Inequities in Air Pollution Exposure in the U.S.: An Exploration of Disparity Metrics Across Geographic and Temporal Scales

by

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Abstract

In the United States (U.S.), exposure to ambient $PM_{2.5}$ – fine particulate matter smaller than 2.5 micrometers in diameter– is responsible for the largest share of premature deaths associated with air pollution. Despite declines in average annual concentrations, significant disparities in $PM_{2.5}$ exposure between racial and ethnic groups continue to persist. Existing research characterize $PM_{2.5}$ exposure disparities across a range of different indicators, but few studies compare these metrics against one another nor do these studies explore these metrics at different geographic scales and demographic shifts over time. As policy makers begin to prioritize environmental justice concerns through the identification of disproportionately impacted communities, careful selection of indicators and metrics will be vital for ensuring that inequities are properly captured in decision making processes.

Using population demographics from the U.S. Census and land-use regression $PM_{2.5}$ concentration estimates from the Center for Air, Climate, and Energy Solutions (CACES), we compare the calculations of absolute and relative exposure disparities at different geographic scales and changing demographic shifts. Further, we discuss the policy implications of our findings and provide recommendations for both regulatory and community centered measures to address existing racial/ethnic disparities.

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Chapter 1

Introduction

In the United States (U.S.), exposure to ambient $PM_{2.5}$ – fine particulate matter smaller than 2.5 micrometers in diameter– is responsible for the largest share of premature deaths associated with air pollution [29]. Researchers attributed 4.2 million premature deaths globally to in 2015, ranking it as the 5^{th} highest mortality risk factor [12]. Average concentrations $PM_{2.5}$ across the U.S. have declined considerably (70 percent) since 1981 due to a variety of policies and actions [13]. These policies include the Clean Air Act (CAA), which has –through the National Ambient Air Quality Standards (NAAQs)– set limits for maximum allowable concentrations for 6 criteria air pollutants: ground-level ozone, particulate matter (including $PM_{2.5}$), carbon monoxide, sulfur dioxide, nitrogen dioxide, and lead. Despite these improvements, significant disparities in $PM_{2.5}$ exposure between racial and ethnic groups continue to persist due to regulatory and systemic forces that have sited pollution sources near disadvantaged communities [13] [24] [34].

Existing research characterizes these pollution disparities across different indicators, such as calculating absolute and percent differences in population weighted $PM_{2.5}$ averages and utilizing metrics of inequality [20] [24][28]. Nonetheless, few studies have compared these metrics against one another, nor have many studies extensively explored these metrics at different geographic scales and demographic shifts over time. These questions are particularly relevant as policy makers prioritize environmental justice concerns by identifying disadvantaged communities most impacted by environmental hazards. Depending on which metrics are used to define pollution exposure disparities, different conclusions can be made on the status of the gap in pollution exposure across racial/ethnic groups [13] [20]. Further, understanding the how these metrics represent disparities at different geographic scales can help determine which levels of governance (city, state, national) can be most effective at addressing gaps in pollution exposure. Finally, community demographics are not static. As people move and change residences over time, exploring changing demographics and pollution levels over time can serve as additional metrics for identifying regions that are showing improvements (or lack thereof) in pollution disparities.

Given these factors, this thesis explores the following questions:

1. **Exploration of $PM_{2.5}$ Disparities at Different Geographic Scales**: Do National pollution disparities exist at different geographic scales?

2. **Disparity Metrics Comparison**: How do absolute and relative disparity metrics differ in identifying the communities that experience the highest disparities in pollution exposure?

3. **Temporal Trends in Changing Demographics and Pollution Levels**: What conclusions regarding pollution disparities can be drawn when exploring the relationship between changing demographics (as a proxy for relative mobility) and changing pollution levels over time?

The following sections further elaborates on the significance of each of these questions, summarizes existing research on $PM_{2.5}$ pollution disparities and highlights the ways this paper provides additional perspectives to current literature.

1.1 Question 1: Disparities at Different Geographic Scales

A majority of existing studies exploring gaps in racial/ethnic pollution exposures calculate disparities at a national aggregation [13] [20] [24]. Few studies explore intra-urban disparities, and do so only for particular metropolitan area of interest [9] [10]. For example, Chambliss et. al. use localized monitoring data in four counties in San Francisco to conclude that differences pollution exposure across racial/ethnic groups are driven by regional variability rather than intra-urban differences. It is unclear whether the conclusions for the city of San Francisco can be applied to other regions in across the U.S.

Further, understanding whether disparities exist at lower geographic scales is important for two reasons. First, this question can help to determine what levels of policy governance will be influential in addressing these pollution disparities. For example, local governing bodies have influence in siting and permitting of pollution sources as well as zoning of residential areas. Second, this question can serve as a method to compare the differences between various disparity metrics, explored in the next section.

1.2 Question 2: Comparison of Relative and Absolute Disparity Metrics

There are two main types of disparity metrics used in characterizing gaps in pollution exposure between racial/ethnic groups: (1) absolute disparities (2) relative disparities. Absolute disparities are assessed as absolute differences between groups, while relative disparities are scale invariant.

Different papers have calculated variations of the absolute disparity metric to tailor the index to their specific research questions– e.g. taking the normalized difference [24], percent difference [24], or changing the two units of comparison (e.g. difference between highest and lowest concentration exposures vs. difference between exposures of two target ethnic groups) [14]. Nonetheless, the overall mathematical definition of an absolute disparity across these papers is consistent and follows that of taking the absolute difference between two measurements.

The relative disparity metric on the other hand is not consistently defined across air quality literature and has been quantified and characterized differently across various papers. For example, Colmer et. al. found that while differences in $PM_{2.5}$ between more or less polluted areas declined substantially in the last two decades (declines in absolute disparity), the most polluted areas remained the most polluted and the least polluted areas remained the least polluted (relative disparities persist) [13]. Colmer et al. does not provide a quantification of relative disparity, but rather demonstrates relative disparity as a relational concept through which ranks of pollution concentrations have not changed over time. Jbaily et al. expands on this research by attaching a numeric metric to relative disparities using the coefficient of variance (CoV), a statistical method that calculates the variability of a given data set [20]. Finally, Pisoni et al. defines and quantifies relative disparities using an inequality indicator based on the Gini coefficient, usually applied in the field of economics to identify income inequality [28].

Few studies compare the range of disparity metrics that exist across absolute and relative pollution metrics. More commonly, a singular metric is identified to capture an author's specific definition of disparity given their research question. Further, the author is not aware of any studies that use disparity metrics to spatially identify areas in the U.S. that show the highest racial/ethnic pollution exposure disparities. The usefulness of such an analysis would be two-fold: (1) comparison of disparity metrics can help researchers and policymakers identify which metric may be most suitable for their application proposes, (2) identification of communities experiencing high pollution disparities across racial/ethnic groups can help policy makers pin point areas requiring targeted policy measures.

This study compares two metrics of absolute and relative disparities: absolute difference in population weighted average (PWA) $PM_{2.5}$ concentrations and relative disparities as represented by the coefficient of variance. We choose these two metrics because (1) both have a numeric value attached to it, which allows for ease of comparison and (2) these metrics are easily interpretable and (for the case of PWA $PM_{2.5}$ concentrations) are commonly used in the literature.

While numeric disparity metrics offer the benefit of interpretability and comparability, inequality/disparity is a relational concept that contains both qualitative and quantitative elements [30]. Reducing definition of "disparity" to a metric may have the unintended consequence of removing important nuances in air pollution trends. As such, our final research question utilizes the characterization of relative disparities presented in Colmer et al. in order to explore the relationship between changing demographics and pollution levels over time.

1.3 Question 3: Temporal Trends in Changing Demographics and Pollution Levels

The combined force of various political and systemic processes have concentrated people of color in neighborhoods that are often racially segregated, socioeconomically disadvantaged, and disproportionately exposed to a variety of environmental hazards [34]. These disparities in part reflect systematic environmental racism, including long-lasting consequences of discriminatory practices such as redlining where racially-biased mortgage appraisals favored white people and resulting in people of color living in more polluted neighborhoods [23].

However, recently scholars have found that after the turn of the 21st century, trends show a shift in non-Hispanic White population shares towards urban neighborhoods with higher pollution levels [24] [14]. While this shift in demographics is not significant enough to overturn trends in air pollution disparities (i.e. non-Hispanic Whites on average are still experiencing pollution levels lower than racial and ethnic minorities despite movement of white populations to more urban locations), these trends signal to more nuanced story lines in trends in pollution exposure overtime. Specifically we note that these studies do not explore what the rate of improvement is in these urban locations that white populations are moving to. It is possible that these areas, while relatively more polluted, are improving faster than previous residences.

These questions have important policy implications in that they may influence the ways policy makers identify environmental justice communities. For example, in 2022, the New York state-appointed Climate Justice Working Group, identified Williamsburg, a predominately white neighborhood where the average household income is $166,600, as a "disadvantaged environmental justice community" given its high pollution levels and **legacy** as an industrial area with a large minority population [18]. As policy makers determine which communities to identify as locations of most concern, it is important that we explore not only current pollution and demographic data, but also how mobility of different racial/ethnic groups relate to **changes** in air quality.

To do so, we implement methods used by Colmer et. al. to explore relative disparities by conducting rank-rank analysis of pollution levels. For this paper, we employ a similar rank-rank analysis by exploring **demographic changes** across the top and bottom percentile of pollution exposures. We apply the same analysis on **changes in pollution concentrations** across the top and bottom percentile of demographic shifts. In doing so, we aim to quantify and explore demographic changes within census county and track regions.

1.4 Organization of Key Research Questions

To summarize, this paper explores three aspects of air pollution disparities in the U.S.:

1. **Exploration of $PM_{2.5}$ Disparities at Different Geographic Scales**: When considering disparities at various geographic scales, do the observed gaps resemble those present at the national level?

2. **Disparity Metrics Comparison**: How do absolute and relative disparity metrics differ in identifying the communities that experience the highest disparities in pollution exposure?

3. **Temporal Trends in Changing Demographics and Pollution Levels**: What conclusions regarding pollution disparities can be made when exploring

the relationship between changing demographics (as a proxy for relative mobility) and changing pollution levels overtime?

This paper is organized as follows: Chapter 2 introduces data sources and methods for the three questions presented. Chapter 3 explores research question (1) on disparities at different geographic scales and (2) comparison of disparity metrics. Chapter 4 explores research question (3) on temporal trends in demographics and pollution levels. Finally, Chapter 5 includes key conclusions and discussion on policy relevance.

Chapter 2

Methods and Data Sources

This paper uses two sources of data: (1) population demographics from the 2000, 2010 2020 U.S. Census and (2) estimates of $PM_{2.5}$ concentrations between years 2000-2015 from the Center for Air, Climate, and Energy Solutions (CACES) land use regression model in order to explore the trends in air quality exposure across four racial and ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, non-Hispanic Asians, and Hispanics. Non-Hispanic racial groups will simply be referred to as White, Black or Asian respectively in this paper. These two sources of data are merged at the census block-group level using the methods described in Section 2.2.2 in order to calculate population weighted $PM_{2.5}$ exposures and explore (4) different definitions of pollution disparities (Section 2.3)

2.1 Air Pollution Data

The U.S. Environmental Protection Agency (EPA) has identified six air pollutants known as "criteria" pollutants, which are specifically regulated due to their significant harm to human health and the environment. In the United States, these criteria air pollutants, which include $PM_{2.5}$, are measured at fixed regulatory monitoring stations within the National Ambient Air Quality Standards (NAAQS) network (Solomon et al., 2014). However, these regulatory monitors provide air pollution measurements that are limited in both space and time, as they are constrained by the location of monitoring stations and year in which a monitor is established. Given that air pollution can exhibit spatial variability due to land-use characteristics such as street canyons effects, complex terrain, and urban heat island effects, land-use regression (LUR) models provide improved exposure estimates by combining monitoring data with land-use variables. These LUR model predictions are also commonly used to assess the health effects of pollution [16] and exposure disparities [11] [23].

As such, for this project, we characterize $PM_{2.5}$ concentrations using empirical land-use regression (LUR) models developed by the Center for Air, Climate and Energy Solutions (CACES) [1]. These models estimate ambient concentrations for six criteria pollutants (carbon monoxide, lead, nitrogen oxides, ground-level ozone, sulfur oxides, and particle pollution, including $PM_{2.5}$) using U.S. EPA regulatory monitors, satellite-derived estimates of air pollution for locations without measurements, and roughly 350 geographic characteristics, including locations of major and minor roads, measures of traffic, elevation, and land type (urban or rural) [22]. LUR models make use of actual pollution estimates from regulatory monitors and satellite derived estimates as variables for its "training data set" or set of inputs and outputs used to fit/train a model. Each monitoring site is characterized by a set of potential predictors such as the geographic characteristics listed above (population density, land use and various traffic-related variables). In the case of this model, our inputs are these potential predictors and our outputs are the measured/satellite estimates of $PM_{2.5}$ concentrations. Statistical modeling is used to determine which predictors best explain the pollution concentrations observed in the training data set. [1]

LUR models for this study derive their estimates using a statistical method known as the universal kriging framework, which partitions annual average concentrations into two components: variance and mean. Components are estimated by partial least squares (PLS) of geographic variables. Together with these components, PLS predictors offer a unique characteristics in that they not only incorporate various geographic characteristics, they also help to avoid the issue of over fitting to the training data by regularizing the model such that it is able to better predict on new data sets. The best performing models were then selected to generate annual ambient concentration estimates for all residential census block-groups in the contiguous US. The selection of "best" performing models are tested using cross validation, or out-of-sample testing. This method assesses how well the model is able to predict new data that was not used to in the training dataset (data that was used to create the model, aka. satellite derived estimates). The cross-validated R-squared value, which represents how well model predicts new data, for $PM_{2.5}$ was 0.85. Generally, an R-squared value of 0.7 or higher is considered a good fit [22].

We select this data set for a number of reasons in addition to the ones previously noted. First, LUR models can provide estimates of air pollution concentrations for many locations simultaneously and at a much finer spatial resolution than traditional monitoring stations. This data set in particular predicts pollution concentrations at census block centroids.

Additionally, compared to traditional monitoring data sources which may move or change over time, LUR models are particularly useful for analysis that explore pollution across time periods, as is done in this analysis. Finally, the interoperability and transparency of land use regression models allow for easier interpretation of results. Further, this data is freely available online, which can allow for reproduction of results and as such build trust and confidence in in both model development and research findings derived from these pollution predictions.

2.2 Census Demographics Data

Population data is sourced from the IPUMS National Historical Geographic Information System (NHGIS), a database that provides access to summary statistics and GIS files for the U.S. Census and other nation wide surveys [27]. We utilize data from the 2000, 2010 and 2020 U.S. census. As census block codes and geographies have changed between each Census report, NHGIS provides standardized data across various time series. For the purposes of this project, census demographics for years 2000 and 2020 are standardized for the 2010 census geographies.

NHGIS standardizes the 2000 and 2020 data in these time series tables to 2010 census geography in two steps, first allocating census counts from 2000/2020 census blocks to 2010 census blocks and then summing the reallocated 2000/2020 counts for all 2010 blocks that lie within each target 2010 unit. Where a 2000/2020 block intersects multiple 2010 blocks, NHGIS applies areal interpolation to estimate how the 2000/2020 block characteristics are distributed among the intersecting 2010 blocks. [27]

Demographics are reported to the Census at a ten year interval. NHGIS provides annual census demographics data at the census tract level only for years 2000-2019. In order to match census block-group level $PM_{2.5}$ estimates sourced from the CACES, which are provided for years 2000-2015, this study utilises census block-group demographics for years 2000, 2010, and 2020 and interpolates demographics between years 2010 and 2020 to arrive at estimates for 2015 block-group demographics. We do so using piece wise linear interpolation from NumPy Python library. The findings of this report are subject to the robustness of the interpolation methods. Once 2015 demographics are determined, census demographics for years 2000, 2010 and 2015 are merged with $PM_{2.5}$ estimates. This merge is described in Section 2.2.1.

In addition to interpolation sensitivities, we note that there are a number of equity concerns surrounding census data usage, particularly the limitations in capturing unrepresented minorities, neighborhoods with limited English proficiency, people experiencing homelessness, and other marginalized communities. As such, the findings of this report are subject to data limitations in capturing a complete understanding of disparities across all populations in the country. We explore these equity and diversity concerns, along with recommendations for improving between year interpolation estimates further in Chapter 4.

2.2.1 Estimating Exposures to Pollutants using Population Weighted Average

This paper estimates annual $PM_{2.5}$ exposures for years 2000, 2010, and 2015 based on population-weighted averages (PWA) for each demographic group. To to do, we merge $PM_{2.5}$ concentration estimates from the CACES data-set (described in Section X) with census demographics (described in Section X) using GeoPandas spatial join. Spatial join uses binary predicates such as intersects and crosses to combine two GeoDataFrames based on the spatial relationship between their geometries. In this case, the intersection between census block centroids in the CACES pollution estimates and the census block group shape files are identified in order to merge the two data sets. This process is replicated for years 2000, 2010, and 2015 across all census block groups in the contiguous United States.

Next, the population weighted average $PM_{2.5}$ of for each a given racial/ethnic group in a geographic region of interest is computed as:

$$PWA = \frac{\sum_j (P_i C)}{\sum (P)}$$

Where P_i, j is the population of racial/ethnic group i within a census block group j, P is the total population of in census block group j, C is the predicted $PM_{2.5}$ concentration in a census block group j and N is the number of census block groups in the geographic region of interest. Population weighted averages for $PM_{2.5}$ are computed for the following geographic regions: county, state, regional and national levels.

Population-weighted average $PM_{2.5}$ is a commonly used metric of exposure in air pollution literature given that the metric proportionally assigns a greater weight to pollution located where there is a larger number of people living. Population weighted pollution exposure provides a more accurate estimate of the average exposure to air pollution for a population as opposed to simply accessing pollution over a geographic region. [25]

Population weighted $PM_{2.5}$ averages as a representation of pollution exposures will be used as the basis for calculating exposure disparities as described in the next section.

2.3 Defining Disparities

Exposure disparities are defined a number of different ways in existing literature. This paper employs the following definitions of disparities:

1. Absolute Disparities based on Racial/Ethnic groups [24]

2. Relative Disparities across all racial ethnic groups as defined by the Coefficient of Variance [20]

3. Relative Disparities across geographic regions using Rank-Rank comparison [13]

As described in the introduction, absolute disparity metrics (1) are often connected to pollutant-specific health impacts (Harper et al. 2013). In the case of this paper, absolute disparity is defined as the difference between population weighted $PM_{2.5}$ exposure of the racial/ethnic group with the highest mean exposure ("most-exposed group") and the PWA $PM_{2.5}$ exposure of the racial/ethnic group with the lowest mean exposure ("least exposed group"). We define absolute disparity based on differences between most- and least-exposed racial/ ethnic groups to avoid preselecting two specific groups for comparison. Further, this accounts for exposure disparities across multiple racial/ethnic groups [24].

As described in the introduction, there exist many variations in calculating absolute differences in pollution exposure. Researchers have also calculated percent differences and normalized absolute differences (where the difference is divided by the national mean exposure).

An important limitation of using absolute disparities is that they represent the differences in exposure across racial/ethnic groups but do not include information about disparities across the full exposure distributions. For example, absolute disparity measures the differences in mean exposures (PWA $PM_{2.5}$). However, two populations may have the same population weighted average (absolute disparities is zero) but one population may have a much wider range in exposures than the other. In this case, an disparity metric that focuses on a difference between two groups would not capture the differences in exposure distribution and would underestimate the true disparities in exposure burden.

To address this limitation, we also employ two additional definitions of relative exposure disparities.

In definition (2), we employ the definition of relative disparities as described by Jbaily et.al., where the coefficient of variation (CoV) is used to measure the variability of population weighted average $PM_{2.5}$ exposures across all racial/ethnic groups. Using the CoV, we explore the variability across the percent of each racial/ethnic group that is exposed to $PM_{2.5}$ above a certain threshold [20]. This metrics provide a more nuanced and comprehensive measure of exposure inequality by capturing differences in the distribution of exposures across different populations or subgroups, rather than just focusing on differences in mean exposure levels. Calculation of this disparity metric, along each of the other metrics, are defined in the sections below.

In definition (3) we employ the definition of relative disparity as described by Colmer et al., where relative disparity is represented by change in pollution exposure **rank** over the years relative to other regions, e.g. "Rank-Rank" comparison [13]. As such, even if the absolute disparity or normalized disparity has decreased, if the rank of a census tract has not changed over time, "relative" disparities persist. This definition captures the distribution of pollution exposures in that we are provided with the pollution rank of a region and can understand that regions pollution levels in relationship to the rest of the sample size (exploration across exposure percentiles). Further details on the calculation of definition (3) is provided in the sections below.

2.3.1 Relative Disparities calculated using the Coefficient of Variation

The coefficient of variation (CoV) is a statistical measure used to measure the relative variability or dispersion in a data set and is commonly used in measures of income inequality. It is calculated as the ratio of the standard deviation (SD) to the mean of the data set, expressed as a percentage.

A lower CoV indicates lower variability or dispersion in the data set, while a higher CoV indicates greater variability or dispersion. The coefficient of variation is a useful measure when comparing variability between data sets with different units or scales.

We apply the coefficient of variation to measure the relative variability of the percent of a population group that is exposed to pollution levels higher than a threshold of interest. [20]. In this case, this study selects the annual threshold that represents the 90^{th} percentile in PWA $PM_{2.5}$ exposure levels across the U.S. for each year. As such, the thresholds for each year are as follows: (2000: 16 $\mu g/m^3$, 2010: 12 $\mu g/m^3$, 2015: 10 $\mu g/m^3$). As a metric of comparison, the current National Ambient Air Quality Standard (NAAQ) for $PM_{2.5}$ is $12 \mu g/m^3$ [32].

The steps to calculate the CoV are as followed: (1) First, we define a variable q, which represents the percentage of a population exposed to $PM_{2.5}$ above a certain threshold, in this case $12 \mu g/m^3$. This variable is calculated for each racial and ethnic population. (2) Next, the the CoV for each geographic region can be computed as:

$$CoV = \frac{\sqrt{Var(q)}}{\mu(q)}$$

where Var is the variance of q across the geographic region of interest and μ is the mean of q.

In employing the coefficient of variation in the following manner, we would define relative disparity as the variation in exposure among all racial/ethnic groups relative to the mean exposure levels. CoV provides several unique attributes: (1) CoV is independent of ordered social groups and avoids pre-selecting two specific groups for comparison (2) CoV does not require an "inequality aversion parameter," which may introduce a subjective element to the analyses. Inequality aversion parameters are used in income inequality metrics to represent a society's aversion to inequality and there is not an universally agreed upon value for this parameter. [1] (3) CoV is sensitive to large differences from the average .

[1]These parameters are chosen under the discretion of the researcher and the particular case that this index is being used, as such, the resulting indices will be sensitive to magnitude of the parameter. There are cases where such a parameter can be useful for reflecting inequities.

2.3.2 Relative Disparities across geographic regions using Rank-Rank comparison

As stated in the introduction, Colmer et al. expands on existing air pollution disparity literature by providing a new perspective on exploring gaps in exposure: exploring relative disparities by ranking census tracts based on a percentile distribution [13]. The study explores the correlation between $PM_{2.5}$ percentile ranks in 1981 and average corresponding $PM_{2.5}$ percentile rank in 2016. Rank-rank comparisons have statistical advantages and have been used for analyzing distributional changes over time, specifically for studies that explore inter-generational mobility (Chetty, 2014). Colmer et al. found that on average, the least polluted census tracts in 1981 remain the least polluted in 2016 and the most polluted census tracts in 1981, maintaining relative disparities in pollution [13].

For this paper, we employ a similar rank-rank analysis by exploring **demographic changes** across the top and bottom percentile of pollution exposures. First, we identified the counties with the largest increase in each racial and ethnic group. We defined the largest increase as counties experiencing the top 10^{th} percentile of population increase in one racial/ethnic group and the smallest increase as counties experiencing the bottom 10^{th} percentile of increase.

Next, we identified the counties with most and least improvements in $PM_{2.5}$ concentrations. Similarly as with the previous analysis, counties experiencing the most improvements in $PM_{2.5}$ are identified as those in the top 10^{th} percentile of air quality improvements, and vice versa for counties experiencing the least improvements.

Finally, we combined these two analyses to explore the overlap between the counties identified as the most and least improvements in $PM_{2.5}$ and the counties identified as having the largest increase in each of the four largest racial/ethnic groups.

Chapter 3

Results- Disparity Metrics

This chapter explores the first two research questions proposed in this study:

1. **Exploration of $PM_{2.5}$ Disparities at Different Geographic Scales**: When considering disparities at various geographic scales, do the observed gaps resemble those present at the national level?

2. **Disparity Metrics Comparison**: How do absolute and relative disparity metrics differ in identifying the communities that experience the highest disparities in pollution exposure?

3.1 Geographic Aggregation of $PM_{2.5}$ Exposure

First, we explore the calculation of population weighted $PM_{2.5}$ at different geographic aggregation. This question will be important for understanding what geographic levels policy makers should focus on when development plans and policies to address racial/ethnic disparities. Further, this question will help to identify if our data source is granular enough to identify pollution disparities. As described in the introduction, researchers have found that differences in pollution exposures are driven by **regional** differences, but only conducted such analyses for four counties in San Francisco [10]. To explore this question at the national scale, we compare the calculation of population weighted $PM_{2.5}$ at different geographic aggregations (as described in Methods).

Figure 3-1 on **Page 34** plots the mean population-weighted average $PM_{2.5}$ at different geographic scales across all census block groups for years 2000-2015. Panel (a) plots the National aggregation, where we calculate the population-weighted average $PM_{2.5}$ across all census blocks in the nation for each racial and ethnic group, and for the total population. Panels (b), (c), and (d) respectively plot the "State", "County" and "Tract" **mean** populated-weighted average $PM_{2.5}$ across each geographic scale. For example, in Panel (d) "Tract" level aggregation is derived by taking the population-weighted average (PWA) $PM_{2.5}$ across all census block groups within each tract for each racial/ethnic group. Once a PWA $PM_{2.5}$ value is derived for each census tract, these PWA $PM_{2.5}$ values are averaged across all tracts in the nation.

We observe a decline in PWA $PM_{2.5}$ between years 2000 and 2015 across all geographic aggregations, which is consistent with existing literature [**?**]. Average $PM_{2.5}$ exposure levels decline from the range of 12-14 $\mu g/m^3$ to 7-8 $\mu g/m^3$. Further, as one decreases the geographic scale of PWA $PM_{2.5}$ aggregation from a national scale to tract-level aggregation, **absolute differences** between racial/ethnic $PM_{2.5}$ exposure levels becomes almost non-existent. Specially in panels (a) and (b), which show aggregations at the National and State level respectively, White populations are shown to be exposed to the lowest levels of PWA $PM_{2.5}$ concentrations while Black populations are shown to be exposed to the highest. In panels (c) and (d) for county and tract level aggregation, there is very little difference in $PM_{2.5}$ exposure across racial/ethnic groups.

Figure 3-2 on **Page 35**further demonstrates this point by plotting the $PM_{2.5}$ absolute disparity gap between minority groups and non-Hispanic Whites for years 2000-2015. Panel (a) plots the absolute difference between non-Hispanic White and population-weighted average (PWA) $PM_{2.5}$ exposure and non-Hispanic Black PWA $PM_{2.5}$ across each geographic region (National, State, County and Tract). This is replicated for non-Hispanic Asian and Hispanic populations in panels (b) and (c) respectively.

As observed in panel (a) year 2000, the gap between White and Black PWA $PM_{2.5}$

exposure at the national aggregation was roughly 2.0 $\mu g/m^3$. This means that at the national average, non-Hispanic Black populations are exposed to pollution levels that are 2.0 $\mu g/m^3$ (14 percent higher) higher than that of the non-Hispanic White population. Nonetheless, in the same year, the gap at the tract level is almost zero (0.03 $\mu g/m^3$), the average PWA $PM_{2.5}$ exposure for Black populations at the **tract** level aggregation is only slightly higher than that of White exposure. Trends also hold when calculating normalized disparity, which (as defined in Chapter 2) divides the absolute disparity by the national average.

We further note the changes in signs when averaging across different geographic scales. For example, in **Figure 3-2** on **Page 35**, Panel (a) we observe that the gap in disparity between White and Black populations is positive for National, State and County aggregations. This means that on average cross these geographic ranges, White populations are exposed to $PM_{2.5}$ levels that are lower than that of Black populations. Nonetheless, at the tract level, these gaps are negative, suggesting the opposite for within-tract differences. What is driving this contrast is the difference between taking the population weighted average and the mean at different geographic scales. As a reminder, tract level aggregation is calculated by calculating the population-weighted average (PWA) $PM_{2.5}$ across all census blocks within a tract, then averaging these PWA $PM_{2.5}$ values for all census tracts to arrive at national pollution concentrations. As one increases in geographic aggregation, we see incorporate population weighting for a larger number of blocks. At National aggregation, population weighting is applied to all census blocks. We surmise that as geographic scale increases, there is a broader range in the demographic composition across regions, as such, population weighting becomes more important in capturing the differences in population. Further work can be done to explore these sign changes by exploring the distribution of tract-level PWA $PM_{2.5}$ concentrations.

These findings suggest three things. First, national disparities in air quality exposure exist at state level scales, but they appear to be minimal at tract level aggregation–in other words, an individual living in the same tract as another individual will likely be exposed to the same levels of pollution, regardless of race/ethnicity.

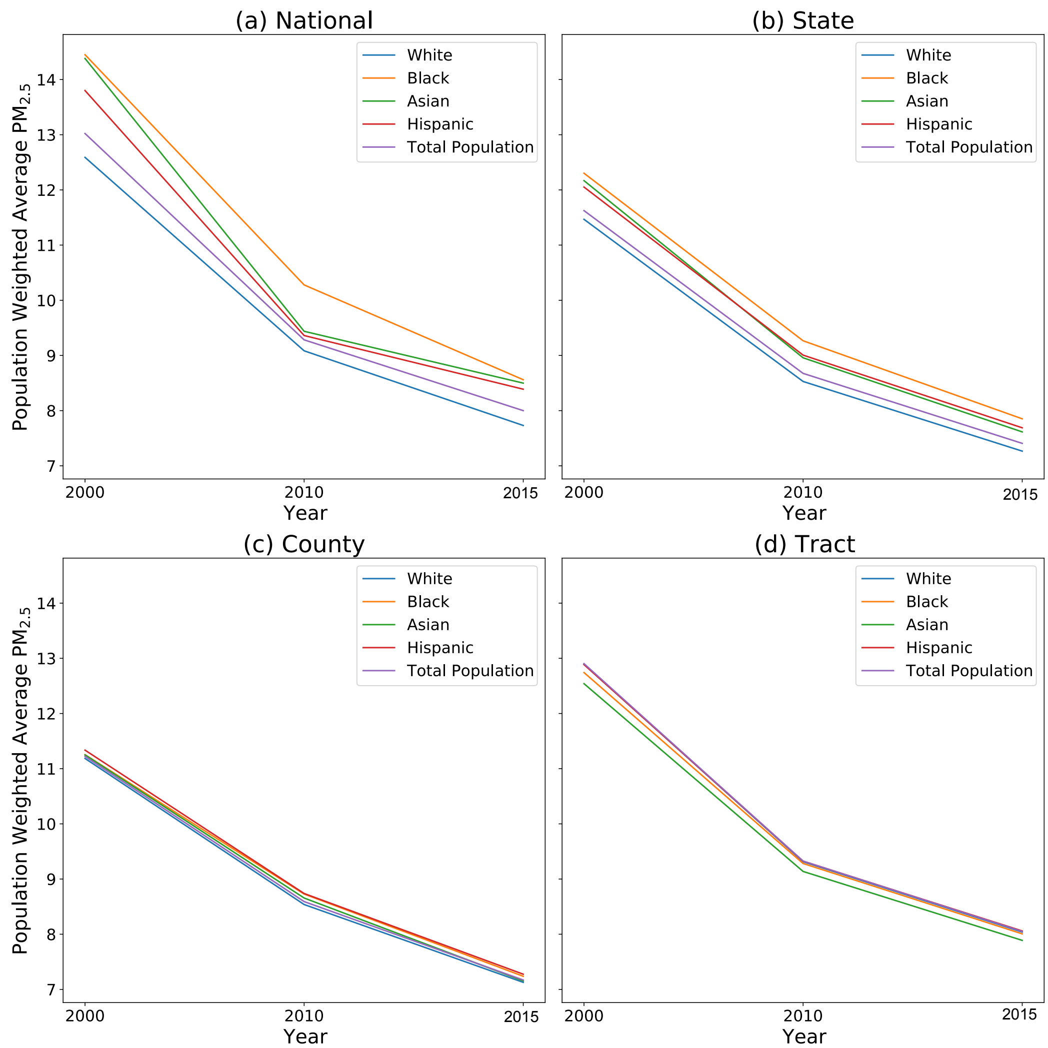

Figure 3-1: Population Weighted $PM_{2.5}$ by Different Geographic Aggregation.

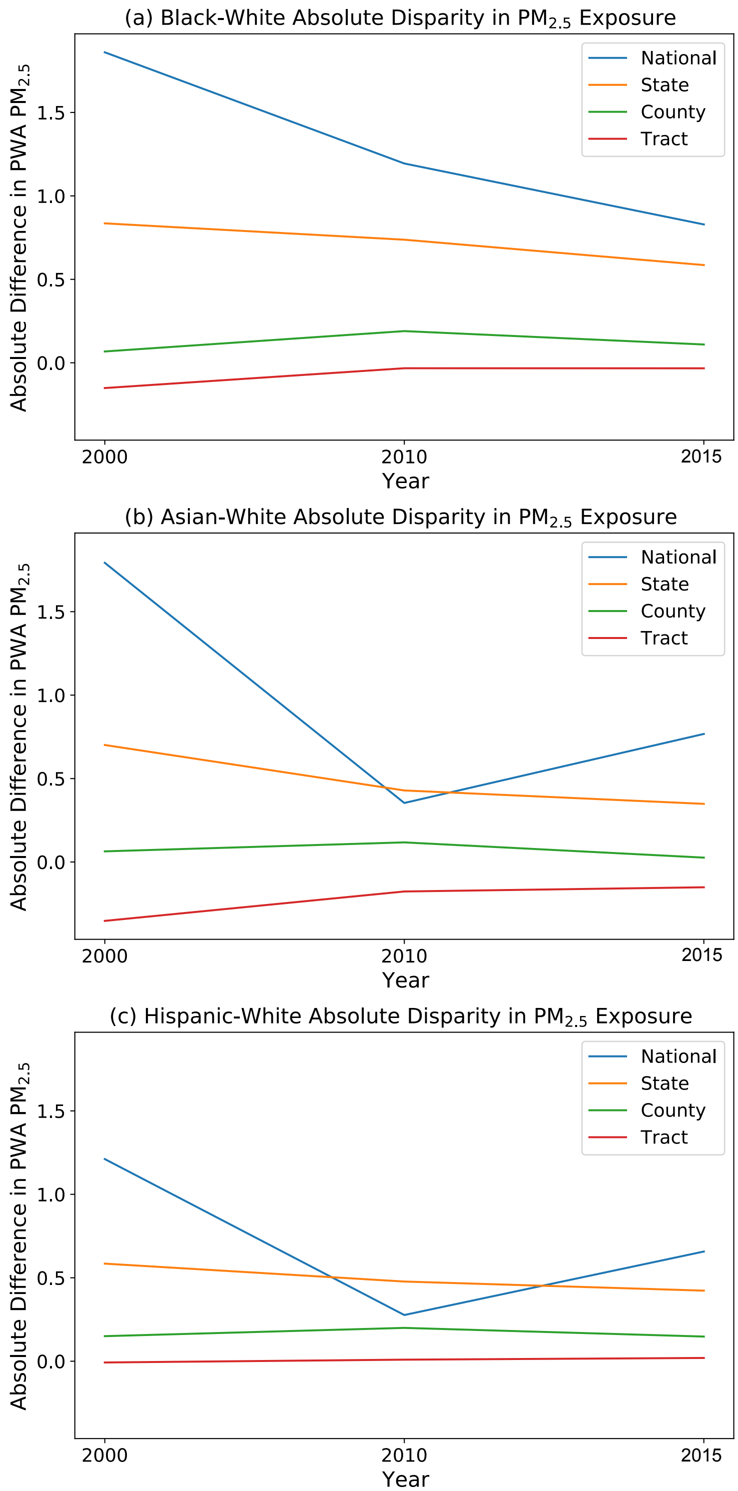

Figure 3-2: Absolute Difference in $PM_{2.5}$ Exposure by Different Geographic Aggregation.

Second, as within-tract disparities are close to zero, in order for these national/state level disparities to exist, racial/ethnic minorities must be exposed to higher levels of pollution in tracts **across** the nation/state. In other words, if one were to live in the same state as another individual, one's exposure to pollution will be driven by which tract one lives in. Finally, this comparison across geographic scales suggest that the data granularity needed to capture disparities in pollution across racial/ethnic groups would at a minimum need to cover an average census-tract geography. Given that our data set provides $PM_{2.5}$ concentrations at the census block group level, this data more than granular enough to identify disparities in $PM_{2.5}$ exposures.

Overall,these plots highlight the importance of tract level residence in not only determining pollution exposure but driving trends observed at a national level. Further, these results have policy implications in that they point to the influence of state regulatory bodies in siting pollution sources at the tract level and suggests further exploration of land-use policies (which influence places of residences) in working to reduce environmental disparities. These policy implications are further explored in Chapter 5. While this analysis highlights the differences in geographic aggregation, it does not identify the areas that are experiencing pollution disparities. As such, in the next section we explore the identification of within-county pollution disparities using two different metrics of disparities.

3.2 Comparison of Absolute and Relative Disparities

In this section, we compare two disparity metrics, absolute disparities and relative disparities using Coefficient of Variance (CoV), to understand how these metrics differ in their identification of disparities. We do so by calculating the absolute disparity and relative disparity (CoV) for each county using the formulas identified in the Methods section. These metrics represent **within county** disparities in pollution exposure across racial/ethnic groups. We select counties as the level of geographic aggregation for two reasons. First, the findings in the previous section suggest that that tract level residence is important in determining pollution exposure. Conducting this analysis at the county level would then help capture disparities that exist **across** tracts rather than **within** tracts. Second, areas deemed in non attainment with the Federal NAAQ standards are identified at the county level. It would then be helpful to compare the areas deem as having the highest racial/ethnic exposure disparities with the areas with pollution levels that exceed federal standards.

To avoid comparing counties that may have low overall pollution levels but high disparities between racial ethnic groups, we explore these disparities for only the counties identified as experiencing pollution levels higher than the top 90^{th} percentile of $PM_{2.5}$ exposures. These 90^{th} percentile thresholds are 16 $\mu g/m^3$, 12 $\mu g/m^3$ and 10 $\mu g/m^3$ for years 2000, 2010 and 2015 respectively. Note that the current NAAQ annual standard for $PM_{2.5}$ is 12 $\mu g/m^3$ [32].

Figure 3-3 on **Page 38** plots the absolute disparity across all racial ethnic groups for the most polluted counties in years 2000, 2010 and 2015. **Figure 3-4** on **Page 38** plots the relative disparity, represented by the CoV, for the most polluted counties in years 2000, 2010 and 2015.

We point out two key differences in how these two metrics identify the counties exhibiting the highest racial/ethnic disparities. These points are summarized in **Table 3.2** on **Page 44**.

3.3 Changes in Magnitude Over time

First, we see a decline in absolute disparities in **Figure 3-3** on **Page 38** between years 2000-2015. This is particularly significant in California, where the absolute disparities have halved by 2015. This is in contrast the calculation of relative disparities in **Figure 3-4** on **Page 39**, where relative disparities increase between the years 2000-2015. This is driven by the difference in which each metric captures variation in the data with respect to magnitude. Absolute disparity is declining over time because the overall magnitudes of emissions are declining [14]. The CoV metric is able to represent relative differences in the data independent of changes in magnitude. For example, consider the hypothetical set of q values (aka. percentages of populations exposed

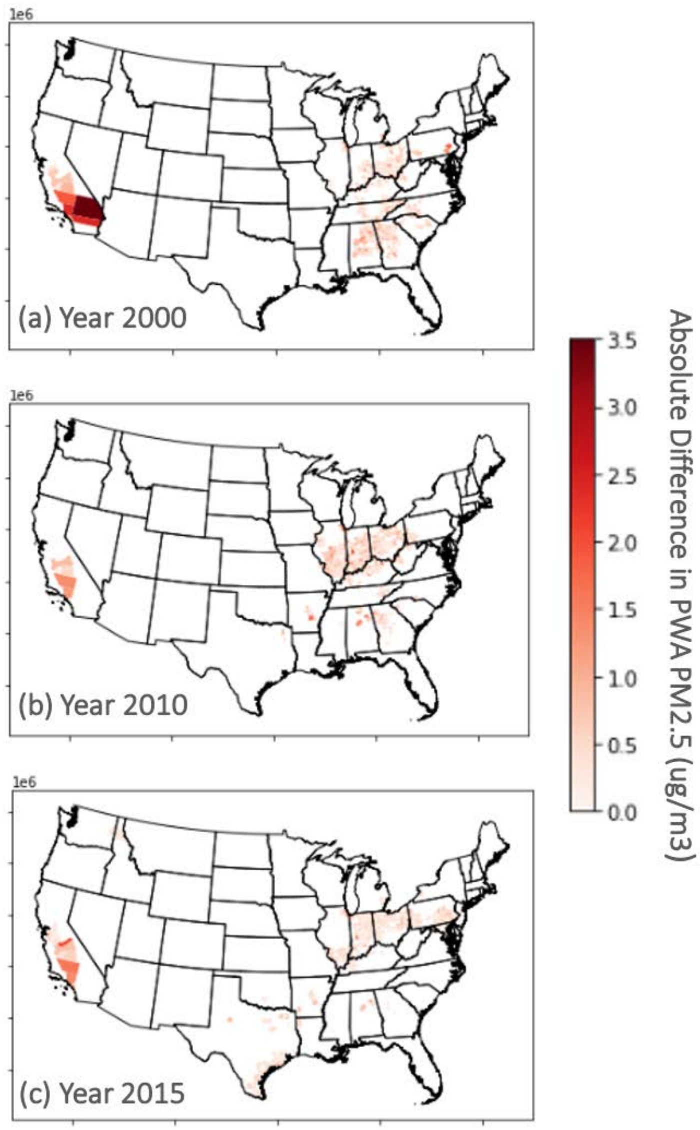

Figure 3-3: Absolute Disparity across the Most Polluted Counties in Years 2000-2015

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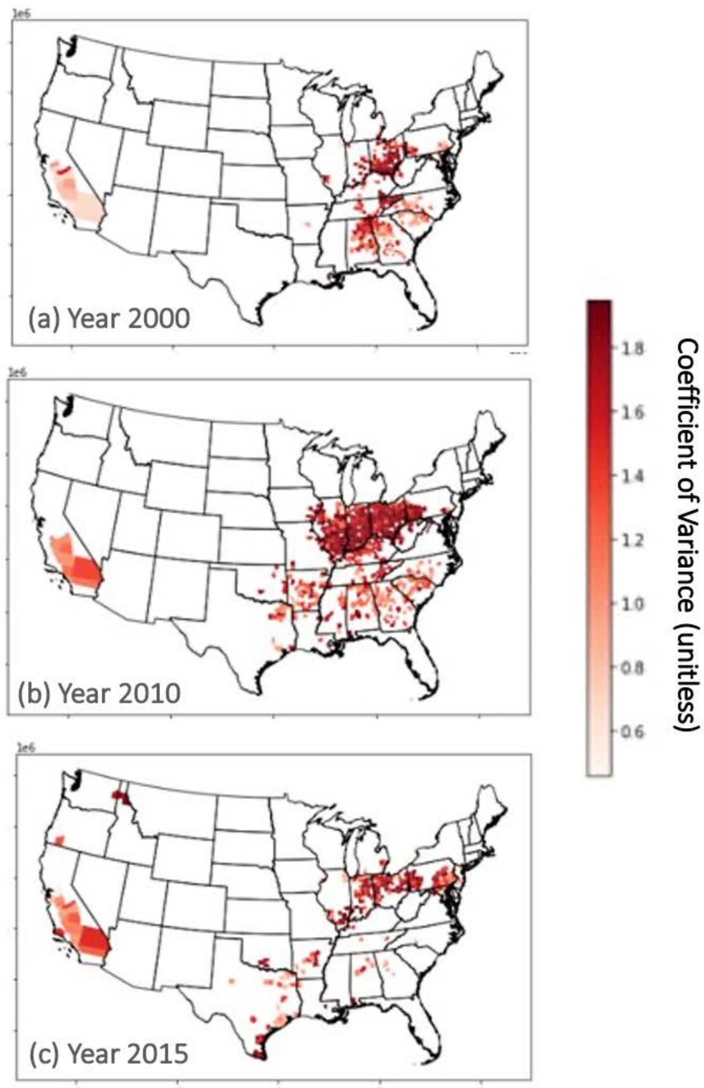

Figure 3-4: Relative Disparity (CoV) across the Most Polluted Counties in Years 2000-2015.

Year	White Q	Black Q	Asian Q	Hisp Q	CoV	Abs.D.
2000	10	12	14	18	0.226	8
2010	1	1.2	1.4	1.8	0.226	0.8

Table 3.1: Hypothetical Example Comparing CoV and Absolute Disparity (Abs.D.)

to $PM_{2.5}$ concentrations above our selected threshold) shown in **Table 3.1** on **Page 40**. The CoV for q values in year 2000 would be 0.226 while the absolute disparity (Abs.D.) would be 8 (18-10). Given the q values for year 2010, the CoV would not change (CoV=0.226) while the absolute disparity would decline by a factor of 10 and be 0.8 (1.8-1). This example is provided for illustrative purposes and we note that absolute disparities in this paper are calculated using the absolute difference in **population weighted average PWA** $PM_{2.5}$ rather than the percentage of a population living in concentrations above a certain threshold.

What is driving the increase in **relative disparities** in California in particular is the increase in the percentage of Hispanic and non-Hispanic Asian populations being exposed to concentrations higher than the 90^{th} percentile of concentrations across the country. Between years 2000 and 2015, the mean percentage of non-Hispanic White and non-Hispanic Black populations in California living in regions above the 90^{th} percentile threshold declined by 52 and 58 percent respectively. On the other hand, the mean percentage of Hispanic and Asian populations in California living in pollution levels above the 90^{th} percentile threshold increased by 17 and 60 percent respectively. The increase in variation across this exposure is driving the increase in the CoV metric for California.

This characteristic of the CoV metric is particularly useful for assessing changes in pollution over time, especially given that $PM_{2.5}$ concentrations have declined drastically in the last several decades. While absolute disparities as measured by population weighted averages may not capture this nuance, incorporating magnitude into a pollution disparity metric may not necessarily be a negative attribute, depending on the specific use case. We explore this in our second observation.

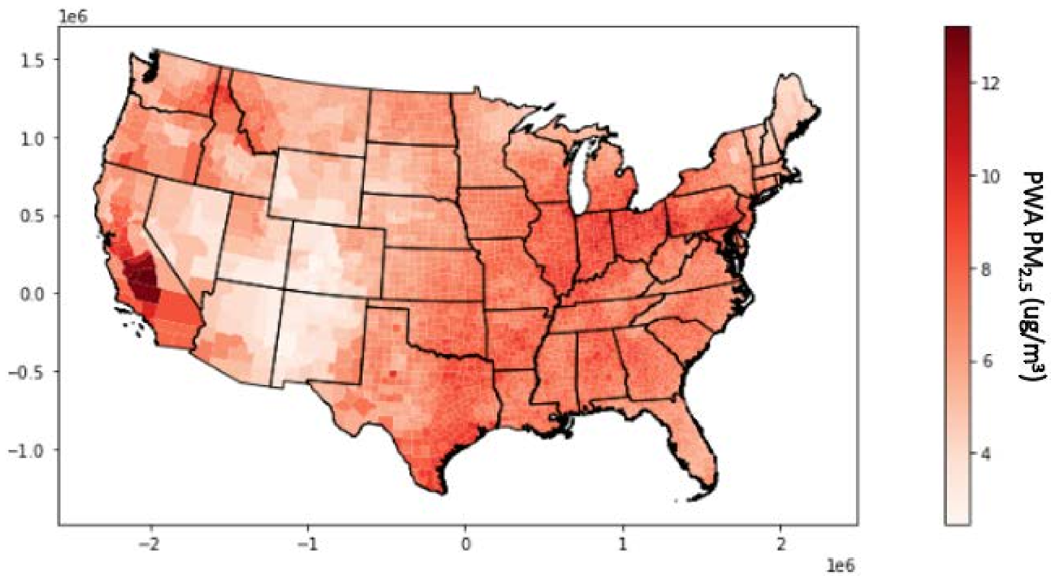

Figure 3-5: Population Weighted $PM_{2.5}$ Concentrations for Year 2015)

3.3.1 Sensitivity to Larger Groups

The second difference in the ways these metrics identify disparities is influenced by the size of the ethnic/racial groups. As shown in **Figure ??** on **Page 39**, the CoV metric emphasizes the disparities in the Rust Belt states (which includes Illinois, Indiana, Missouri, Ohio, Pennsylvania, and West Virginia) while the absolute disparity metric in **Figure 3-3** on **Page 38** de-emphasizes these exposure differences. This is due to two characteristics of the absolute disparity metric as defined in this report. First, as observed in **Figure 3-5** on **Page 41** the average $PM_{2.5}$ exposure levels are smaller in the Rust Belt regions than those in California, as such, absolute disparities reflect this difference. Second, the intermediate metric used to calculate the absolute disparity is population-weighted $PM_{2.5}$, through which the differences in size of each racial/ethnic group is accounted for.

In the case of relative disparities as defined by the CoV metric, relative disparities in the Rust Belt states are highlighted due to existing bias towards larger racial groups. As a reminder, the CoV metric is calculated first through the intermediate variable q, which represents the percent of the population within the county that is exposed to concentrations above that of the 90^{th} percentile. Then the CoV is calculated by taking the ratio of the standard deviation of these q values to the mean of these q values. If the population in the county of interest is majority White, q values for White populations will be much higher than q values for other minority groups, resulting in a larger standard deviation across q values. As such the CoV may be less reliable for comparing variability between groups with vastly different sample sizes, such as comparing variability in exposure levels between non-Hispanic Whites and a minority groups in regions with over-representation of a particular group.

As observed in **Figure 3-6** on **Page 43**, the demographics of these Rust Belt counties tend to show an over-representation of non-Hispanic Whites and an under-representation of racial/ethnic minorities. For example, the average percent of non-Hispanic Whites in these Rust Belt counties is 84 percent, which is above the national average of 74 percent. On the other hand, the average percentage of non-Hispanic Blacks in these regions is 4.7 percent, which is just over half of the national average of 8.6 percent. This bias may not necessarily be a deterrent against using the CoV metric as a measure of relative disparities.

Table 3.2 on **Page 44** summarizes the key differences between these two metrics. The absolute disparity metric (absolute difference in PWA $PM_{2.5}$) is more sensitive to magnitude of pollution levels while relative disparity as measured by the CoV is more sensitive to population demographics. These opposing characteristics can both be useful in analyses depending on the goals and interests of those using these metrics. For example, the fact that the absolute disparity metric highlights the absolute differences in California as opposed to the Rust Belt can be useful for researchers/policy makers who would like to prioritize addressing overall emissions together with minimizing racial/ethnic gaps in exposure. We discuss this further in the conclusion in Chapter 5. Finally, we note both relative and absolute disparity maps identify regions with high exposure disparities that are not identified as NAAQ non-attainment counties (see **Figure 3-7** on **Page 45**). This is because many of these regions do not meet the threshold for non-attainment (which requires an annual arithmetic mean, averaged over 3 years, of 12 $\mu g/m^3$). However, given that previous studies [14] attributed declines in pollution disparities to NAAQ standards, these results may serve

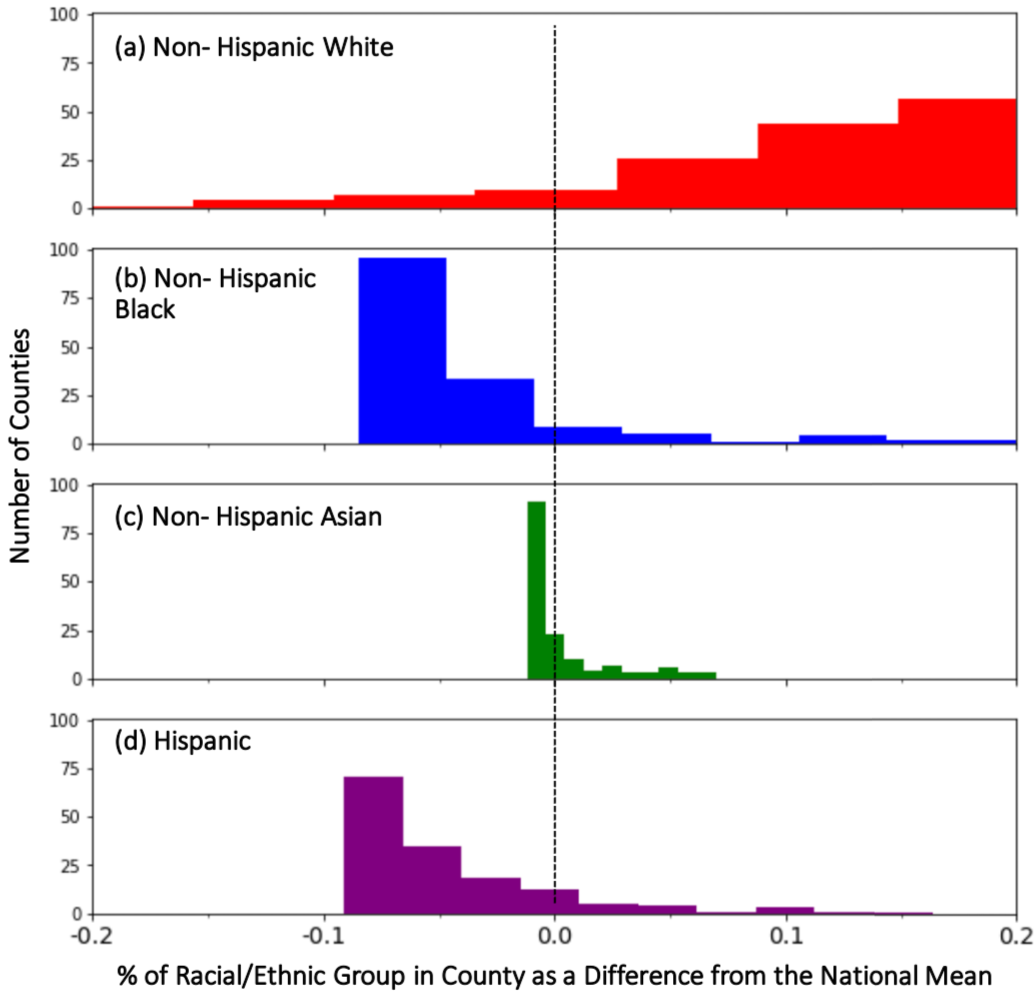

Figure 3-6: Demographics of Rust Belt Counties showing $PM_{2.5}$ Exposures at the 90^{th} Percentile.

	Absolute Disparity (PWA)	**Relative Disparity (CoV)**
Intermediate Metric	Population Weighted $PM_{2.5}$ Concentrations	Q, which represents the % of racial/ethnic population that lives above a certain threshold (e.g. 12 $\mu g/m^3$)
Sensitivity to Magnitude of $PM_{2.5}$ Concentrations	Highlights the differences in magnitude of $PM_{2.5}$ concentrations	Independent of magnitude of $PM_{2.5}$ concentrations
Sensitivity to Population Size	Population weighting helps with accounting for large size differences in racial/ethnic populations	More sensitive to the difference in size of racial/ethnic groups
Cases for Preferred Uses	Most useful for capturing absolute differences in exposure for a single time frame	Most useful for capturing changes in pollution over time and changes in population sizes

Table 3.2: Comparison of Absolute Disparity using differences in PWA $PM_{2.5}$ and Relative Disparity using CoV

as supporting analyses to push for strengthened NAAQ standards as a policy lever for reducing disparities. We explore these policy implications further in the discussion in Chapter 5.

In this Chapter, our exploration of these two metrics uncovered the influence of changing demographics over the years on trends in disparities over time, as observed in the California case presented in Section 3.3. As such, our final research question utilizes the characterization of relative disparities presented in Colmer et al. in order to explore the relationship between changing demographics and pollution levels over time.

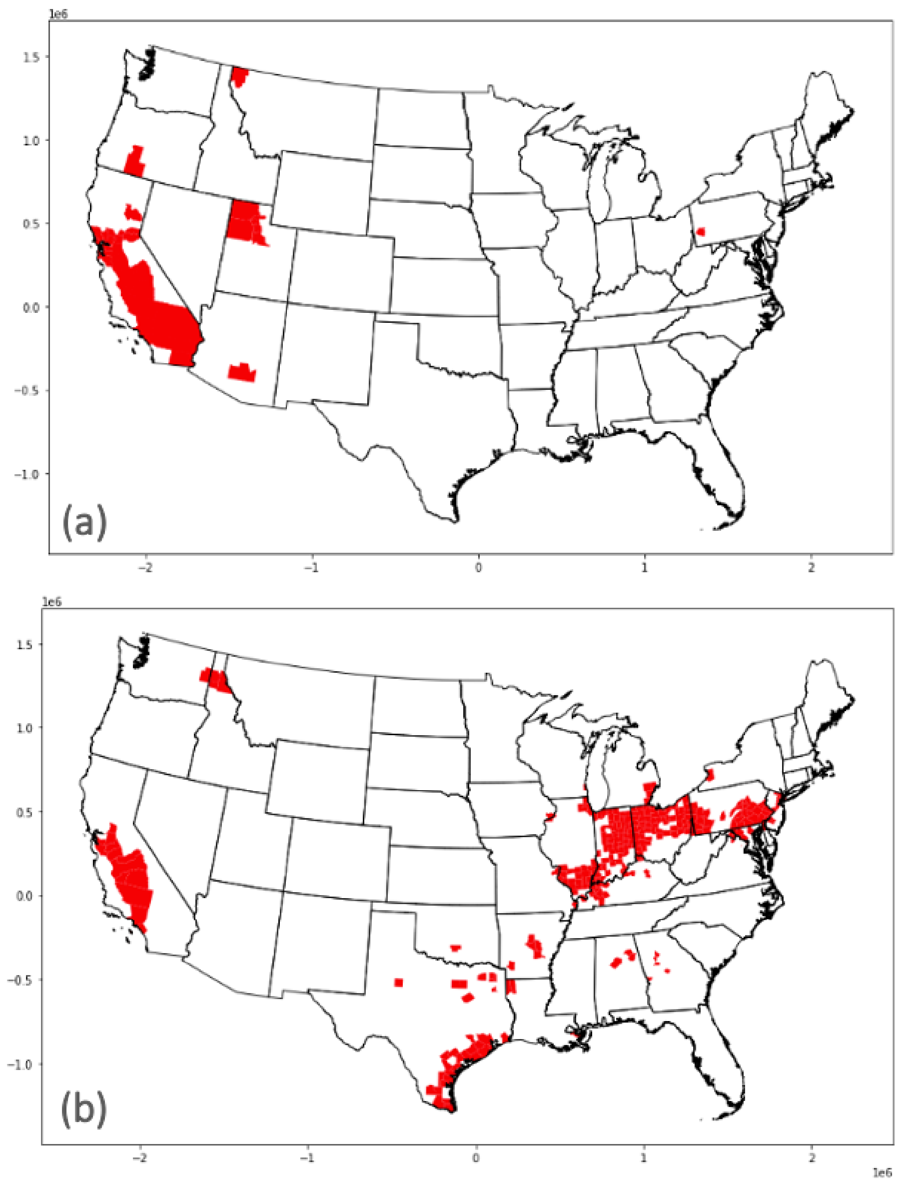

Figure 3-7: (a) Counties designated for non-attainment of the NAAQ $PM_{2.5}$ Standards (1997, 2006 and or 2012 Standards) vs. (b) Counties used in this Disparity Analysis

Chapter 4

Results- Changes in Demographics and Pollution Levels

Racial/ethnic inequities in pollution exposures over time are driven by two main interacting factors: location and magnitude of pollution concentrations and location of populations (demographics). Both factors are not constant, and have shifted considerably overtime. As such, this chapter explores research question number (3) Temporal Trends in Changing Demographics and Pollution Levels: What conclusions regarding pollution disparities can be made when exploring the relationship between changing demographics (as a proxy for relative mobility) and changing pollution levels overtime?

4.1 Migration Counterfactual

One method of understanding the relationship between changes in air pollution and changes in demographic patterns is conducting a counterfactual exercise [24] [14]. In this exercise, one can fix populations to their 2000 locations but pair these locations to pollution levels in 2015. This would represent pollution concentrations across populations assuming that no changes in demographics (e.g. no movement) occurred. In conducting such an exercise, one would be able to compare pollution exposures with actual 2015 pollution levels to arrive at an understanding of the relative mobility of these populations. In this case, changes in demographics over time serves as a proxy for "migration", which can include immigration and other shifts in demographic patterns. **Table 4.1** on **Page 49**)below summarizes the results of this analysis for the top four racial and ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, non-Hispanic Asians and Hispanics.

From these results we find that when comparing the counterfactual 2015 scenario with actual 2015 population weighted average $PM_{2.5}$ exposures using the equation explained in Chapter 2, all minority racial/ethnic groups show lower actual 2015 $PM_{2.5}$ exposures than in the counterfactual 2015 scenario. This suggests that if these populations did not move, or demographics have not changed between years 2000-2015 (counterfactual 2015), $PM_{2.5}$ concentrations are higher. Put a different way, this counterfactual suggests that these minority groups are moving to cleaner neighborhoods. The opposite trend is found for non-Hispanic Whites–White populations are moving to dirtier neighborhoods.

Previous studies have conducted this counterfactual exercise for only non-Hispanic White and Black populations and found counterfactual $PM_{2.5}$ concentrations similar to those reported here in on **Page 49** [24] [14]. Our results adds to these previous studies by including other racial/ethnic minorities, specifically non-Hispanic Asian and Hispanic populations. Further, these trends are consistent with existing literature within urban economics that show that urban populations are becoming Whiter and more college educated after year 2000 and suburbs are becoming more diverse [6]. This shift means that white populations moving to urban centers are experiencing higher levels of pollution than if they were to remain in suburban locations, which are often further away from pollution sources. Nonetheless, this exercise does not answer what the rate of improvement is in the urban locations these white populations are moving to. This information is useful in that it can help policy makers determine which regions to prioritize resources to eliminate ethnic/racial pollution disparities.

As such, the next section aims to explore the relationship between the regions that show increases in non-Hispanic White populations and changes in air pollution over time.

Year	Total Pop PWA	White PWA	Black PWA	Asian PWA	Hispanic PWA
Actual 2000	13.02	12.59	14.45	14.38	13.80
Counterfactual 2015	8.11	7.87	8.80	8.73	8.70
Actual 2015	8.00	7.93	8.56	8.50	8.39

Table 4.1: Counterfactual Migration Analysis.

4.2 Relative Ranks in Pollution and Demographic Changes

Previous sections found evidence to suggest that white populations are increasing in relatively more polluted locations, but does not explore what the rate of improvement in pollution levels has been over these years. To do so, we identify the following regions based on ranks in pollution and population changes:

(1) the most polluted (top 10^{th} percentile in $PM_{2.5}$ exposure) and the least polluted (bottom 10^{th} percentile) census tracts, (2) the census tract experiencing the most improvement (e.g. most negative change) in $PM_{2.5}$ exposure between 2000-2015 (bottom 10^{th} percentile) and the census tracts experiencing the least improvement (top 10^{th} percentile) [1]. (3) the tracts that experience the highest increase in a specific demographic population between years 2000 and 2015(top 10^{th} percentile) and the smallest increase (bottom 10^{th} percentile).

Once these regions are identified, we explore temporal trends across all regions.

4.2.1 Regions with Most Improvements in $PM_{2.5}$

To begin this analysis, I first explore regions with the most improvements in $PM_{2.5}$ exposure to determine if there is a relationship between communities that are showing increases in non-Hispanic White populations and declines in air pollution in these areas. To do so, I employed three different explorations of the data. These analyses

[1] Note, the changes in the top 10^{th} percentile represent both the tracts with the least improvement and regions that have experienced increases in pollution levels as well.

were conducted at both county and census tract level.

As shown in **Figure 4-1** on **Page 51** below, counties that are seeing the largest increase in non-Hispanic White and Hispanic populations show larger improvements (most decline) in air pollution between years 2000-2015 compared to counties that experience the largest increases in Black populations. These trends are consistent at a percent and absolute change in population and pollution and consistent with census tract results.

As seen in **Figure 4-2** on **Page 52**), counties with the most improvement in $PM_{2.5}$ are seeing a larger increase in NHL Whites, NHL Asians and Hispanic population than counties with the least improvement in $PM_{2.5}$. Conversely, counties with most improvement in $PM_{2.5}$ are seeing smaller increases in Black population than Counties that are getting more polluted.

The Venn diagram in **Figure 4-3** on **Page 53** illustrates how the counties showing the largest increase in non-Hispanic Whites (purple) are more likely to also be the counties seeing the largest pollution improvements (green) than the counties showing the least pollution improvements (red). Specifically, 47 counties are identified as being in the top 10^{th} percentile in improvements in $PM_{2.5}$ and increases in white populations. This is in comparison to only 19 counties that are identified as being in the bottom 10^{th} percentile of pollution improvements and the top 10^{th} in increases in white residents. The opposite trend is observed for non-Hispanic Blacks.

These findings suggest that there is a strong positive correlation between counties that are cleaning up the most and counties that are showing the largest increase in non-Hispanic White populations. This may be that non-Hispanic Whites are moving into communities with the most air quality improvements or that communities that are becoming Whiter are cleaning up the fastest.

Further, based on previous literature, one would expect that these neighborhoods showing both improvements in pollution levels and increase in White residents are originally neighborhoods with a large population of racial and ethnic minorities[20]. As such, additional exploration of the overlaps between the counties experiencing the largest increase in non-Hispanic White populations and the counties experiencing the

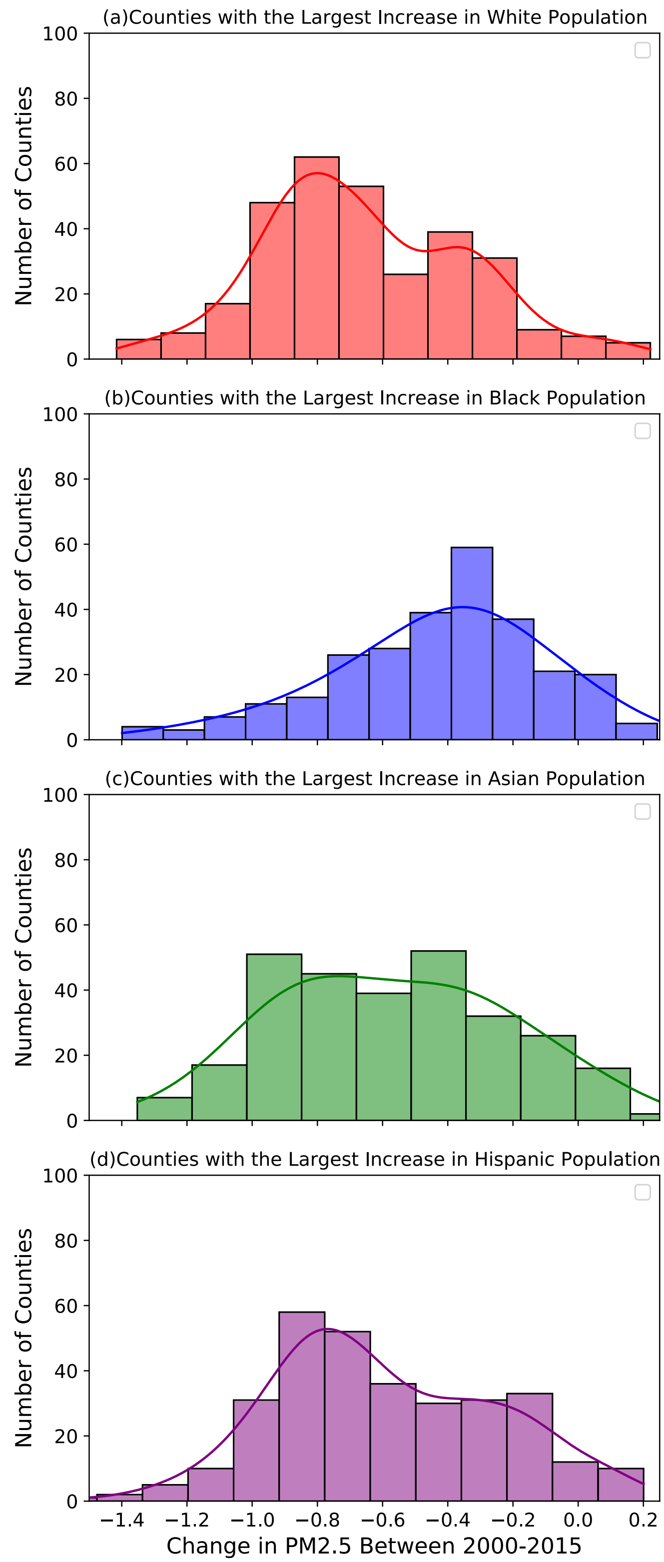

Figure 4-1: Changes in PWA $PM_{2.5}$ Grouped by Counties with the Highest Increase in a Specific Racial/Ethnic Group.

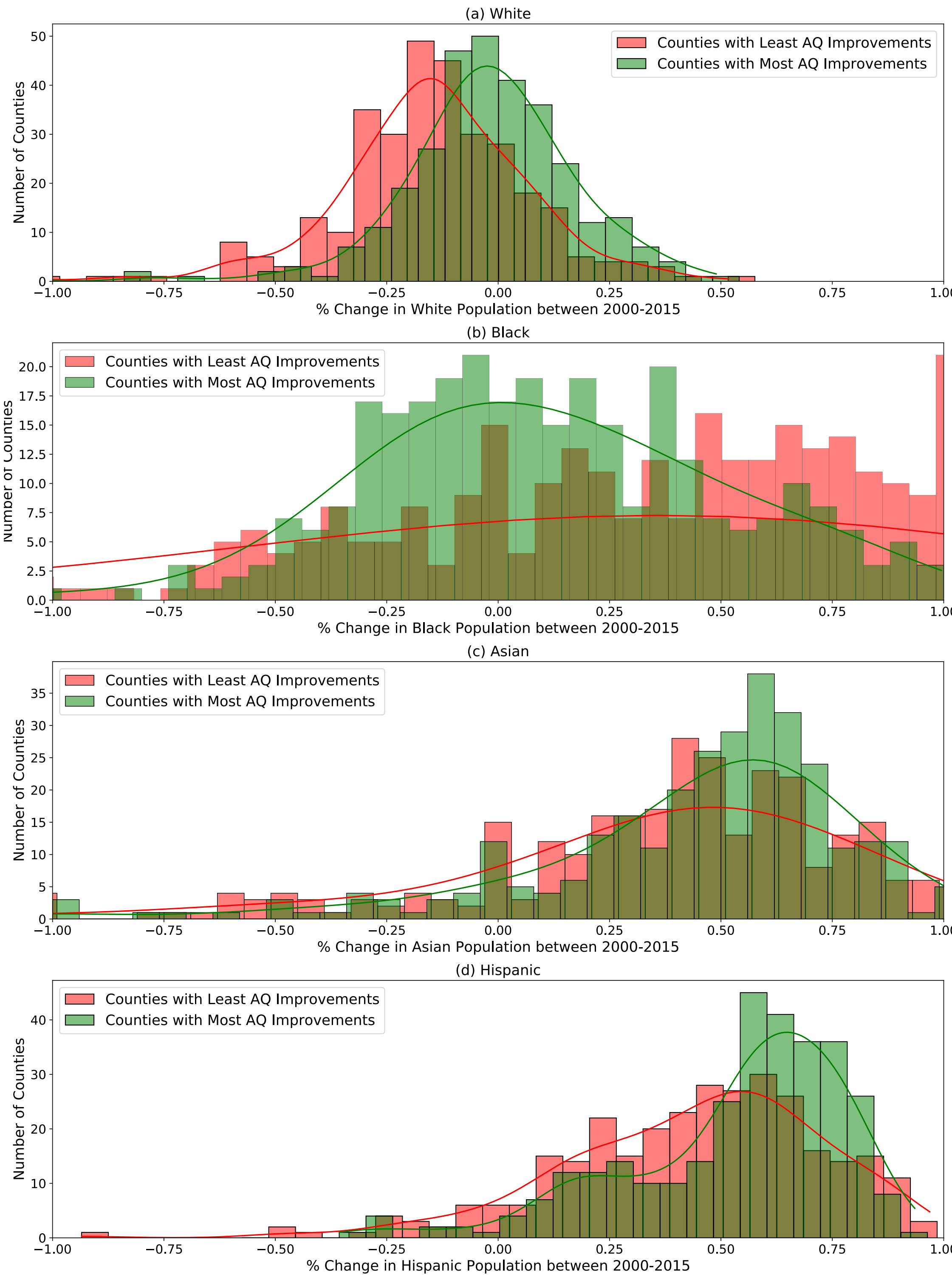

Figure 4-2: Changes in Percent Population Grouped by Counties with the Most and Least Improvements in $PM_{2.5}$.

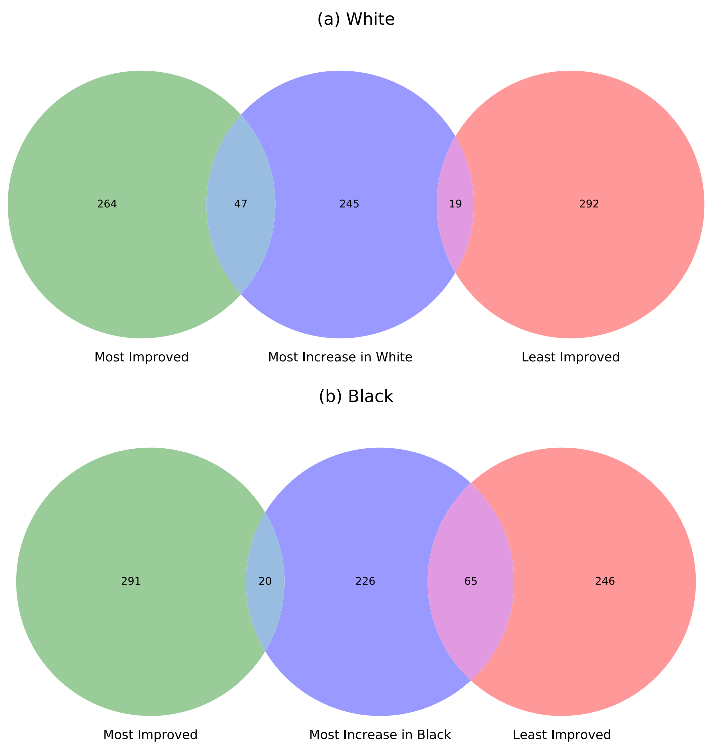

Figure 4-3: Overlaps between Counties with the Most and Least Improvements in $PM_{2.5}$ Concentrations and Counties with the Largest Increase in a White and Black Populations

greatest air quality improvements show that these counties had an over-representation of non-Hispanic Black residents in years 2000 and 2010. We define over-representation as any percentage of a racial/ethnic group that is above that of the U.S. mean average percentage of a specific racial group.

The significance of these results imply that communities observing the **most** $PM_{2.5}$ **improvements** are experiencing declines in non-Hispanic Black residents and instead increases non-Hispanic White residents. In the subsequent sections, this study explores demographic trends of communities observing the **least** $PM_{2.5}$ **improvements**.

4.2.2 Regions with Least Improvements in $PM_{2.5}$

Consistent with previous literature [13], this study finds that counties with the least pollution in 2000 are generally the same counties with the least pollution in 2015. This is depicted geographically in **Figure 4-4** on **Page 55** , where there is significant overlap between counties identified as the most polluted across all years. These overlaps are colored in purple. Additionally, through the years, a majority of these counties are also counties that rank as the counties showing the least improvements in $PM_{2.5}$ concentrations.

This is demonstrated by the Venn diagrams in **Figure 4-5** on on **Page 56**, which shows the overlap between the counties identified as having the lowest ("Best") pollution levels in years 2000, 2010, and 2015 respectively (colored in purple), and the counties that show the most improvement in air pollution (green) and least improvements in air pollution (red). The circles showing the most and least improvements do not change overtime as they represent the difference between 2015 $PM_{2.5}$ levels and 2000 $PM_{2.5}$ levels.

Nonetheless, this is not the case with counties showing the most pollution. While there is some overlap, the counties experiencing the most pollution in year 2000 are not necessarily the counties experience the most pollution in year 2020. **Figure 4-6** on **Page 57** shows overlap between the counties identified as having the **worst pollution levels** in years 2000, 2010, and 2015 respectively (colored in purple), and the counties

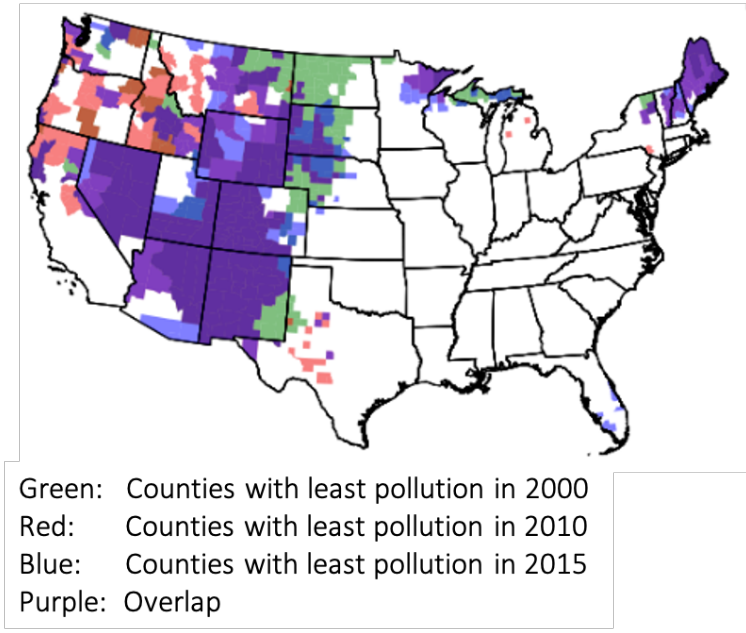

Figure 4-4: Counties Identified as having the bottom 10^{th} percentile in $PM_{2.5}$ Concentrations ('Least Pollution') by year

that show the most improvement in air pollution (green) and least improvements in air pollution (red). This Figure demonstrates that between years 2000 and 2015, the counties identified as having the worst pollution have fewer overlaps with the counties showing the most improvement and instead, begin to show overlaps with counties showing the least improvements in $PM_{2.5}$. In other words, as the dirtiest counties clean up, new counties are identified as the "dirtiest" and the rate of improvement slows.

In particular, there are 25 counties that are identified as having the top 10 percentile in $PM_{2.5}$ levels ("Worst" $PM_{2.5}$ exposure) and are showing the least improvements between years 2000-2015. These counties reside south of Texas, parts of Oklahoma and Idaho. These high pollution levels may be the result of energy production (e.g. hydraulic fracking) or forest fires [13]. When exploring the racial makeup of these regions, I find that these regions show an over-representation of Asian and Hispanic populations in 2015. This is demonstrated in **Figure 4-7** on **Page 59**, which plots the racial/ethnic makeup of these counties based on the difference from the U.S.

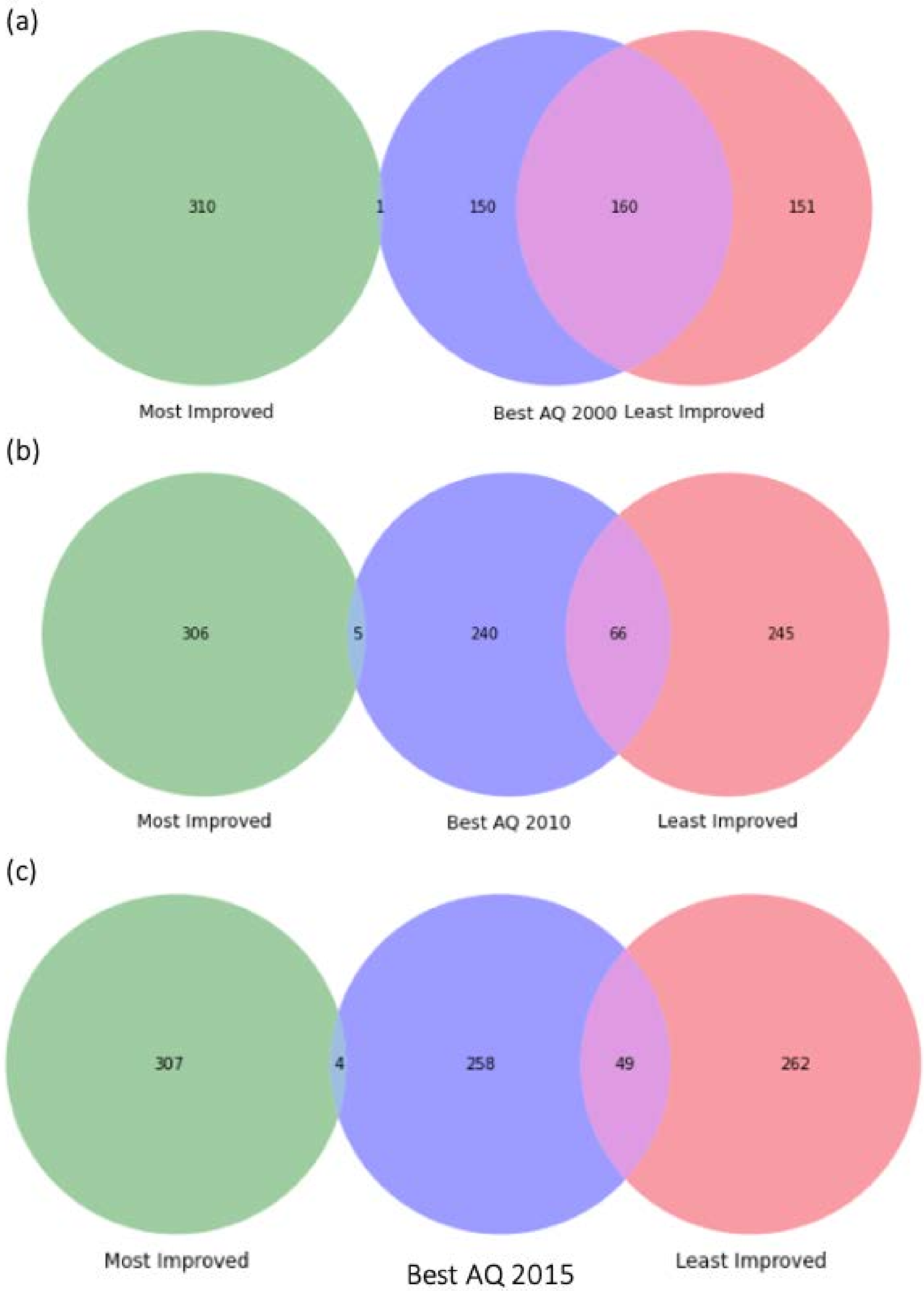

Figure 4-5: Counties identified has having the bottom 10^{th} percentile in $PM_{2.5}$ concentrations ("Best AQ") across all years are consistently overlapping with the counties identified as showing the least improvement in $PM_{2.5}$ concentrations between years 2000-2015

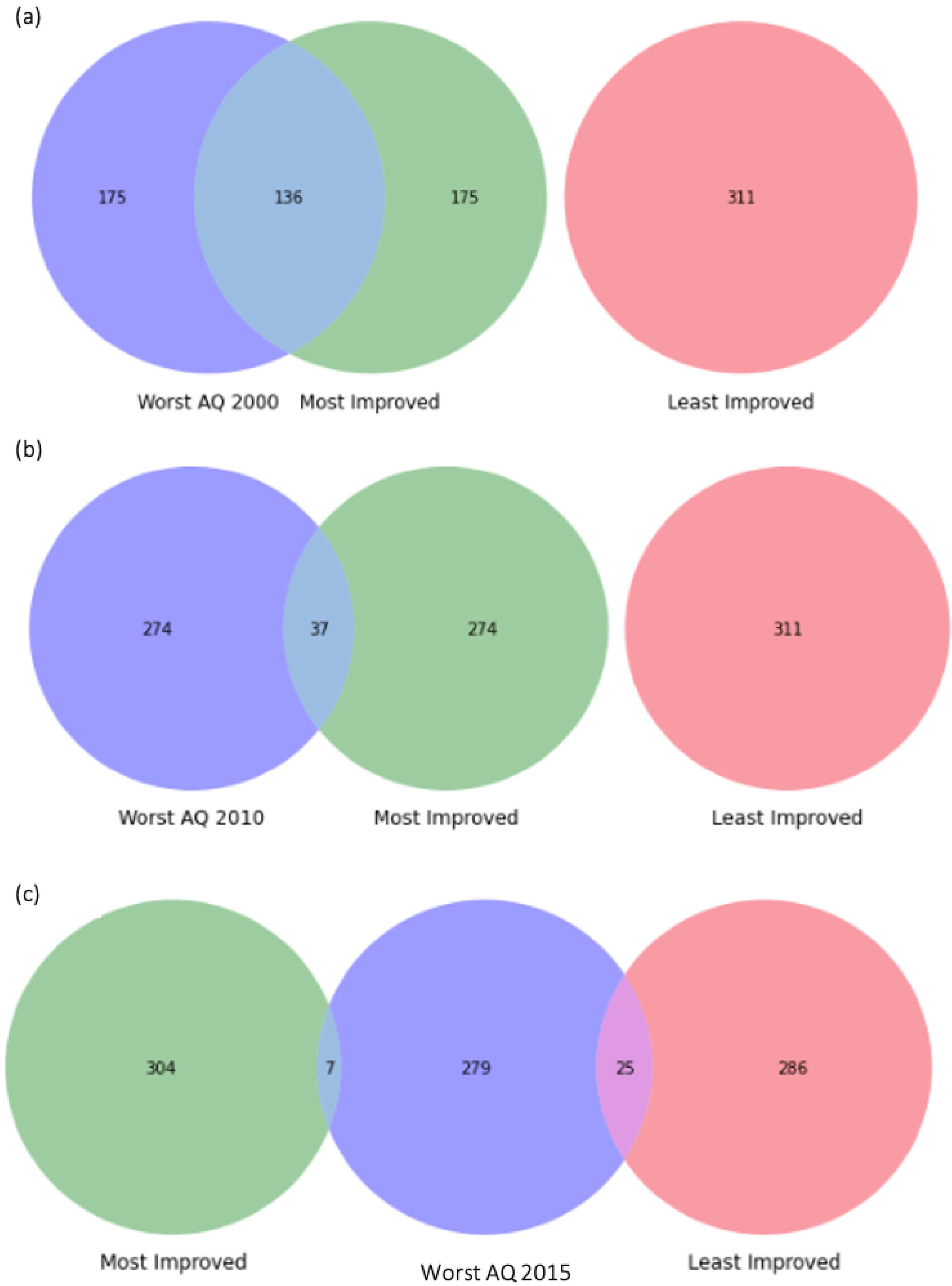

Figure 4-6: Counties identified has having the top 10^{th} percentile in $PM_{2.5}$ concentrations ("Worst AQ") across all years and overlaps with counties identified as having the most and least improvements in $PM_{2.5}$ concentrations between years 2000-2015

average racial/ethnic percentages. Most notably, 4 of these counties are counties that show highest increase in Asian populations across the country.

These findings are still consistent with conclusions by Colmer et al., which also found some local variations in rank changes that serve as exceptions. For example, California's Central and Imperial Valleys, southwestern Arizona, southern Texas and western Arkansas and eastern Oklahoma saw increases in $PM_{2.5}$ percentile rank, i.e. became relatively more polluted [13].

The significance of these findings are two-fold. First, while there exists a general correlation between regions that have experienced the worst pollution and regions that are seeing the greatest improvements in pollution, there are notable exceptions to these trends. In particular, there are regions that are not only identified as having the top 10^{th} percentile of $PM_{2.5}$ exposure, but are also seeing minimal improvements in $PM_{2.5}$ levels over time. Second, the counties identified as having these characteristics in this study are showing an over-representation of Asian and Hispanic populations. This is significant in that several studies exploring air pollution disparities only focus on gaps in exposure between White and Black populations. In order to provide nuanced and robust understanding of the disproportionate impacts on communities of color, studies should explore exposure disparities across all racial and ethnic minorities.

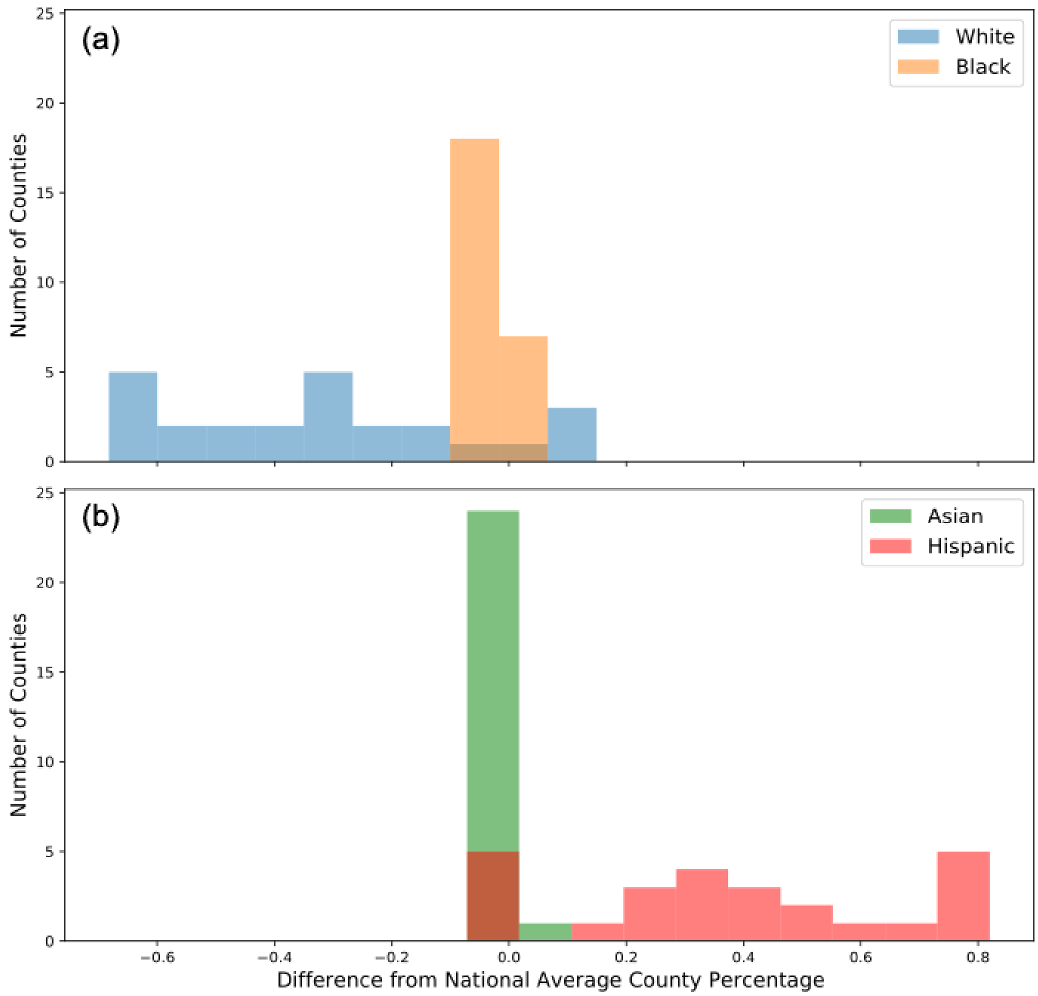

Figure 4-7: Racial Make up in Counties that are showing the top 10^{th} percentile in $PM_{2.5}$ levels ("Worst" $PM_{2.5}$ exposure) and are showing the least $PM_{2.5}$ pollution between years 2000-2015. The x-axis represents the difference between the population percentage from the U.S. national average for each ethnicity.

Chapter 5

Conclusion and Discussion

5.1 Key Conclusions

The key conclusions from this study are as follows:

1. **Exploration of PWA $PM_{2.5}$ Disparities at Different Geographic Scales**: Through calculating PWA $PM_{2.5}$ concentrations at different geographic scales, this study finds that national racial/ethnic disparities in $PM_{2.5}$ exposure are driven by differences in the census tracts where populations live rather than the within tract differences in exposure. As pollution exposure is driven by (1) where people live and (2) locations of sources of pollution, this finding suggests that the residences of racial/ethnic populations and the siting of pollution sources across tracts is influential and driving pollution disparities.

2. **Comparing Disparity Metrics**: We find that the absolute disparity metric (absolute difference in PWA $PM_{2.5}$) is more sensitive to magnitude of pollution levels while relative disparity as measured by the CoV is more sensitive to population demographics. Specifically, these two metrics differ in (1) the characterisation of changes in pollution magnitudes over time and (2) bias towards racial/ethnic groups with larger populations. Further, regardless of which metric is used, both relative and absolute disparity metrics identify regions that are not identified as in non-attainment with the Federal NAAQ standards, despite

showing pollution levels at the top 90^{th} percentile of national annual averages.

3. **Trends in Changing Demographics**: Results show a correlation between counties/tracts that are experiencing increases in non-Hispanic White populations and improvements in air quality. Further, there is evidence that counties/tracts with improvements in air quality are also correlated with decreases in non-Hispanic Black populations. This study also finds that regions experiencing the highest $PM_{2.5}$ concentrations but the least improvements in $PM_{2.5}$ are showing an over-representation of Asian and Hispanic populations.

In this chapter, I explore the policy implications for each of these main takeaways. Then, I consider policy levers to address persisting $PM_{2.5}$ inequities in exposure. Lastly, I present areas limitations of this study and areas for future research.

5.2 Policy Implications

5.2.1 Policy Implications for Conclusion (1)

Conclusion (1) as described in the previous Section 4.1 demonstrates that differences **across** different census tracts (rather than **within** census tracts) drive racial/ethnic disparities observed at the county/state/national level. These results imply that careful regulation within the tracts where pollution sources are permitted/sited and the tracts where people live can make substantial impacts in improving (or worsening) racial/ethnic disparities in $PM_{2.5}$ exposure. Currently, the regulations involved with siting/permitting of pollution sources and the land-use policies that influence where citizens live are two separate processes. We briefly describe the two regulatory regimes below, noting that these processes can vary greatly based on local and state regions, and then offer examples and suggestions for further integration of the two policy realms.

With the exception of highly regulated states, such as California, most permits for major sources of air pollution are issued by state/federal agencies rather than local governments[33]. Through the federal Environmental Protection Agency's (EPA)

New Source Review (NSR) permitting process, new (or modified) sources of pollution are reviewed for pollution impacts. NSR permits are typically issued by the EPA or by a state agency, but are sometimes issued by local air pollution control agencies (such as those in California) (EPA). As these permitting processes are highly technical, they have served to be relatively inaccessible to public and community input. Polluting industries are more likely to be located in disenfranchised neighborhoods, where low-income people of color disproportionately residents, due to lack of access to the decision making processes that determine where such polluting sources are located [19]. In December 2022, The EPA released a document for principals for addressing environmental concerns in air permitting, but the document lacks backing of an official regulatory document, and does not point to specific requirements that industries applying for permits must meet [32].

Land-use regulations that address issues such as zoning and land development are typically guided and enforced by local governments, such as city councils or planning commissions, but can be strongly influenced by federal guidelines. Zoning regulations in the U.S. that determine areas where specific housing developments (and other buildings) are built, and such processes have often been laced with implicit and explicit racial biases [26]. An example of such a policy in the residential sector is redlining, a historic race-based discriminatory mortgage appraisal system from the 1930s. There are a number of studies that outline the associations between HOLC designations and determinants of health, rates of emergency visits due to asthma, and, most recently, with present day pollution levels [?] [?] [23].

While there may be some interaction between these two regulatory processes, the permitting of pollution sources and the regulatory processes that influence places of residence are governed by separate laws and regulations. Given the important of these two factors in driving pollution exposures, this paper argues for further integration these pollution siting and land use policies as levers to reduce pollution inequities.

5.2.2 Considering Disparity Metrics as Indicators in Community Based Program and to support strengthening of existing NAAQ Standards

Conclusion (2) finds that the use of one disparity metric (absolute disparity) versus another (relative disparity using CoV) can result in different conclusions in identifying communities deemed as experiencing the highest disparities. We believe that these findings have two policy implications. First, these metrics can be used in support of strengthening existing NAAQ standards as a policy lever to reduce disparities. Second, these metrics can be used as indicators of improvement (or lack thereof) in racial/ethnic pollution disparities in community focused programs.

These metrics identify regions that are not included in the list of counties in non-attainment with the Federal NAAQ standards, despite being counties with the top 90^{th} percentile in pollution exposure. This is because many of these regions do not meet the threshold for non-attainment (which requires an annual arithmetic mean, averaged over 3 years, of 12 $\mu g/m^3$). Nonetheless, many of the regions showing high disparities (both absolute and relative) are in counties showing pollution levels above 10 $\mu g/m^3$. Further, previous literature has shown that those exposed to $PM_{2.5}$ levels well below 12 $\mu g/m^3$ have experienced substantial adverse health effect [15]. This may provide a compelling argument for tightening of existing NAAQ standards to lower thresholds given the potential for these standards to reduce both pollution levels and disparities.

Multiple studies have highlighted the effectiveness of command and control policies, such as the National Ambient Air Quality Standards (NAAQS), in not only reducing overall $PM_{2.5}$ but also reducing absolute inequities among those disproportionately affected by air pollution [21] [14]. Specifically, Currie et al. highlight that while this was not the regulation's intent, the NAAQ standards reduced gap between black-white exposure disparities by targeting counties with the highest pollution levels, which happened to be areas with the highest non-Hispanic Black populations. Further tightening of the standards may help include these areas identified as having high racial/ethnic pollution disparities as non-attainment zones, thereby allowing for targeted policy mechanisms to address these pollution concerns [14]. Section 5.3.1 further describes the Federal NAAQ standards and the policies in place to encourage attainment.

Next, absolute and relative disparity metrics can be used as indicators of progress made on reducing racial/ethnic disparities in communities already identified as disadvantaged communities experiencing disproportional pollution burden. Currently, community based programs that identify environmental justice communities (or disadvantaged communities (DAC)), require these communities to work with local air quality districts and officials to development plans to reduce overall emissions. The author is unaware of any plans that explore disparity metrics, such as the ones described in this paper, as performance indicators on the effectiveness of programs and plans in reducing emissions. These programs, which often employ local monitoring of pollutants, can use localized pollution data to calculate relative and absolute pollution disparities at geographic scales far more granular than the ones explored in this paper. Doing so can provide these communities with key performance indicators that mark the progress towards reducing pollution disparities. Section 5.3.2 further describes these community based programs.

5.2.3 Considering Disparity Metrics and Changes in Pollution Levels in Identifying Environmental Justice Communities

Conclusion (3) highlights the nuances that analyzing **Changes** in pollution levels brings to understanding trends in air quality disparities. As described in the introduction of this paper, Williamsburg, a predominately white neighborhood where the average household income is 166,600, was recently identified as a "disadvantaged environmental justice community" given its high pollution levels and **legacy** as an industrial area with a large minority population [18].

As policy makers determine which communities to identify as locations of most concern, it is important that we explore not only current pollution and demographic data, but also how mobility of different racial/ethnic groups relate to **changes** in air quality over time. This should be of consideration in screening tools that are used to identifying communities experiencing disproportionate environmental burden as such communities are often given state funding resources to improve pollution levels.

There are a number of environmental justice screening tools currently used at the metropolitan, state and federal level to identify environmental justice communities [5]. While each tool approaches the definition of an environmental justice community differently, most screening tools issue a score to a given region (most commonly the census tract region) based on a number of factors. We note here that as of 2022, the New York state and metropolitan screening tool does not include an explicit inclusion of air quality (neither pollution concentrations nor historical pollution levels) in its tool. Instead, under the New York State Climate Act, disadvantaged communities are identified based on socioeconomic factors and the discretion of the state's Climate Justice Working Group committee [5] [3].

Other tools adopt more methodological approaches to EJ community identification. Currently the scores for the EPA's EJ SCREEN (Environmental Justice Screening and Mapping Tool) are calculated based on three factors: environmental burden, sensitive populations, and socioeconomic vulnerability [2]. Each factor is given a weight, and the scores are calculated by combining the indicators within each factor using a formula that takes into account the distribution of the indicator values within a community and how they compare to the distribution of values across all communities in the U.S. None of the 12 environmental indicators consider the rate of pollution improvement.

In the case of this analysis, we find that by exploring pollution data holistically, researchers can uncover nuances in exposure trends over time. As such, by coupling metric based EJ community identification methods (such as using screening tools) with additional data analysis (such as the exploration of pollution trends over time) and finally community engagement, policy makers can better identify and address pollution disparities within the most disadvantaged communities.

5.3 Policy Levers to Reduce Inequities

In this section, we provide some more details on the some of the policies mentioned previously and detail how they can effectively reduce persisting racial/ethnic inequities in $PM_{2.5}$ exposure.

5.3.1 Command and Control Policies (NAAQS)

Multiple studies have highlighted the effectiveness of command and control policies such as the National Ambient Air Quality Standards (NAAQS) in not only reducing overall $PM_{2.5}$ but also reducing absolute inequities among those disproportionately affected by air pollution [21] [14]. As such, one pathway to mitigate air pollution disparities is to tighten these air quality standards under the Clean Air Act (CAA).

The CAA amendments of 1970 and the establishment of the EPA increased federal power to regulate air pollution in order to protect public health and the environment from harmful air pollutants. As stated in the introduction, the NAAQS specify maximum allowable concentrations for 6 criteria air pollutants: ground-level ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, and lead. These standards govern both stationary and mobile sources.

Pollutant-specific NAAQS were initially established for sulfur dioxide, carbon monoxide, nitrogen dioxide, lead, particulates, and eventually ozone. Each year, counties that are in violation of these standards are deemed in "non-attainment," and state governments are then required to develop pollutant-specific plan, known as a State Implementation Plan, describing how areas will improve air quality and come into compliance.

Failure to develop an adequate plan results in severe consequences, such as the withholding federal funding for the state air pollution control program, highway construction, and the construction of sewage treatment plants. The EPA can also ban permits for construction of major new and/or modified sources of a pollutant in communities that are out of compliance with NAAQS.

In Janurary of 2023, the EPA announced a proposal to tighten existing annual

$PM_{2.5}$ NAAQS from 12 $\mu g/m^3$ to between 9-10 $\mu g/m^3$ [31]. The existing annual NAAQ standard was set in 2012. Multiple studies have demonstrated the adverse health effects of $PM_{2.5}$ levels well below $12\mu g/m^3$, particularly for marginalized sub-populations disproportionately impacted by pollution [7] [8]. Josey et al found that more stringent NAAQS standards would not only benefit all populations across racial/ethnic identities and socioeconomic status, but also result larger reductions in mortality among older Americans and marginalized minorities [21].

While many have argued that there is no $PM_{2.5}$ level that will be low enough to fully protect public health and mitigate environmental health inequities, strengthened standards can lead to larger reductions in mortality and, as recently literature has demonstrated, work to reduce racial/ethnic disparities as well [13] [21].

5.3.2 Community Focused Programs

A popular debate in recent years surrounding the use of cap-and-trade policies as market mechanisms to reduce carbon emissions is the potential for these policies to result in increasing local pollution given the opportunities for polluters to "trade" permits and continue polluting in neighborhoods that are already deemed most disadvantaged. This debate was raised in the state of California during the proposal of Assembly Bill (AB) 32, which among other provisions, would establish a cap-and-trade program. AB617 was designed to directly address environmental justice concerns by identifying disadvantaged communities, development emission reduction programs, and providing funding for pollution mitigation efforts.[17]

Administered by the California Air Resources Board (CARB), the AB617 Community Reduction Program involves a variety of strategies, including community engagement, air monitoring, emission reduction strategies, and enhanced enforcement of air quality regulations. One of the unique features of the AB617 program is the development of its community reduction plan, which brings together community members, industry representatives, and local government officials to identify and implement targeted strategies for reducing air pollution in the area. [17]

After the establishment of California's AB617 program, other states also adopted similar programs. This includes Michigan's Environmental Justice Public Advocate Program, established by Governor Gretchen Whitmer in 2019. Similarly in Washington, the Climate Commitment Act (Senate Bill 5126) was passed in 2021 to establish a economy-wide "cap-and-invest" policy that also integrates an environmental justice companion bill, Senate Bill 5141. Under SB 5141, also known as the Health Environment for All (HEAL) Act, the following initiatives were implemented: (1) 35 percent of investments from the state's "cap-and-invest" program would be directed to communities disproportionately affected by air pollution (2) 10 percent of these investments would be directed to Tribal nations and (3) bi-annual environmental justice will be held to reassess criteria pollutant standards. [4]

A key shortcoming of these programs is the community identification process, as highlighted in previous sections. Existing studies have identifying key concerns with screening tools, many of which include lack of up-to-date data, limited disaggregation of race and ethnicity demographics, and finally, inconsistent calculation and aggregation of environmental and social indicators. For example, researchers have found that communities most exposed to PM 2.5 and lead paint score poorly on the EPA EJScreen's scoring system because their share of low-income individuals and/or people of color is below the national average [5].

Additionally, some states develop their definition of an "environmental justice" community, or a "disadvantaged community" before the creation of their specific screening tool, while others develop these definitions after. The order in which a state agency develops these definitions and the creation of these indices can make a significant impact on the granularity of these definitions and what metrics are used to calculate thresholds of identification. Despite these shortcomings, screening tools are an important first step to identifying existing environmental disparities. [5]

5.4 Limitations of this Study and Suggestions for Future Work

This analysis provides valuable insight for understanding the spatial and temporal aspects of calculating disparity metrics, setting the stage for future analysis in this area. Nonetheless, our study can be strengthened by addressing the following limitations:

5.4.1 Scale and Source of Pollution Data

While our study shows that racial and ethnic disparities in exposure are driven by differences **across** tracts rather than **within**, previous literature has shown that mobile monitoring of $PM_{2.5}$ pollution data at the hyper-local scale (<100m) can help to reduce localized peaks in emissions observed in urban areas [10]. Reducing localized concentration extremes may be of particular interest to environmental justice communities such as those within California's AB617 program. Further work can be done implement the methods used in this study to explore effectiveness of local policies and actions on reducing pollution extremes within a specific community.

Further, future studies can explore other sources of pollution data to confirm the results in this paper. Pollution estimates from land-use regression models (LURs) may be sensitive to the choice of predictor variables or model parameters. For example, population demographics are used as a variable in our pollution estimates, but we also use these estimates to explore demographic trends. As such, this may influence the result of our analysis. Implementing these calculations of disparity metrics with different data sources can help to add to the robustness of these analyses.

5.4.2 Equity Concerns with Census Data

There are a number of equity concerns when utilizing census data for ensuring that under served communities are accounted for and included in data analysis First, with regards to under-counting, the census may not accurately capture the true population size, particularly for hard-to-count populations such as immigrants, people experiencing homelessness, and those living in poverty. This can lead to an misrepresentation of these populations in the data, which can skew the analysis and limit the ability to identify and address disparities.

Other limitations include incomplete data and inadequate geographic resolutions. The census collects a limited set of demographic data, such as race, ethnicity, age, and gender. However, these categories may not fully capture the diversity and complexity of individuals and communities, particularly for populations that identify as multiracial or non-binary. This can limit the ability to identify and address equity issues that are specific to these populations. Additionally, Census data are typically aggregated at the block, tract, or county level, which may not be granular enough to capture disparities at the neighborhood or sub-neighborhood level. This can obscure the existence of pockets of disadvantage or privilege within larger geographic areas. Further, sampling errors may add to a reduction in accuracy. The census relies on a sample of the population to collect data, which can introduce sampling errors, which can particularly problematic for smaller geographic areas or sub-populations, where the sample size may be too small to provide reliable estimates.

Finally, there is an issue of access. The census is conducted in English and Spanish, which may create barriers for non-English or non-Spanish speaking populations. This can limit the ability of these populations to participate in the census and contribute to inaccuracies in the data. Overall, despite equity limitations, census data remains an important and useful tool for understanding demographic patterns and identifying disparities, and is widely used by researchers, policymakers, and community organizations alike.

It is important for studies on explore racial/ethnic disparities to highlight and emphasize the shortcomings of existing data. Given these limited data on racial/ethnic groups that do not fall within the four major categories (Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian, Hispanic/Latino), the author wants to emphasize the importance of collecting data for underrepresented populations, particularly Native/Pacific Islander populations that do not reside in the 48 contiguous U.S. states. Further, the groupings of these racial/ethnic categories may obscure trends related to the sub-groups within these categories. For example, non-Hispanic Asians represents a vastly diverse population that covers racial/ethnic groups across different cultures and languages.

5.4.3 Interpolation Methods

The findings of this report are subject to the robustness of the interpolation methods that estimate demographics for year 2015 using U.S. Census data for years 2010 and 2020. Linear interpolation assumes a constant rate of change in demographics, which may not necessarily be true. There are two options for improving the accuracy of demographic data in years between the decennial census reports. First, future work can be done to improve inter-year estimates by exploring other interpolation methods such as cubic spline, monotone cubic interpolants, and interpolations using piece wise polynomials. Second, future studies can use annual tract level demographics data from NHGIS, as mentioned in the Methods section, but would need to compromise on the geographic granularity.

5.4.4 Correlation/Causation Movement and Demographic Trends

This study explores the correlations between demographic changes (as a proxy for migration) and changes in air pollution levels over time. Future work can be done to explore the casual mechanisms for this relationship to determine the direction of causality. For example, are non-Hispanic Whites moving into communities with improving pollution levels, or are pollution levels improving for communities that have seen recent increases in non-Hispanic White populations?

5.4.5 Additional Disparity Metrics

This study employs three definitions of pollution disparities: (1) Absolute disparities using the differences in absolute $PM_{2.5}$ exposures [24], (2) Relative disparities using the coefficient of variance [20], and (3) Relative disparities using rank-by-rank analysis of pollution concentrations at county and census tract levels [13]. Future work can explore inequality metrics such as the Gini Coefficient and the Atkinson's index, metrics commonly used to identify income inequality, and employ them for measuring air quality disparities. Comparisons of the advantages and disadvantages of these indexes can help to inform the identification of inequities in pollution exposure in future research and in development of future environmental justice screening tools.

5.5 Conclusions

Capturing the cumulative impacts across a wide range of factors (environmental, socioeconomic, physical and mental health, and climate indicators) is a complex task given the inherent difficulties of capturing non-quantifiable factors into numeric metrics. Quantitative measures of inequality cannot fully represent the multi-faceted nature of environmental burdens faced by a disadvantaged community, and environmental justice screening tools and researchers should be transparent about the limitations of the indicators used. Nonetheless, inequality measures can provide important insight into pollution exposure are changing over time and space. Careful selection of these indicators and use can have consequential impacts to reducing exposure inequities for those most impacted.

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