.

For the heart disease regression, SES is the only statistically significant independent variable. The R^2 value for this equation is 0.113, which means that the independent variables can explain just over 11 percent of the heart disease mortality rate. The coefficient for the ALICE variable was 1.53, which means that for every increase in percentage of people living below the ALICE threshold in a given community, there is a corresponding increase in the heart disease mortality rate by 1.53 deaths per 100,000 people per year. There are no independent variables that are statistically significant for the coronary heart disease regression, due to relatively high p-values, and t-statistics that are closer to 1 than desirable. Additionally, the R^2 value was 0.021, which means that the independent variables could account for 2 percent of the data, which is not ideal for establishing a causal relationship.

Conclusions and Suggestions for Future Research

The results from this project are presented in a variety of ways, which each seek to explain different aspects of the intersectional relationships of socioeconomic status (SES), negative health outcomes, and air pollution exposure for residents in the city of Chicago.

The relationship between SES and the heart disease mortality rate is the strongest relationship found in this research, as evidenced by the linear equation earlier and this regression equation. which could warrant further exploration into the subject. While the relationship found was not extremely strong, it is consistently present. This is also the case for the link between ozone and the crude CLRD mortality rate, as suggested by the regression equation results. While coronary heart disease was not found to have statistically significant relationships with air pollution and SES, coronary heart disease is highly associated with heart disease. Since heart disease mortality's relationship with SES is the strongest found in this paper, it may be worthwhile to further explore the link between coronary heart disease and SES, since these are simply two different types of heart conditions.

Some weaknesses from this research may be because the data was using annual averages, rather than finding correlations between particularly poor air quality days and acute negative health events. The literature suggests that short time frames are the strongest basis for examining impacts of air quality on health outcomes, and this data was limited because it was not able to examine that key component. Additionally, there was little variation overall in exposure to air pollution, due to the relatively low levels of air pollution that exist in Chicago, as compared to other global cities with more extreme wealth stratification and poor air quality. Due to the little variation in air pollution itself, it holds that there would be correspondingly little variation in health outcomes due to changes in air pollution.

The relationship between SES and exposure to pollutants was the strongest correlation this paper found, albeit still a somewhat weak correlation. This paper explored the direct link between SES and health, but it may be beneficial to indirectly use the differences in pollutant exposure from SES to then explain health outcomes. In this way, SES can be used as an indirect measure to explain negative health outcome differences, instead of directly examining the relationship between SES and health. The direct approach used here may not be suitable to finding the true underlying causes of the negative impacts to health from air exposure.

Much of the data presented here only begins to explore the relationship between these variables. Geographic distributions of SES suggest that there is a geographic component to it, due to the Moran analysis showing clustering, which holds promise for further research. Additionally, the data may benefit from further trimming prior to calculations due to the high number of observations that were available, but unable to be loaded into the data set. Additionally, there was an attempt to run a geographically weighted regression using GIS, but due to the limited number of data points, a regression could not be run. Future research should use this tool to further understand the geographic patterns of SES and air quality, given there is a larger data set that would be suitable for running this regression.

The list of health outcomes explored here was not exhaustive. Future research could include other health outcomes that are more closely linked to poor air quality, such as asthma, to gain a more robust understanding of the relationship between health and poor air quality.

The literature and this research suggest there is a meaningful and significant relationship between SES, exposure to poor air quality, and negative health outcomes. While this paper was not able to find particularly strong evidence to support the existing literature, there are any number of reasons why this evidence failed to materialize, such as flaws in the data, project design, or lack of available data. My hypothesis in this paper was that residents of Chicago of a lower SES will experience higher exposure to poor air quality and negative health outcomes was proven somewhat, as I did find relationships between these three variables, but not entirely supported due to the relatively weak relationships found. To draw more concrete conclusions, future researchers should examine more data points on a smaller time scale, with more categories of negative health outcomes, in order to provide proper evidence for what the literature would predict.

References

American Heart Association. (n.d.). Facts: Danger in the Air. Retrieved September 2019, from http://www.heart.org/idc/groups/heart-public/@wcm/@adv/documents/downloadable/ucm_463344.pdf

Anderson, J. O., Thundiyil, J. G., & Stolbach, A. (2011). Clearing the Air: A Review of the Effects of Particulate Matter Air Pollution on Human Health. *Journal of Medical Toxicology*,*8*(2), 166-175. doi:10.1007/s13181-011-0203-1

Case Summary. (2016, November 14). Retrieved from https://serc.carleton.edu/woburn/Case_summary.html.

Chicago Health Atlas, & Illinois Department of Public Health. (2019). Chronic Lower Respiratory Disease Deaths. Retrieved October 16, 2019, from https://www.chicagohealthatlas.org/indicators/chronic-lower-respiratory-disease-deaths

Chicago Health Atlas, & Illinois Department of Public Health. (2019). Coronary Heart Disease Deaths. Retrieved October 16, 2019, from https://www.chicagohealthatlas.org/indicators/coronary-heart-disease-deaths

Chicago Health Atlas, & US EPA Air Quality Systems (30 April 2019). Fine Particle Pollution Inverse Distance Weighting. Retrieved October 20, 2019, from chicagohealthatlas.org/indicators/fine-particle-pollution--inverse-distance-weighting

Chicago Health Atlas, & Illinois Department of Public Health. (2019). Heart Disease Deaths. Retrieved October 16, 2019, from https://www.chicagohealthatlas.org/indicators/heart-disease-deaths.

Chicago Health Atlas, & US EPA Air Quality Systems (28 May 2019). Ozone Annual Concentration Pollution Inverse Distance Weighting. Retrieved October 20, 2019, from https://www.chicagohealthatlas.org/indicators/ozone-annual-concentration--inverse-distance-weighting

Coal and Air Pollution. (2008, July 28). Retrieved October 17, 2019, from https://www.ucsusa.org/resources/coal-and-air-pollution.

Environmental Protection Agency. "Environmental Justice." *EPA*, 19 Aug. 2019, https://www.epa.gov/environmentaljustice.

Evans, G. W., & Kantrowitz, E. (2002). Socioeconomic Status and Health: The Potential Role of Environmental Risk Exposure. *Annual Review of Public Health*, *23*(1), 303–331. doi: 10.1146/annurev.publhealth.23.112001.112349

Externalities – Page 2. (2016, March 18). Retrieved December 4, 2019, from https://econfix.wordpress.com/category/externalities/page/2/.

Forastiere, F., Stafoggia, M., Tasco, C., Picciotto, S., Agabiti, N., Cesaroni, G., & Perucci, C. A. (2007). Socioeconomic status, particulate air pollution, and daily mortality: Differential exposure or differential susceptibility. *American Journal of Industrial Medicine*, *50*(3), 208–216. doi: 10.1002/ajim.20368

Hajat, Anjum, et al. "Socioeconomic Disparities and Air Pollution Exposure: a Global Review." *SpringerLink*, Springer International Publishing, 18 Sept. 2015, https://link.springer.com/article/10.1007/s40572-015-0069-5.

Holliday, D. (2016, April 20). What's In A (Neighborhood) Name? Retrieved November 24, 2019, from https://www.wbez.org/shows/wbez-news/how-are-chicago-neighborhoods-formed/0ea9a3d1-9719-4e95-ab51-b53fa477bdad.

Ksenija. (2016, December 19). Environmental Problems of Modern Cities. Retrieved October 15, 2019, from https://owlcation.com/stem/Environmental-problems-of-modern-cities.

Ruppenthal, A. (2017, April 11). Report: Chicago's Health At Risk with 151 Dirty Air Days. Retrieved from https://news.wttw.com/2017/04/11/report-chicago-s-health-risk-151-dirty-air-days.

United Way of Illinois. (Unpublished). *2019 Alice Report - Illinois*. *2019 ALICE Report - Illinois*.

Wilson, Aaron. "Faculty Advising Session." 17 Sept. 2019

World Health Organization. (2018, May 2). Ambient (outdoor) air quality and health. Retrieved October 7, 2019, from http://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health