ABSTRACT

Title of Thesis: USING THE INDEX OF CONCENTRATION AT THE EXTREMES TO EXAMINE THE IMPACT OF AIR POLLUTION EXPOSURE ON INFANT MORTALITY IN THE UNITED STATES

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Background: The concentration of privilege in a geographic area can determine how vital resources are distributed among certain groups in that area, thus influencing a community's health. High air pollutant exposure is often concentrated in deprived neighborhoods with lack of vital resources. Objective: Determine whether states with a high concentration of air pollution exposure have higher infant mortality rates (IMR) than states with lower concentrations of air pollution exposure. Methods: The Index of Concentration of the Extreme was utilized to measure the concentration of air pollution exposure for each state. Incidence Rate Ratios and 95% Confidence Intervals for state infant mortality rate were computed using Poisson regression in Statistical Analysis Software. Results: States with high concentrations of air pollution exposure had 19%

lower IMR than states with low air pollution exposure (95%CI:0.70 – 0.94). Conclusion: These findings can enable researchers to conduct census-tract research on adverse health outcomes and societal distributions.

USING THE INDEX OF CONCENTRATION AT THE EXTREMES TO EXAMINE THE IMPACT OF AIR POLLUTION EXPOSURE ON INFANT MORTALITY IN THE UNITED STATES

by

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Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Public Health
2019

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Acknowledgments

I would like to thank my MPH academic advisor, Dr. Quynh Nguyen and three thesis committee members, Dr. Payne-Sturges, Dr. Slopen, and Dr. Ma for supporting and mentoring me throughout this entire process.

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List of Abbreviations

ACS American Community Survey
AQI Air Quality Index
BRFSS Behavioral Risk Factor Surveillance System
CDC Centers for Disease Control and Prevention
CI Confidence Interval
CO Carbon Monoxide
D.C District of Columbia
EJ Environmental Justice
EPA Environmental Protection Agency
ICE Index of Concentration at the Extremes
IMR Infant Mortality Rate
PM Particulate Matter
PM2.5 Particulate Matter 2.5
PM10 Particulate Matter 10
NO_2 Nitrogen Dioxide
SO_2 Sulfur Dioxide
US United States
WONDER Wide-ranging ONline Data for Epidemiologic Research

Chapter 1: Introduction

1.1 Rationale

Privilege is a concept that has many indirect consequences for one's health, well-being, and overall livelihood. Privilege can be defined as "when one group has something of value that is denied to others simply because of the groups they belong to, rather than because of anything they've done or failed to do…"(Witten & Maskarinec, 2015). The notion of privilege is multifaceted, is often seen as relative, and can be determined by a variety of factors including but not limited to gender, socioeconomic status, and race. Furthermore, the concentration of privilege in a geographic area can determine how vital resources are distributed among certain groups within that area. This phenomenon can lead to disparities in quality of life and health. One important marker of privilege is air pollution exposure.

Air pollution can be defined as "the presence of toxic chemicals or compounds (including those of biological origin) in the air, at levels that pose a health risk" (Environmenal Pollution Centers, 2017). Although there are natural causes of air pollution such as wildfires and volcanic eruptions, air pollution is primarily caused by human activities such as the burning of fossil fuels, exhaust from manufacturing companies, animal agriculture, and coal mining.

Air pollution poses numerous threats to human health. Such threats vary greatly by the age and underlying or pre-existing health of the person/group that is exposed, level and amount of time one is exposed to the air pollutant, and type of pollutant one is exposed to. Some adverse health outcomes associated with air pollution include but are not limited to asthma, cardiovascular hospitalization, and mortality (Committee on Environmental Health, 2004). Air pollution exposure should be considered a marker of privilege because it has been found that vulnerable populations, namely racial minorities and people with lower incomes, are disproportionately exposed compared to whites and people with higher incomes respectively (Harper et al., 2013; Mahalik, Mallick, Padhan, & Sahoo, 2018; Scheers et al., 2011).

Unequal air pollution exposure regarding race, income, socioeconomic status, etc. is a major concern for environmental justice (EJ). Environmental justice refers to both "the spatial distribution of environmental risks and amenities and the resulting disparities among socio-economic and racial groups" (Kruize, Droomers, van Kamp, & Ruijsbroek, 2014). EJ literature has found that although there have been successful efforts to improve air quality in the United States (US), "these and other environmental health improvements vary locally, often neglecting disadvantaged urban populations such as minority groups and low-income populations who have traditionally little political sway over environmental policy decisions impacting their communities" (Zhao, Gladson, & Cromar, 2018). Additionally, "low-income, high-minority-population communities…tend to be closer to industrial sources of pollution, including chemical plants, steel mills, oil refineries, and hazardous waste incinerators" (Collins, 2011). Further, disadvantaged populations may respond to and recover from the stressors of air pollution exposure inadequately or not as well as the general population due to preexisting health status and biological sensitivity (Kruize et al., 2014). To explore this phenomenon further, this study will examine the relationship between unequal air pollution exposure and an important marker of community health; infant mortality.

1.2 Background

Infant Mortality

Infant mortality is defined as the death of an infant before their first birthday. Infant mortality is often measured by the Infant Mortality Rate (IMR), which is the number of infant deaths per 1,000 live births. The IMR in a community can reveal crucial health concerns, including but not limited to access to health services, the pervasiveness of poverty, and health care quality (Stampfel et al., 2012). Infant mortality is also an important indicator for maternal health and can reflect the nutritional status, income, and education of women (Ruiz et al., 2015). Moreover, how privileged one is in a particular facet of life can determine their access to healthy foods, prenatal care, and safe neighborhoods to raise children, all of which are crucial in preventing infant mortality (“Infant Mortality Toolkit: Tackling the Root Causes | IDPH,” n.d.). Furthermore, measuring infant mortality is important because it can inform and enable health professionals and/or policymakers to find solutions to health disparities.

Air Pollution Exposure and Infant Mortality

There are six criteria air pollutants that have adverse impacts on human health and are regulated by the Environmental Protection Agency (EPA) under the Clean Air Act. One of the most heavily researched air pollutants are particulate pollutants. Particulate pollutants, also known as particulate matter (PM) are solid and liquid particles derived from automobile exhaust, burning garbage and landfill, smelting, and processing of metals. Due to the small size of the fine particles, people can inhale PM and the particles can enter the bloodstream and circulatory system. The two forms of Particulate Matter are Particulate Matter 10 (PM10) and Particulate Matter 2.5 (PM2.5). PM10 is particulate matter that have diameters that are equal or less than 10 microns and PM2.5 consists of particulate matter that are less than or equal to 2.5 microns. PM2.5 is a more serious health concern since it is small enough to travel deeply into the lungs. Moreover, exposure to PM2.5 has been shown to lead to asthma attacks, heart attacks, and strokes and numerous studies have linked PM2.5 exposure to high preterm birth and infant mortality rates (Geer, Weedon, & Bell, 2012; Heft-Neal, Burney, Bendavid, & Burke, 2018; Son, Bell, & Lee, 2011; Woodruff, Parker, & Schoendorf, 2006) as well as growth retardation (Gray et al., 2014; Salihu et al., 2012; van den Hooven et al., 2012).

Five additional air pollutants that have adverse impacts on human health and are regulated by the EPA are lead, ground-level ozone, carbon monoxide, sulfur dioxide, and nitrogen dioxide. Lead is a soft and malleable heavy metal. According to the EPA, "major sources of lead in the air are ore and metals processing and piston-engine aircraft operating on leaded aviation fuel"("Basic Information about Lead Air Pollution | Lead (Pb) Air Pollution | US EPA," n.d.). Lead is an extremely dangerous air pollutant and the health effects of lead exposure include but are not limited to "mental retardation, stunted growth, loss of motor control, permanent hearing, and visual impairment, and at high-enough levels, death" (Brittle & Zint, 2003). Ground-level ozone is formed by chemical reactions between volatile organic compounds and oxides of nitrogen. This process occurs when "pollutants emitted by cars, power plants, industrial boilers, refineries, chemical plants, and other sources chemically react in the presence of sunlight" (US EPA, 2015). Ground-level ozone is dangerous because it can cause muscles in the airways to constrict. Thus, leading to wheezing and increased frequency of asthma attacks. Another air pollutant, carbon monoxide (CO) is a colorless, odorless gas that can be harmful if inhaled in large amounts. CO is released when something is burned, and the greatest sources of CO include trucks and other vehicles or machinery that burn fossil fuels (US EPA, 2016b). Carbon monoxide poses serious health risks because if one breathes air with a high concentration of CO, it can reduce the amount of oxygen that is transported to the heart and brain via the blood stream.

Sulfur dioxide (SO_2) is another dangerous colorless gas. However, unlike the aforementioned air pollutants, it is not odorless and has a very potent unpleasant smell. SO_2 is primarily derived from industrial activities that burn fossil fuels and/or processes sulfur containing materials such as the generation of coal, oil, and gas. SO_2 is dangerous for human health because, if breathed in, it can irritate the airways and nose, leading to shortness of breath and wheezing. The last air pollutant is nitrogen dioxide (NO_2), is "a group of highly reactive gases known as oxides of nitrogen or nitrogen oxides" (US EPA, 2016a, p. 2). NO_2 is primarily gets into our air due to the burning fossil fuels and is formed from emissions from vehicles, power plants, and off-road equipment. NO_2 can increase one's susceptibility to respiratory infections. These five aforementioned air pollutants have not been individually directly linked to infant mortality; however, several studies have aggregately linked these pollutants to poor infant health outcomes and/or mortality (Ha et al., 2003; Héroux et al., 2015; Lin et al., 2004; Olivier et al., 2008).

Air pollution is especially dangerous for pregnant women because the fetus' nervous system is still in a critical development stage. When fetuses are exposed to noxious stimuli found in air pollution, "fetal programming is altered, and lung cells may undergo dysfunctional remodeling. Maternal environmental exposures may thus alter fetal lung development, predisposing the fetus to future respiratory disease"(Lee et al., 2018). Further, specific air pollutants have been individually or aggregately linked to adverse birth outcomes such as low birth weight, small for gestational age, preterm mortality (before 65 years old), and infant mortality. For example, Lin et al., found that maternal exposure to PM10 and NO_2 was "inversely associated with fetal growth during the second and third trimester and with weight at birth" (Lin et al., 2004). Additionally, one study found that concentrations of PM2.5 and O3 were associated with a reduction in birth weight and increased risk of being born low birth weight and small for gestational age. This study also found that maternal race and education, and household income were associated with adverse birth outcomes (Gray et al., 2014). Lastly, researchers have found that exposure to environmental pollutants including CO, PM10, and NO_2 can result in adverse birth outcomes that are similar to "the association between maternal active and passive smoking and impaired reproductive outcomes" (Srám, Binková, Dejmek, & Bobak, 2005).

Although, it has been found that a given level of air pollution exposure can have "a larger impact on some groups than others." (Bell & Ebisu, 2012), the majority of air pollution/infant mortality literature does not consider how extreme levels of inequality can influence the infant mortality rate. This is important to know because increased levels of air pollution exposure for vulnerable populations may lead to further inequalities in impaired health (Williams et al., 2018). Therefore, there is a gap in the literature on examining whether the unequal distribution of air pollution exposure in a geographic region leads to a disparity in infant mortality rates. This research study will aim to fill this gap and examine how extreme levels of air pollution influences the infant mortality rate at the state-level in the United States.

1.3 Study Aims and Hypothesis

Since the United States has one of the highest infant mortality rates in the developed world (Chen, Oster, & Williams, 2016) and a strong prevalence of disproportionate air pollution exposure (Woodruff, Parker, & Schoendorf, 2006), this research study will examine whether or not concentration of the extremes of the six aforementioned air pollutants influence infant mortality in the United States (all 50 states and District of Columbia). The first objective of this study is to examine whether there is a bivariate association between the concentration of the air pollutants that have been linked to adverse birth outcomes and infant mortality rate at the state level. The hypothesis for this aim is that there will be a statistically significant association between the two variables; as lower state air pollution exposure inequality will be associated with lower state-level infant mortality rates. The second objective of this study to examine whether any observed associations are retained after adjusting for state-level demographic and health characteristics. Due to the literature on the association between air pollution exposure and infant mortality, the hypothesis for this objective is that any observed associations will be retained when the model is adjusted for state-level demographic and health characteristics.

Chapter 2: Research Design and Methods

2.1 Study Design

This study will be making inferences about a large group of people in a geographic area; therefore, an ecological study will be conducted. An ecological study is a study in which “at least one variable, either an exposure or the outcome, is measured at the group (not individual) level…The occurrence of disease is compared between groups that have different levels of an exposure…”(Debbink & Bader, 2011). Two advantages of ecological studies are that they are inexpensive and representative of large groups and geographic areas. One major disadvantage of ecological studies is the ecologic fallacy, which argues that there can be a failure in interpretation when making individual level inferences using aggregate data.

In order to quantify the distribution of how many people in a given area are concentrated into the most and least deprived groups for air pollution exposure, this study will utilize the Index of Concentration of the Extremes (ICE). ICE is a measure that was developed in 2001 by sociologist, Douglas Massey in order to reveal the “extent to which an area’s residents are concentrated into groups at the extremes of deprivation and privilege”(Krieger et al., 2016). The formula for ICE is as follows:

$$ICE_i = (A_i - B_i) / T_i$$

A_i represents the number of individuals in the privileged category and is subtracted by B_i, which is the number of individuals in the deprived category. This value is then divided by the total population across the ICE category, T_i. The $_i$ in the ICE formula represents the geographic area for the variables. Furthermore, an ICE value of –1 means that 100% of the population is concentrated in the most deprived group and an ICE value of 1 means that 100% of the population is concentrated into the most privileged group.

ICE has been primarily used in the social sciences and "a handful of etiological public health investigations" (Krieger et al., 2016). In the six existing studies utilizing ICE assess if measures of racial and economic segregation are associated with adverse health outcomes an inverse relationship was found between ICE and the adverse health outcome (Table 4). The exposure/ICE variables for those studies included income, education, race/ethnicity, and race/ethnicity and income together. The adverse health outcome variables examined for those studies included one-year cumulative average exposure to ambient black carbon, risk of hypertension, infant mortality, premature mortality (before age 65), diabetes mortality, breast cancer estrogen receptor status, and fata and non-fatal weapon-related assault. Of the six studies, one (*Black Carbon Exposure, Socioeconomic and Racial/Ethnic Spatialpolaraization, and the Index of Concentration at the Extremes (ICE)*) explored air pollution exposure. The authors of this paper examined how economic and racial/ethnic spatial polarization (exposure variables) influenced one's exposure to black carbon (outcome variable). The authors found that there was an inverse relationship between ICE and ambient black carbon exposure (Krieger, Waterman, Gryparis, & Coull, 2015). There were no ICE studies conducted that examined how air pollution exposure influenced birth outcomes. This research study aims to fill that gap in the literature.

2.2 Outcome Variable

The outcome variable for this thesis is the infant mortality rate (number of infant deaths per 1,000 live births) at the state level. The study population is defined as infants that died (before turning one year old) in the United States during 2016.

2.3 Predictor Variable

In order to measure unequal air pollution exposure at the state level. In accordance with air pollution exposure and infant mortality literature (Gray et al., 2014; Salihu et al., 2012; van den Hooven et al., 2012), this study aimed to measure maternal air pollution exposure prior to birth to examine if extreme air pollution exposure influences infant mortality rates. However, since the infant mortality data available only provided the year of the infant death (2016) and not the exact date, we used the year prior to the infant deaths (2015), as the dates of exposure year for air pollution exposure. Further, I utilized the Environmental Protection Agency's (EPA) county level Air Quality Index (AQI) aggregated to the state level to measure air pollution exposure during pregnancy. The AQI is an index that is measured and reported daily by the EPA for five major air pollutants that were all found to be associated with poor birth outcomes including infant mortality: particle pollution, ground-level ozone, carbon monoxide, sulfur dioxide, and nitrogen dioxide. The daily concentrations of these five air pollutants are calculated using data from 75,368 air quality monitors throughout the United States (for 2015). The raw measurements from these monitors are converted into AQI values based on the national air quality standards set by the EPA for that pollutant. The Clean Air Act requires the EPA to set national air quality standards for the six criteria air pollutants. There are two types of air quality standards are primary standards, protecting the health of sensitive populations such as children, elderly, and people with asthma, and secondary protections, which “provide public welfare protection, including protection against decreased visibility and damage to animals, crops, vegetation, and buildings” (US EPA, 2014). These standards are required to reflect the latest scientific knowledge regarding that pollutant and must be reviewed every five years by the Clean Air Scientific Advisory Committee. The primary goal of the AQI is to inform communities and individuals of how clean or polluted their air is and what level of health concern they should have.

The AQI has values that range from 0 to 500 for each pollutant. These values are broken down into six categories which each correspond to a different level of health concern. AQI values of 0 to 50 are in the “Good” category, which means that air pollution poses no to little risk to human health. AQI values of 51 to 100 are considered acceptable and are in the “Moderate” category, posing little risk to a small number of vulnerable groups such as those sensitive to ozone. AQI values of 101 to 150 are in the “Unhealthy for Sensitive Groups” category in which members of sensitive groups such as those with asthma and older individuals may experience health effects but the general public is not likely to be affected. AQI values between 201 and 300 are considered “Very Unhealthy” and is considered a health alert in which everyone may experience serious health effects. AQI values between 301 and 500 (the max AQI value) are considered “Hazardous” and are health warnings of emergency conditions.

In order to create an ICE value for air pollution, we used annual AQI data downloaded from the EPA Annual Summary datafile for AQI. A single aggregate value was calculated daily at the county level in the United States based on the five major pollutants previously mentioned. For the purpose of calculating the ICE formula for air pollution, persons who live in counties with a maximum annual AQI of 100 or less will be considered the privileged group due to the fact that AQI values in this range are considered healthy for nearly all groups. Persons who live in counties with a maximum annual AQI of 101 or above will be considered the deprived group due to the fact that AQI values in this range pose health risks to vulnerable groups as well as the general population. Furthermore, the formula for air pollution ICE values is the number of persons that live in counties with a maximum annual AQI of 100 or less in 2015 (privileged group) subtracted by the number of persons that live in counties with a maximum annual AQI of 101 or above in 2015 (deprived group) divided by the total number of people in that same state (Figure 1.). An ICE value of -1 is an extreme concentration of deprivation and an ICE value of 1 is an extreme concentration of privilege.

Figure 1. Index of Concentration at the Extremes Formula for Air Pollution Exposure

$$ICE_{State} = (A_{State} - B_{State})/T_{State}$$

A_{state} = Number of persons that live in counties with maximum AQI of 100 or fewer in 2015 within the same state
B_{state} = Number of persons that live in counties with the maximum AQI of 101 or more in 2015 within the same state
T_{state} = Total population in the state
ICE value of -1 = extreme concentration of deprivation
ICE value of 1 = extreme concentration of privilege

2.4 Confounding Variables

The confounding variables included in this analysis are the population density, adult smoking prevalence, and the percentage of college graduates of the state from which the infant resided before they died. Population density (people per square mile) of the state will be included as a covariate since rural residents often have difficulty getting access to healthcare services due to proximity to health care services and have higher rates of infant mortality than urban or suburban areas (Saikia, Singh, Jasilionis, & Ram, 2013). Additionally, geographic regions with large cities and high population density have been found to have higher air pollution exposure than geographic regions with smaller cities and lower population density (Butz et al., 2011). Current cigarette usage among adults in the state will also be included due to the fact that maternal smoking has been linked to infant mortality (Salihu, Aliyu, Pierre-Louis, & Alexander, 2003) and adult smoking in general has been associated with high levels of air pollution exposure (Hao & Wang, 2005). Lastly, the percentage of people who have a college degree in the state will be added as a confounder since maternal education attainment has been found to be negatively correlated with adverse infant and child health outcomes (Anyamele, Ukawuilulu, & Akanegbu, 2017; Mensch, Chuang, Melnikas, & Psaki, 2019). College education has also been associated with low air quality along with other socioeconomic factors (Jiao, Xu, & Liu, 2018). The dates for all three confounding variables will be 2015.

2.5 Data Sources

The data sources used in this study include the Centers for Disease Control (CDC) Wide-ranging ONline Data for Epidemiologic Research (WONDER)

Database, American Community Survey (ACS), EPA Air Quality Index, and the Behavioral Risk Factor Surveillance System (BRFSS).

The first data source is the CDC WONDER database, which has collections of public-use data on U.S. births, deaths, environmental exposures, and population estimates, among many other topics. The Infant Deaths collection will be utilized to create the infant mortality outcome variable. This collection provides counts and rates for deaths of children under 1 year of age, occurring within the United States to U.S. residents. One strength of this data source is that the infant mortality data in this dataset go through a rigorous and uniform review process. One limitation is that there is a chance of under- or over-reporting of conditions on the death certificate by certifying physicians.

The second data source, the American Community Survey (ACS), is the largest household survey annually conducted by the United States Census Bureau. ACS data is collected via mail, telephone interviews, internet, and in-person interview and has an initial sample of approximately 3.5 million housing unit addresses. These responses are aggregated into estimates at a variety of geographic summary levels including census tract, county, city, congressional district, and state level. One advantage of ACS is that it measures economic, demographic, and housing characteristics at the county level for all counties in the United States. One limitation of ACS is that estimations can be more reliable for larger geographic regions with larger populations compared to smaller geographic regions with smaller populations. This data source covers the entire study population and will be used ACS to create the population density and education covariate variables.

The third data source for this study is the EPA Air Quality Index. As previously mentioned, the EPA AQI is an index that measures air quality at the county level in the United States. One strength of this EPA AQI is that the AQI calculations are very straight forward and supported by the EPA's comprehensive quality assurance program. One limitation of this data is that there are spatial gaps in air quality monitoring in rural areas throughout the United States, meaning there are not an adequate number of air quality monitors in rural areas compared to urban areas. Spatial representation for air quality monitoring is an ongoing issue in environmental health research. J.P Majra, author of *Air Quality in Rural Areas*, found that "research, policy makers, and governments have focused their attention on air quality in the urban areas only…the common belief is that rural areas are free from air pollution" (Majra, 2011). The EPA Air Quality Index will be utilized to create the air pollution exposure variable.

Lastly, the Behavioral Risk Factor Surveillance System will be used to create the adult cigarette usage covariate variable. The BRFSS is a national system of health-related telephone surveys coordinated by the Centers for Disease Control and Prevention that collect state data about the Americans' overall health. Survey questions include but are not limited to health-related risk behaviors, use of preventative services, and chronic health conditions. One strength of this data source is that the CDC's has "strong control over survey questions to be used ensures that data collected by each state's BRFSS are reasonably comparable to data collected by other states" (Diseases, 2011). One limitation of the BRFSS is that it is a self-reported survey, which can lead to recall and social desirability bias. In order to create the state smoking prevalence covariate variable, data on crude prevalence of adults who are current smokers from the 2015 BRFSS questionnaire were utilized.

2.6 Analytic Approach

The first step in the analysis was to calculate the infant mortality rate and air pollution ICE values for each state. The next step was to evaluate the correlation between the state infant mortality rate and ICE values to answer the first objective. An analysis of the distribution (mean and standard deviation) of the ICE values was also conducted. Next, quintiles from the ICE values were created by sorting the ICE values from smallest to largest. Next, the first eleven values (highest air pollution exposure) were assigned to first quintile since there were an odd number of values (all 50 states and D.C), the next ten values to the second quintile, and so on. The last 10 state ICE values were assigned to quintile five, the least exposed to air pollution and reference group for this study. States with ICE values in Quintile 1 were considered the most deprived group and states with ICE values in Quintile 5 were considered the most privileged group and the reference group. To answer the second objective of this study, incidence rate ratios and confidence intervals of the state-level AQI ICE quintiles and infant mortality were obtained using a Poisson regression analysis.

A Poisson regression is a form of regression analysis in which the dependent variable is a count variable and the independent variables can be continuous or categorical. Poisson regression is also appropriate for modeling the rate data. In this study, we choose to use a Poisson regression since the outcome is the infant mortality rate, the predictor variable air pollution ICE and other covariate variables are categorical or continuous. Due to the recent call to end the use p-values to measure the degree of an association (Amrhein, Greenland, & McShane, n.d.), 95% confidence intervals of the Poisson model were used to determine the range of values that we can be 95% certain will capture the true population value (i.e. whether the results of this study are statistically significant). All the analysis was conducted using Statistical Analysis Software (SAS).

Chapter 3: Results

3.1 State Infant Mortality Rates

This was a national study in which 2016 infant mortality data from all 50 states and The District of Columbia (D.C) were included (Table 1). The average IMR in 2016 in the United States was 6.06 infant deaths per 1,000 births. Vermont had the lowest infant mortality rate at 3.47 infant deaths per 1,000 births and Alabama had the highest infant mortality at 9.03 infant deaths per 1,000 births.

Table 1: State Infant Mortality Data

State	Number of Births	Number of Deaths	Infant Mortality Rate
Alabama	59151	534	9.03
Alaska	11209	58	5.17
Arizona	84520	450	5.32
Arkansas	38274	314	8.2
California	488827	2063	4.22
Colorado	66613	317	4.76
Connecticut	36015	172	4.78
Delaware	10992	86	7.82
District of Columbia	9858	71	7.2
Florida	225022	1382	6.14
Georgia	130042	972	7.47
Hawaii	18059	109	6.04
Idaho	22482	131	5.83
Illinois	154445	985	6.38
Indiana	83091	614	7.39
Iowa	39403	235	5.96
Kansas	38053	228	5.99
Kentucky	55449	376	6.78
Louisiana	63178	504	7.98
Maine	12705	73	5.75
Maryland	73136	478	6.54
Massachusetts	71317	281	3.94
Michigan	113315	727	6.42
Minnesota	69749	358	5.13

Mississippi	37928	329	8.67
Missouri	74705	492	6.59
Montana	12282	71	5.78
Nebraska	26589	161	6.06
Nevada	36260	209	5.76
New Hampshire	12267	45	3.67
New Jersey	102647	414	4.03
New Mexico	24692	152	6.16
New York	234283	1056	4.51
North Carolina	120779	874	7.24
North Dakota	11383	73	6.41
Ohio	138085	1026	7.43
Oklahoma	52592	393	7.47
Oregon	45535	214	4.7
Pennsylvania	139409	857	6.15
Rhode Island	10798	60	5.56
South Carolina	57342	402	7.01
South Dakota	12275	60	4.89
Tennessee	80807	594	7.35
Texas	398047	2277	5.72
Utah	50464	274	5.43
Vermont	5756	20	3.47
Virginia	102460	599	5.85
Washington	90505	391	4.32
West Virginia	19079	138	7.23
Wisconsin	66615	420	6.3
Wyoming	7386	37	5.01

3.2 Distribution of State AQI ICE Values

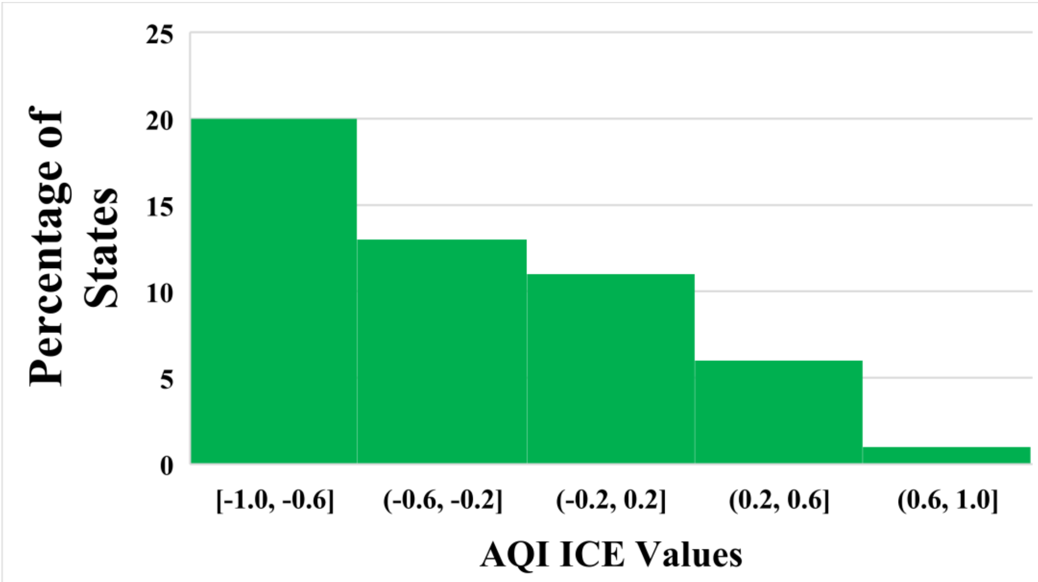
An Index of Concentration of the Extremes value for Air Quality Index was generated for each state (Table 2). Twenty percent of the 50 states and D.C had ICE values between -0.60 and -1.00 and over half of the states had negative ICE values (Figure 2.). The mean ICE value was -0.34 and the Standard Deviation of all the ICE values was 0.44. D.C and Connecticut had the lowest AQI ICE value of -1.00, meaning nearly all the residents of both states were extremely concentrated in counties with high levels of air pollution exposure. Hawaii had the highest AQI ICE value of 0.73, meaning nearly all the residents of the state were concentrated in counties with low levels of air pollution exposure.

Table 2: State AQI ICE Values

State	AQI ICE Value
Alabama	-0.22
Alaska	0.27
Arizona	-0.81
Arkansas	0.26
California	-0.90
Colorado	-0.78
Connecticut	-1.00
Delaware	-0.23
District of Columbia	-1.00
Florida	0.27
Georgia	-0.31
Hawaii	0.73
Idaho	-0.63
Illinois	-0.54
Indiana	-0.29
Iowa	0.05
Kansas	0.30
Kentucky	-0.30
Louisiana	0.22
Maine	0.01
Maryland	-0.67
Massachusetts	-0.70
Michigan	-0.60
Minnesota	-0.56
Mississippi	0.22
Missouri	-0.33
Montana	-0.79
Nebraska	0.03
Nevada	-0.95
New Hampshire	-0.61

New Jersey	-0.88
New Mexico	-0.20
New York	-0.28
North Carolina	-0.02
North Dakota	-0.41
Ohio	-0.61
Oklahoma	-0.13
Oregon	-0.89
Pennsylvania	-0.72
Rhode Island	-0.88
South Carolina	0.31
South Dakota	-0.39
Tennessee	-0.08
Texas	-0.67
Utah	-0.92
Vermont	0.29
Virginia	0.14
Washington	-0.71
West Virginia	-0.10
Wisconsin	-0.40
Wyoming	-0.12

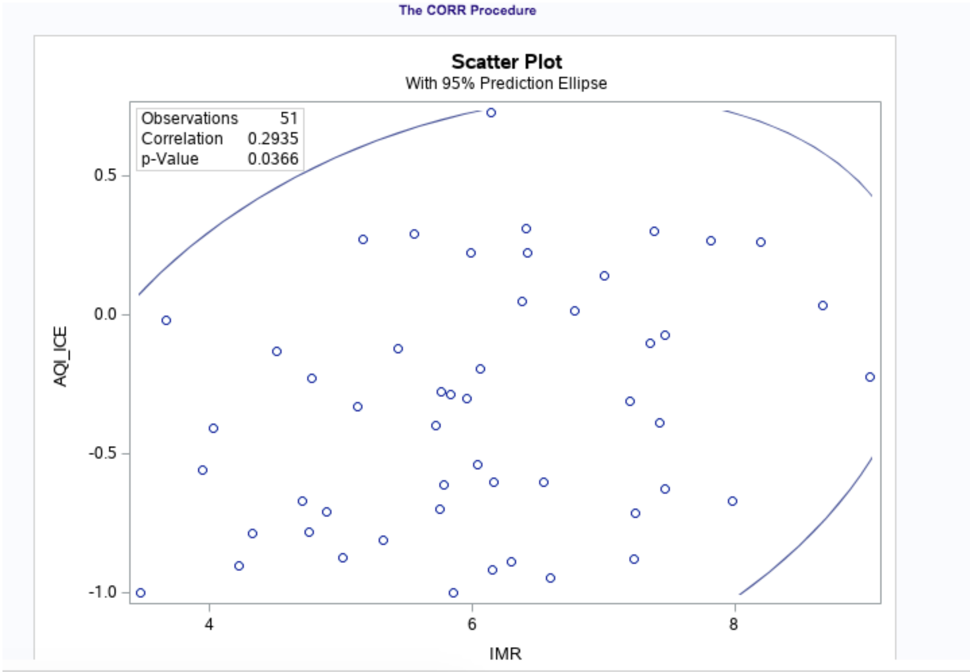
Figure 2: Distribution of State AQI Values



3.3 Correlation Between State AQI Value and Infant Mortality Rate

There was a bivariate strong positive correlation found between state AQI ICE value and infant mortality rate (p-value: 0.04). The correlation coefficient was 0.29, suggesting a small positive association between infant mortality and AQI ICE. In other words, as the state's extreme concentration of privilege (i.e. low air pollution exposure) increases, the likelihood that the state will have a higher infant mortality rate also increases.

Figure 3: Correlation Between State AQI and Infant Mortality Rate



3.4 Poisson Regression Estimates

Overall the unadjusted Poisson model revealed that as the state AQI ICE quintile increased (states moved toward the privileged group for air pollution exposure), the infant mortality rate increased in the unadjusted model. States with ICE values in Q1 had a 19% decrease in infant mortality rate compared to the reference group (95%CI: 0.70 – 0.94). Since the 95% CI did not include the null hypothesis, one, we can conclude such difference is statistically significant. States with ICE values in Q2 had a 9% decrease in the IMR (95%CI: 0.78 – 1.07), states with ICE values in Q3 had a 12% decrease in IMR (95%CI: 0.76 – 1.00), and states with ICE values in Q4 had a 1% decrease in IMR (95%CI: 0.83 – 1.18). Since states in quintiles 2, 3, and 4 included one in the 95%CIwe can conclude such difference is not statistically significant for those states. All quintiles for the unadjusted model were compared to states with ICE values in Q5, the most privileged group (i.e. least exposed to air pollution).

When the Poisson model was adjusted for state smoking prevalence, population density, and proportion of residents with a college education, the results were consistent with the results from the unadjusted model. States with ICE values in Q1 had a 20% decrease in infant mortality rate compared to the reference group (95%CI: 0.69 – 0.92). Since the 95% CI does did not include the null hypothesis, one, we can conclude such difference is statistically significant. States with ICE values in Q2 had a 9% decrease in the infant mortality rate (95%CI: 0.76 – 1.08),states with ICE values in Q3 had a 13% decrease in IMR (95%CI: 0.75 – 1.00), and states with ICE values in Q4 had a 6% decrease in the IMR (95%CI: 0.77 – 1.15). Since states in quintiles 2, 3, and 4 all had one in their 95%CI, we did not consider those results statistically significant. All quintiles for the adjusted model were compared to states with ICE values in Q5, the most privileged group (i.e. least exposed to air pollution).

Table 3: Regression Estimates for Association of State AQI ICE Quintile and Infant Mortality Rate

	Air Pollution Exposure (AQI)*	
ICE Quintile	**Unadjusted RR (CI)**	**Adjusted RR (CI)**
Q1 (low)	0.81 (0.70 - 0.94)	0.80 (0.69 - 0.92)
Q2	0.91 (0.78 - 1.07)	0.91 (0.76 - 1.08)
Q3	0.88 (0.76 - 1.00)	0.87 (0.75 - 1.00)
Q4	0.99 (0.83 - 1.18)	0.94 (0.77 - 1.15)
Q5 (high)	1.00	-

* Adjusted model controls for state smoking prevalence, population density, and proportion of residents with a college education

ICE quintile cutoffs for AQI:
Q1: -1.00 - -0.78
Q2: -0.77 - -0.56
Q3: -0.54 - -0.23
Q4: -0.22 - 0.05
Q5: 0.04 - 1.00

Chapter 4: Discussion

4.1 Discussion of Results

Overall, the findings from this study were not consistent with the literature. There was a negative correlation between air pollution exposure and infant mortality at the state level (or positive correlation between AQI ICE value and infant mortality). Additionally, across ICE quintiles there was a decrease in the infant mortality rate, meaning, for those most exposed to air pollution, there was a decrease in the infant mortality rate compared to states with less exposure to air pollution. While these findings were perplexing, there are some important factors to consider while interpreting these results.

Five out of the ICE six studies examined in section 2.1 used census-tract level data from one or two metropolitan cities or only one state. The sixth paper used zip code level data (Table 4). Further, all six studies found a negative correlation between ICE quintile and their respective adverse public health outcome. Meaning, that as the ICE value increased (towards the privileged group), the likelihood of observing that adverse public health outcome decreased. Although Dr. Nancy Krieger states in her 2015 paper on ICE and black carbon exposure that "ICE can be meaningfully computed for both smaller and larger geographic units (e.g. black group, CT, CD, city, county)" (Krieger et al., 2016), there is greater variability across states in comparison to county (the largest geographic unit Dr. Krieger states in her paper).

One major limitation of state level analysis regarding air pollution exposure is that air pollution exposure can vary greatly depending on the size and demographics of the state. For example, California had one of the lowest ICE values (-0.90) in this study, meaning nearly all the residents of California were highly exposed to air pollution. However, air pollution throughout California differs by county and/or city in terms of which type of air pollutant residents are exposed to, what the health effect of that pollutant are, and the length of time residents are exposed to the pollutant. Additionally, state-level analysis can also fail to detect geographic variation of health disparities that only exist at the county or state level. For example, Hawaii had the highest ICE value, however, one study conducted at the district level found that a community in Hawaii that was continuously exposed to sulfuric volcanic air pollution were at higher risk of acute bronchitis in comparison to the reference community that was not exposed (Longo & Yang, 2008). Furthermore, the due to the variability of air pollution exposure within a state, the fact that this study was done at the state level was a significant limitation.

Table 4. Results from Other ICE Studies

Title	Authors	ICE Predictor Variable(s)	Outcome Variable	Geographic Measure	Findings
Black carbon exposure, socioeconomic and racial/ethnic spatialpolarization, and the Index of Concentration at the Extremes (ICE)	Nancy Krieger, Pamela D. Waterman, Alexandros Gryparis, Brent A. Coull	Income, Education, Race/Ethnicity, Income and Race/Ethnicity	One-year cumulative average exposure to ambient black carbon exposure at the longitude-latitude of their residential address	Census Tract (Boston Metropolitan Area)	Inverse relationship between ICE and ambient black carbon exposure.
Spatial social polarisation: using the Index of Concentration at the Extremes jointly for income and race/ethnicity to analyse risk of hypertension	Justin M Feldman, Pamela D Waterman, Brent A Coull, Nancy Krieger	Income, Race/Ethnicity	Risk of hypertension	Census Tract (Boston Metropolitan Area)	Inverse relationship between ICE and hypertension.
Public Health Monitoring of Privilege and Deprivation With the Index of Concentration at the Extremes	Nancy Krieger, Pamela D. Waterman, Jasmina Spasojevic, Wenhui Li, Gil Maduro, and Gretchen Van Wye	Income, Race/Ethnicity, Income and Race/Ethnicity, Poverty	Infant Mortality, Premature Mortality (before age 65), and Diabetes Mortality	Census Tract (New York City Metropolitan Area)	Inverse relationship between ICE and outcome variables.
Metrics for monitoring cancer inequities: residential segregation, the Index of Concentration at the Extremes (ICE), and breast	Nancy Krieger, Nakul Singh, Pamela D. Waterman	Income, Race/Ethnicity, Race/Ethnicity and Income	Breast Cancer Estrogen Receptor Status	Census Tract (Boston, Massachusetts and New York City)	Inverse relationship between ICE and Breast cancer estrogen receptor status.

cancer estrogen receptor status (USA, 1992–2012)					
Local Residential Segregation Matters: Stronger Association of Census Tract Compared to Conventional City-Level Measures with Fatal and Non-Fatal Assaults (Total and Firearm Related), Using the Index of Concentration at the Extremes (ICE) for Racial, Economic, and Racialized Economic Segregation, Massachusetts (US), 1995–2010	Nancy Krieger, Justin M. Feldman, Pamela D. Waterman, Jarvis T. Chen, Brent A. Coull, David Hemenway	Income, Race/Ethnicity, Race/Ethnicity and Income	Fatal and Non-fatal weapon-related assaults	Census Tract and City/Town (Massachusetts state)	Inverse relationship between ICE and fatal and non-fatal weapon-related assaults
Using Index of Concentration at the Extremes as Indicators of Structural Racism to Evaluate the Association with Preterm Birth and Infant Mortality-California, 2011-2012.	Brittany D. Chambers, Rebecca J. Baer, Monica R. McLemore, Laura L. Jelliffe-Pawlowski	Income, Race/Ethnicity, Race/Ethnicity and Income	Preterm Birth and Infant Mortality	Zip Code (California state)	Inverse relationship between ICE and preterm birth and infant mortality

4.2 Study Strengths and Limitations

One strength of this study is that the study population (infants who died before the age of one years old in 2016) was exposed to the predictor variable (air pollution exposure in 2015) prior to the outcome. This is important because it establishes a temporal relationship, thus strengthening the validity of the findings. Another strength of this study was the inclusion of state level covariates that are highly correlated with both infant mortality and air pollution exposure.

One limitation of this study is that the analysis was done at the state level. As previously mentioned, the majority of ICE studies use census-tract level data, which allows for a more precise analysis. Additionally, air pollution exposure has wide geographic variation, represents many different entities, and "the proportion of the pollution mix, as well as the levels (concentrations) of the various pollutants may vary" (Katsouyanni, 2013) . Further, it is likely more informative and accurate for state and local health professionals to analyze air pollution exposure at the census tract, residential address, or possibly county level within their state rather than examine air pollution exposure of the entire state as a whole. Another limitation is that this was an ecological study and may be subject to ecological fallacy. The ecological fallacy is a limitation because the relationship between "aggregated disease incidence on areal units and average exposure on those units differs from the relationship between the event of individual incidence and the associated individual exposure"(Wang, Wang, Gelfand, & Li, 2017).

4.3 Public Health Significance

As previously mentioned, infant mortality is an important marker of overall health in a society. When one examines the infant mortality rate, they can infer how adequate the health services are, how healthy the mothers are, as well as what the quality of the country, state, county, etc. health program(s). Furthermore, if certain groups of people have access vital resources important for maternal and infant health and are not exposed to adverse dangerous factors simply because they were born into a particular group, it is important to determine if that relationship is causal. Although the findings from this study indicated there was not an inverse relationship between air pollution exposure and infant mortality, further research is needed. States would benefit from conducting analysis on where the extremes of privilege and deprivation lie within their state. However, as previously stated, it would be more beneficial to conduct such a study at the census-tract or county level.

Research study is an ongoing process that will constantly need revision and innovation. It is important to consult a diverse set of research methods when examining the relationship between poor health outcomes and societal distributions. Moreover, it is one of the first steps we can take as a society to develop ways to combat adverse maternal and infant outcomes for those who are less privileged.

Epidemiology Master of Public Health Competencies Addressed in Thesis

1.	Identify vital statistics and other key sources of data for epidemiological purposes
2.	Explain the importance of epidemiology for informing scientific, ethical, economic and political discussion of health issues
3.	Apply the basic terminology and definitions of epidemiology
4.	Differentiate among the criteria for causality
5.	Draw appropriate inferences from epidemiologic data
6.	Demonstrate skills in public health data collection and management
7.	Design, analyze, and evaluate an epidemiologic study
8.	Calculate advanced epidemiology measures.

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