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Socioeconomic and racial disparities in source-apportioned $PM_{2.5}$ levels across urban areas in the contiguous US, 2010

Pablo Knobel[1,*], **Inhye Hwang**[1,*], **Edgar Castro**[2], **Perry Sheffield**[1], **Louisa Holaday**[3], **Liuhua Shi**[4], **Heresh Amini**[5], **Joel Schwartz**[2], **Maayan Yitshak Sade**[1]

[1]Icahn School of Medicine at Mount Sinai, Department of Environmental Medicine and Public Health, New York, NY, USA

[2]Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, MA, USA

[3]Division of General Internal Medicine, Department of Medicine, Mount Sinai School of Medicine, New York, New York, USA

[4]Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA, USA

[5]Department of Public Health, University of Copenhagen, Copenhagen, Denmark

Abstract

Fine particulate matter ($PM_{2.5}$) air pollution exposure is associated with short and long-term health effects. Several studies found differences in $PM_{2.5}$ exposure associated with neighborhood racial and socioeconomic composition. However, most focused on total $PM_{2.5}$ mass rather than its chemical components and their sources. In this study, we describe the ZIP code characteristics that drive the disparities in exposure to $PM_{2.5}$ chemical components attributed to source categories both nationally and regionally. We obtained annual mean predictions of $PM_{2.5}$ and fourteen of its chemical components from spatiotemporal models and socioeconomic and racial predictor variables from the 2010 US Census, and the American Community Survey 5-year estimates. We used non-negative matrix factorization to attribute the chemical components to five source categories. We fit generalized nonlinear models to assess the associations between the neighborhood predictors and each $PM_{2.5}$ source category in urban areas in the United States in

Corresponding author: Pablo Knobel, pablo.knobel@mssm.edu, **Address:** 1 Gustave L. Levy Place, Box 1057. New York, NY 10029.
*Co-first Authors

Credit author statement:
Pablo Knobel: Conceptualization, Methodology, Formal analysis, Visualization, Writing - Original Draft. **Inhye Hwang:** Investigation, Writing - Original Draft. **Edgar Castro:** Data Curation. **Perry Sheffield:** Writing - Review & Editing. **Louisa Holaday:** Writing - Review & Editing. **Liuhua Shi:** Resources. **Heresh Amini:** Data Curation. **Joel Schwartz:** Data Curation. **Maayan Yitshak Sade:** Conceptualization, Methodology, Supervision, Project administration, Writing - Review & Editing.

Declaration of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

2010 (n=25,790 zip codes). We observed higher $PM_{2.5}$ levels in ZIP codes with higher proportions of Black individuals and lower socioeconomic status. Racial exposure disparities were mainly attributed to Heavy Fuel, Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Economic disparities were mainly attributed to Soil and Crustal Dust, Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Upon further analysis through stratifying by regions within the United States, we found that the associations between ZIP code characteristics and source-attributed $PM_{2.5}$ levels were generally greater in Western states. In conclusion, racial, socioeconomic, and geographic inequalities in exposure to $PM_{2.5}$ and its components are driven by systematic differences in component sources that can inform air quality improvement strategies.

INTRODUCTION:

Fine particulate matter ($PM_{2.5}$) air pollution exposure is associated with short and long-term health effects [1]. $PM_{2.5}$ has been found to have the heaviest burden on non-Hispanic Black populations and those of lower socioeconomic status (SES) [2, 3]. An example can be found in a recent study that showed disparities in levels of $PM_{2.5}$ exposure across racial and income groups, with consistently higher exposure levels among the Black and Hispanic populations and those classified within the low-income group [2]. There is a myriad of factors that may predispose specific communities to higher levels of exposure to $PM_{2.5}$ [2]. Identifying these factors is particularly important because of the associated adverse health outcomes [3]. Many studies have found $PM_{2.5}$ exposure to be associated with increased risk for neurologic [3], respiratory and cardiovascular diseases [4]. Moreover, $PM_{2.5}$ exposure was associated with 4.58 million deaths and 142.52 million disability-adjusted life years (DALYs) globally, according to the global burden of disease 2017 [5].

Multiple factors have historically paved the way for $PM_{2.5}$ exposure disparities. For example, redlining: a form of structural racism that graded urban areas across the US in the 1930s and limited access to insurance and loans based mainly on neighborhood racial composition and migrant status [6]. Neighborhoods with “hazardous” redlining grades have been associated with higher levels of pollution [6]. As another example, major roadways which cater to high-density traffic are predominantly located near minority and high-poverty neighborhoods [7], putting disadvantaged populations at a higher risk of exposure to vehicle-related pollutants. The location of highways for the Federal-Aid Highway Act of 1956 – an act that authorized the building of the nation’s highway system and was the most prominent public work project to date - purposely targeted black communities across the US [8].

While studies have investigated $PM_{2.5}$ mass exposure disparities [4, 10, 11], studies that investigate disparities in specific $PM_{2.5}$ chemical components are scarce. One study investigated whether the exposure to different chemical components differed by race/ethnicity, age, and SES. They observed larger disparities for chlorine (Cl), zinc (Zn), and aluminum (Al) than for total $PM_{2.5}$ mass, especially among minority groups and those of lower SES [2]. Another study focused on the chemical components and their varying impacts on mortality and found associations between location-specific relative risks and several chemical components[9]. Lastly, another study found that racially segregated communities in the US are exposed to higher levels of $PM_{2.5}$ components [10].

However, which specific sources drive neighborhood disparities in $PM_{2.5}$ and its components exposure levels remain unclear. Since the health effects of each chemical component and source can be unique and independent from each other [11], it is crucial to investigate disparities in exposure to $PM_{2.5}$ mass and chemical composition.

In this study, we aim to assess the association between ZIP code level socioeconomic and racial characteristics and source-apportioned $PM_{2.5}$ levels incorporating 14 $PM_{2.5}$ chemical components obtained from highly spatiotemporally resolved exposure models across the contiguous US in 2010. We hypothesize that ZIP codes with lower socioeconomic status and higher percent of non-Hispanic Black will have higher exposure levels to all $PM_{2.5}$ sources.

METHODS:

Study population and zip code level sociodemographic data

We conducted a descriptive cross-sectional study including sociodemographic information on urban zip codes across the contiguous United States in 2010. Since urban ZIP codes are considerably smaller geographically compared to rural ZIP codes and cover about 92% of the US population [12], we decided to restrict the analytical dataset to urban ZIP codes in which the spatial variability of the SES variables within ZIP codes is lower. We used Rural-Urban Commuting Area (RUCA) codes from the 2010 Census urban and rural classification to differentiate urban and rural areas. RUCA contains ten primary codes, with lower numbers indicating the more urbanized area and higher numbers indicating more rural areas [13]. This classification is based on population density and nearby geographic areas containing non-urban land use [14]. We included ZIP codes in our analysis if the RUCA code was equal to or less than 6 (code for “Micropolitan low commuting”).

We included three measures that capture different dimensions of socioeconomic status [15] and one measure of racial composition. From the U.S. 2010 Decennial Census [14], we obtained the percentage of the population identifying as non-Hispanic Black and the percentage of housed individuals renting their property. We also obtained information on the percent of the adult population with no high school education and percent of the adult population with income below the poverty line from the American Community Survey (ACS) 5-year estimates [16]. Since zip code tabulation area information was unavailable in 2010, we imputed these variables for 2010 by linearly extrapolating between the measured years (2013–2020). We consider the poverty rate as a measure of extremely low socioeconomic status and home ownership as a measure of wealth. For more straightforward interpretability and comparison, we used the percentage of home renters instead of home ownership. We consider the percentage of the population without a high school diploma as a measure that captures both low socioeconomic status and education level [16]. Finally, since in many studies of exposure and health disparities Black residents are considered a deprived group [17, 18], we treat the percentage of the population who identify as non-Hispanic Black as a measure of racial composition.

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Air pollution exposure

We obtained 2010 annual mean predictions of $PM_{2.5}$ from a generalized additive model ensembling three machine-learning models using predictor variables from satellite data, meteorological variables, land-use variables, elevation, and others [19]. Additionally, we obtained 2010 annual mean predictions of fourteen $PM_{2.5}$ components from national super-learned models. Component concentrations were estimated using machine learning models, combined with generalized additive model ensemble geographically weighted averaging. The model incorporated 166 predictor variables from 987 air pollution and weather monitoring sites across the United States, time and geography information (year, latitude, longitude, elevation, meteorological data (temperature, humidity, wind velocity and direction, planetary boundary layer height, etc), satellite observations (vegetation, water index, nighttime lights, CO and CH4, aerosol optical depth, etc), emitting/surrogate of emission sources (distance to power plants, distance to highways, traffic counts, burning index, etc.)and other sources. The chemical components were the following: elemental carbon (EC), organic carbon (OC), nitrate (NO_3), SO_4, bromine (Br), calcium (Ca), copper (Cu), iron (Fe), nickel (Ni), potassium (K), lead (Pb), silicon (Si), vanadium (V), and zinc (Zn). The R^2 values in unseen test sets were above 0.90 on average ranging from 0.79 for Cu to 0.94 for SO_4. The predictions were made at 50×50m spatial resolution [20, 21]. In addition, we averaged exposures within each ZIP code.

Statistical analysis

We used non-negative matrix factorization (NMF) to attribute the 14 $PM_{2.5}$ chemical components to sources [22] across the contiguous US using the *nmf* R package [23]. This reduces the dimensions of the data and produces factors more translatable to policy action. Due to its non-negative constraint, NMF is an efficient method for dimension reduction of a matrix of $PM_{2.5}$ chemical components into a lower dimension non-negative matrix that best approximates the original components data [24]. We tested for possible 4 to 7 factors and conducted 100 multiple runs to obtain best factorization fit. Although there was no clear inflection point observed on the residuals sum of squares curve, the largest decrease in values was from 4 to 5 factors, followed by a less steep curve. Visual inspection of the mixture coefficient matrix and the lowest correlation between the factors also supported the selection of 5 factors. This model performed best in terms of separating the loadings of the components between factors and estimating independent factors (i.e., yielding the lowest correlation between factors). We then identified factors as sources based on high loadings of chemical components known to be emitted from these sources.

We conducted generalized nonlinear models including each ZIP code characteristic separately to assess the independent associations with each source category using the *gnm* R package [25]. We adjusted for population density, RUCA, % over 65, and % female population. Subsequently, to investigate the potential effect modification by the US region, we conducted the same models but stratified the sample for each of the four US regions [26]. Finally, as a sensitivity analysis, we conducted models including all ZIP code characteristics simultaneously to assess the concurrent associations with each source category. All estimates have been calculated to report the associations with a 10% change in the predictors. All analyses were performed in R version 4.1.1 [27].

RESULTS:

The characteristics of the 25,790 included ZIP codes are presented in Table 1. The included ZIP codes cover about 92% of the U.S population. The mean population density in the included ZIP codes was 311 people per square mile, while the mean population density in the excluded rural ZIP codes is 103.7 people per square mile. In the In 2010, the median percent of the ZIP code population falling under poverty levels was 12.15%, the percentage of people without a high school diploma was 14.52%, the percent of the population identified as non-Hispanic Black was 2.81%, and 25.36% rented the residence they occupied. Overall, the average $PM_{2.5}$ level in 2010 was 9.65 μg/m^3. The zip code characteristics correlations were low to moderate, with the highest correlation of 0.65 between the percent below the poverty line and the percent without a high school diploma and the lowest being 0.18 between the percentage without a high school diploma and the percentage of renters (Supplementary Figure 1).

Of all the included ZIP codes, 26.4% were in the Midwest, 12.9% were in the Northeast, 43.0% were in the South, and 17.7% were in the West region. Figure 1 shows the spatial distribution of $PM_{2.5}$ mass concentrations across urban zip codes in the US in 2010. The average levels of $PM_{2.5}$ were 10.67 μg/m^3 in the Midwest, 9.33 μg/m^3 in the Northeast, 10.22 μg/m^3 in the South, and 6.96 μg/m^3 in the West. Summary statistics of exposure levels to the 14 chemical components incorporated in our analysis are presented in Supplementary Table 1.

Using NMF, we identified five distinct $PM_{2.5}$ source categories. We identify the 1st category as Soil and Crustal Dust based on high loading of Si and Ca [28, 29]; the 2nd as Heavy Fuel Oil and Industrial based on high loadings of Ni, V, EC, and Cu [30]; the 3rd as Metal Processing Industry and Agricultural Sources based on high loadings of Pb, Zn, and NO_3 [23, 24]; the 4th as Coal and Oil Combustion, and Biomass Burning based on high loadings of SO_4, OC, V, and K [28, 31]; and the 5th as Motor Vehicle based on high loadings of EC, OC, Fe, and Cu [21, 25–27] (Figure 2).

Factor 4 includes a wide range of sources since the model was not able to separate these sources well, regardless of the number of factors selected. This source was identified as biomass burning based on high loading of K, and OC commonly attributed to emissions from fire wood burning, waste incineration, and agricultural burning. It was also identified as coal combustion based on high loadings of OC and SO_4 and oil combustion based on high loadings of V.

The spatial distributions of the five source categories are presented in Supplementary Figures 2–6. Overall, we saw higher Motor Vehicle particle concentrations along the coasts. We observed a distinctively higher concentration in the Eastern region for the Coal and Oil Combustion, and Biomass Burning sources. We saw high concentrations along the coasts and in the Western and upper Midwest regions for the Heavy Fuel Oil and Industrial sources. The Metal Processing Industry and Agricultural sources were substantially more pronounced in the Northeast, Midwest, and mid-Atlantic regions. Soil and Crustal Dust spread nationally, excluding the Northeastern region.

As shown in Figure 3 and Supplementary Table 2, we observed higher $PM_{2.5}$ levels in ZIP codes with a higher percentage of non-Hispanic Black residents, higher poverty rates, a higher percent of people without a high school diploma, and a higher percentage of people who rent their place of residence. Assessing each $PM_{2.5}$ source category separately, we found that ZIP codes with a higher percentage of non-Hispanic Black individuals were associated with higher levels of Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Additionally, ZIP codes with a higher percentage of individuals without a high school diploma, individuals below the poverty line, and individuals renting their place of residence – all three socioeconomic predictors - were associated with higher levels of Soil and Crustal Dust, Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Higher levels of Coal and Oil Combustion, and Biomass Burning were associated with lower percentages of non-Hispanic Black residents, poverty, education levels, and renters

As seen in Figure 4 and Supplementary Table 3, the associations with $PM_{2.5}$ mass and all ZIP code variables were more pronounced among ZIP codes in the Western region. Soil and Crustal Dust associations with education and poverty where more pronounced in the West, followed by the South, and then the Midwest. The associations dissipated in the Northeast. Heavy Fuel Oil and Industrial associations with the percentage of non-Hispanic Black individuals were stronger in the West, followed by the Northeast. The socioeconomic associations with Heavy Fuel Oil and Industrial were stronger in the Northeast. Metal Processing Industry and Agricultural effect modification differed by the predictor, with only the South consistently having smaller associations. Motor vehicle associations were consistently stronger in the West, closely followed by the Midwest.

As seen in Supplementary Table 4, most of the associations maintained their direction in the multiple predictor analysis except for poverty, which drastically changed direction in the associations with Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle. We hypostatize this is due to the correlation between poverty and the other predictors.

DISCUSSION:

In this descriptive cross-sectional study, we found higher levels of $PM_{2.5}$ exposure in ZIP codes with proportions of Black individuals, lower education, and lower SES. We also identified disparities in specific source categories of $PM_{2.5}$. Racial exposure disparities were mainly attributed to Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Socioeconomic disparities were mainly attributed to the Soil and Crustal Dust, Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle sources. Upon further analysis through stratifying by regions within the United States, we found that the associations between ZIP code characteristics and source-attributed $PM_{2.5}$ levels were generally greater in Western states.

Consistent with current literature, our results indicate that $PM_{2.5}$ exposure levels are higher among populations of lower socioeconomic status and racial minorities. For example, a nationwide study in the US found that Black, Asian, Hispanic, and Latino populations are exposed to comparable levels of $PM_{2.5}$ and that those levels were lower for the White population. Similarly, the study found consistent differences among income groups, with lower exposure to $PM_{2.5}$ for the high-income group [32]. A Beijing study found that higher average income and a higher percentage of high school graduates were associated with reductions in average annual $PM_{2.5}$ exposure [33]. Another nationwide study in the US found that people of color had higher than average $PM_{2.5}$ exposures while Whites had lower than average [34].

Adding to the existing literature on $PM_{2.5}$ mass exposure disparities, we investigated the contribution of specific $PM_{2.5}$ source categories to racial and economic disparities. We found higher levels of Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle attributed $PM_{2.5}$ in ZIP codes with higher proportions of non-Hispanic Black individuals. This suggests that these Black individuals may be more readily exposed to higher levels of Ni, V, EC, Cu, Pb, Zn, NO_3, OC, and Fe. These results are consistent with a study that found that Black populations had higher estimated exposures for multiple $PM_{2.5}$ chemical components, including V, EC, OC, and the highest average exposure level for Zn [2]. This could potentially be a residual effect of redlining practices that disproportionately graded black communities as undesirable and resulted in them being systemically plagued by the persistence of concentrated poverty [7], where they may be more vulnerable to higher levels of $PM_{2.5}$ exposure.

We used three different measures of SES to assess economic disparities in exposure to $PM_{2.5}$ sources. We found indicators of lower SES associated with higher levels of Soil and Crustal Dust, Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle attributed $PM_{2.5}$. This is consistent with a recent study that found that the road density of high-poverty areas is almost two times that of the least poor neighborhoods [7], which may indicate that ZIP codes with higher poverty rates are more abundantly situated near industrial sites and high-traffic areas. Furthermore, the strength observed associations of the three SES indicators varied from one source to the other: for example, the percentage of renters had the smallest association with Soil and Crustal Dust but the strongest for Heavy Fuel Oil and Industrial. While these results are consistent with the current literature, which suggests that exposure to $PM_{2.5}$ and its chemical components is higher for lower socioeconomic classes [2], our study highlights that these associations are divergent for different SES indicators.

Unlike our hypothesis, we found that neighborhoods with a higher proportion of non-Hispanic Black individuals, renters, poverty, and lower educational levels were associated with lower levels of Coal and Oil Combustion, and Biomass Burning sources. This might be attributed to the lower prevalence of biomass burning sources in larger cities where non-Hispanic Blacks and lower socioeconomic status communities are more likely to live. Since this source factor combines multiple emission sources (i.e. oil, coal, and biomass burning), it is challenging to compare our results to other studies. An example of a similar result, is in a study which found an inverse association with SO_4 [2], a chemical component within this category. This study found lower SO_4 exposure concentrations in neighborhoods with greater proportions of people without a high school diploma. This likely reflects sulfate concentrations and coal combustion being long-range transport pollutants with often lower concentrations in larger cities. Most studies, however, show that groups with lower SES are disproportionally exposed to higher levels of most $PM_{2.5}$ sources. For example, a study found that neighborhoods with low education levels and high unemployment levels, both indicative of an unfavorable SES, resided in cities with higher concentrations of combustion-related air pollutants [35]. Another study found that low-income communities and communities of color in the US have disproportionately high exposure to air pollution from coal-fired power plants [36]. Therefore, this finding requires further investigation.

An important finding of our study are the different associations observed across U.S regions. Comparing the Western region to the rest, we found larger socioeconomic and racial disparities in exposure to the Motor Vehicle, Metal Processing Industry and Agricultural, and partially Heavy Fuel Oil and Industrial sources. Several studies within this region observed exposure disparities among racial and ethnic minorities and disadvantaged populations. A recent study found a greater population-weighted diesel emissions exposure for residents in the lowest median income quintile, with the highest inequalities observed in Phoenix, Arizona, and Los Angeles, California [37]. Another study in Southern California also found that high-poverty areas have almost twice the traffic density of the least poor areas, and racial and ethnic minority areas have almost 2.5 times the traffic density of non-minority areas [7].

The associations between poverty, education level, and Soil and Crustal Dust attributed $PM_{2.5}$ were also more pronounced in the Western region, followed by the South region. This agrees with current literature on wind erosion and dust in the US, as a recent study has found that over two hundred thousand square miles of land in the US is more susceptible than ever to soil erosion caused by wind, and roughly two-thirds of that is on federally managed land in the West [38]. Additionally, current literature finds that in terms of spatial trends, multidimensional poverty is more prevalent in the Western and Southern regions of the US [39]. Therefore, the higher prevalence of multidimensional poverty and land susceptible to soil erosion in the Western region of the US could explain the larger exposure disparities observed in this region.

Our study has several limitations worth noting. First, we used ZIP code as the geographic unit of analysis. Although this increases the potential exposure measurement error due to within ZIP code variation, exposures at a smaller geographic unit will have higher uncertainty values [32], which poses a challenge in attributing $PM_{2.5}$ chemical component exposures to different sources. Additionally, our analysis only studied urban ZIP codes within the United States. Therefore, our results might not be generalizable to rural areas. However, since urban ZIP codes are considerably smaller compared to rural ZIP codes, we have decided to restrict the analytical dataset to urban ZIP codes in which the spatial variability of the SES variables within ZIP codes is lower. Moreover, while rural areas cover more US land, urban areas cover about 92% of the population [12].

CONCLUSIONS:

In conclusion, socioeconomic and racial disparities persist in exposure levels to $PM_{2.5}$ and its chemical components. The racial disparities were driven by higher Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle attributed sources. Socioeconomic disparities in exposure, represented using poverty and home renting rates, and educational attainment were driven by Soil and Crustal Dust, Heavy Fuel Oil and Industrial, Metal Processing Industry and Agricultural, and Motor Vehicle $PM_{2.5}$ sources. Most associations were more pronounced in the Western region of the US. Our results showcase inequalities in the exposure to $PM_{2.5}$ and its components across the US. Recognizing specific population groups suffering higher exposure – either due to racial composition, SES, or geographical location – can guide policymakers in creating policies targeted not only to the general reduction of air pollution exposure but also to ameliorate the situation of the most vulnerable population groups.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights:

- Literature on exposure disparities focuses on $PM_{2.5}$ mass instead of components.
- Each $PM_{2.5}$ component has different sources and health effects.
- There are socioeconomic and racial exposure disparities in $PM_{2.5}$ and its components.
- Exposure disparities differ amongst US regions.

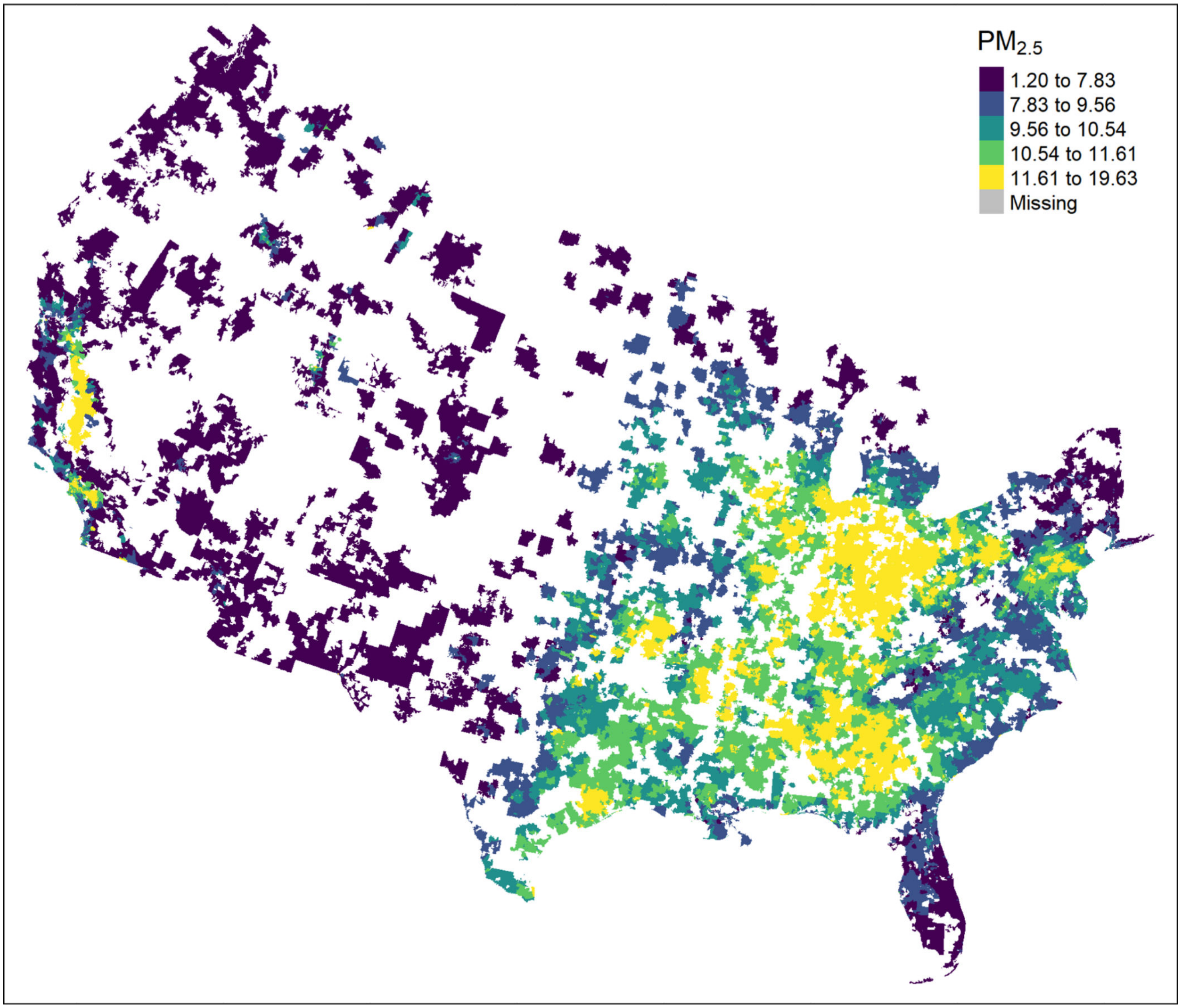

Figure 1:
Map of the spatial distribution of $PM_{2.5}$ mass concentrations in the contiguous U.S for 2010.

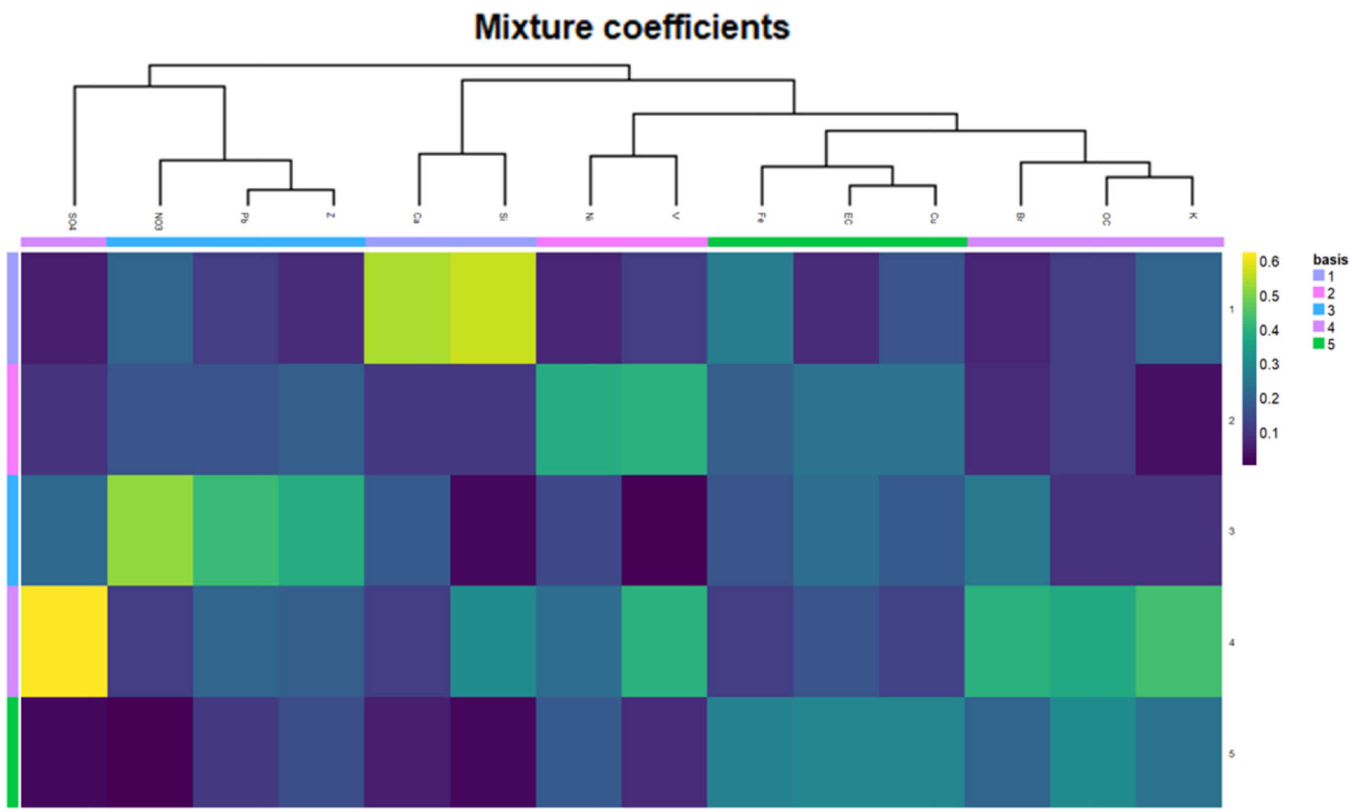

Figure 2:

A heat map of the mixture coefficients matrix. Each column corresponds to a $PM_{2.5}$ component. *Basis* stands for the basis matrix, which shows the clusters obtained by the best fit. Basis 1 was labeled as Soil and Crustal Dust, 2 as Heavy Fuel Oil and Industrial, 3 as Metal Processing Industry and Agricultural, 4 as Coal and Oil Combustion, and Biomass Burning, and 5 as Motor Vehicle.

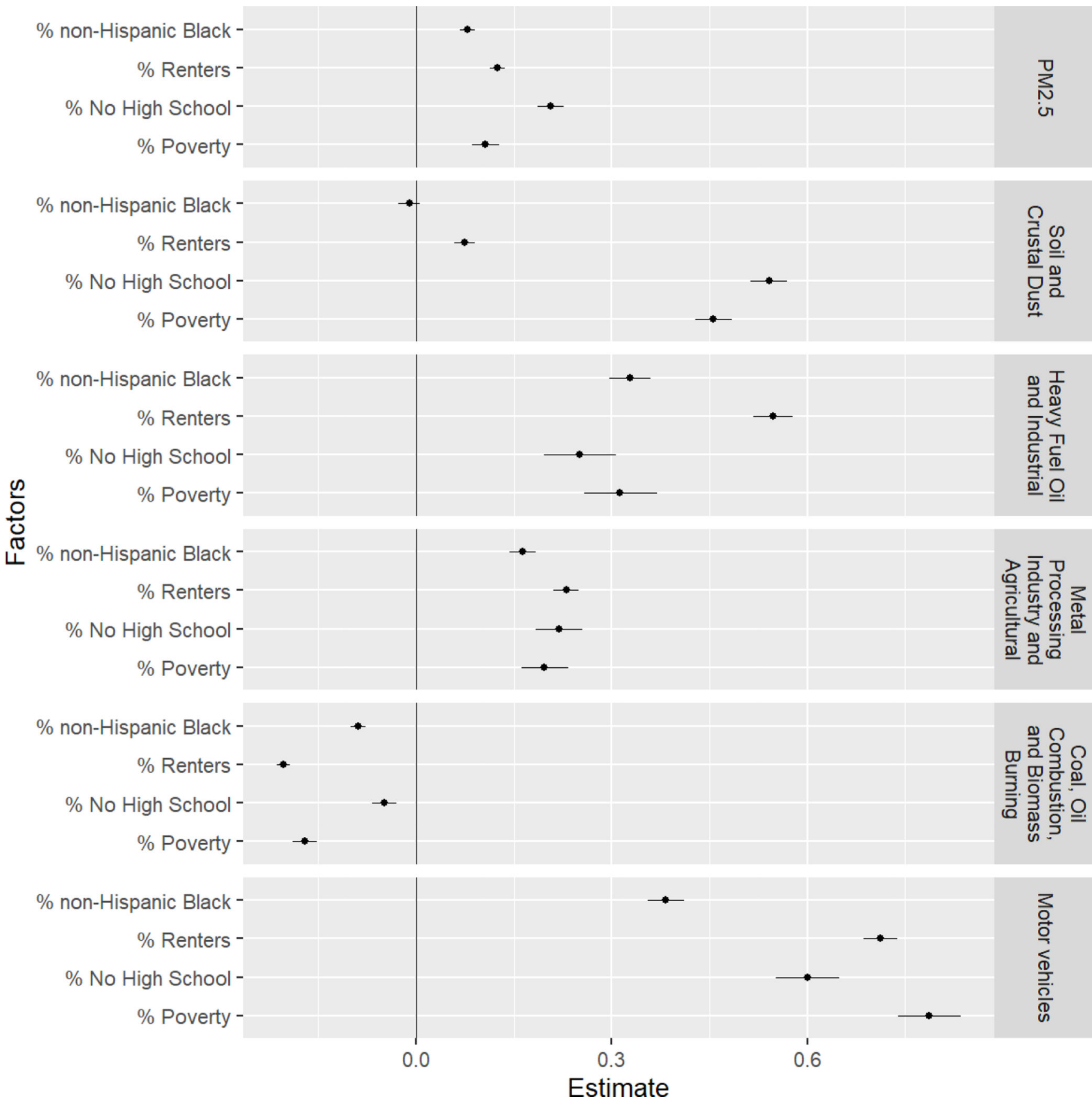

Figure 3:

The associations between 10% increase in zip code characteristics and $PM_{2.5}$ source categories. We conducted generalized nonlinear models, including each zip code characteristic separately, to assess the independent associations with each source category. We adjusted for population density, RUCA, % population over 65, and % female population.

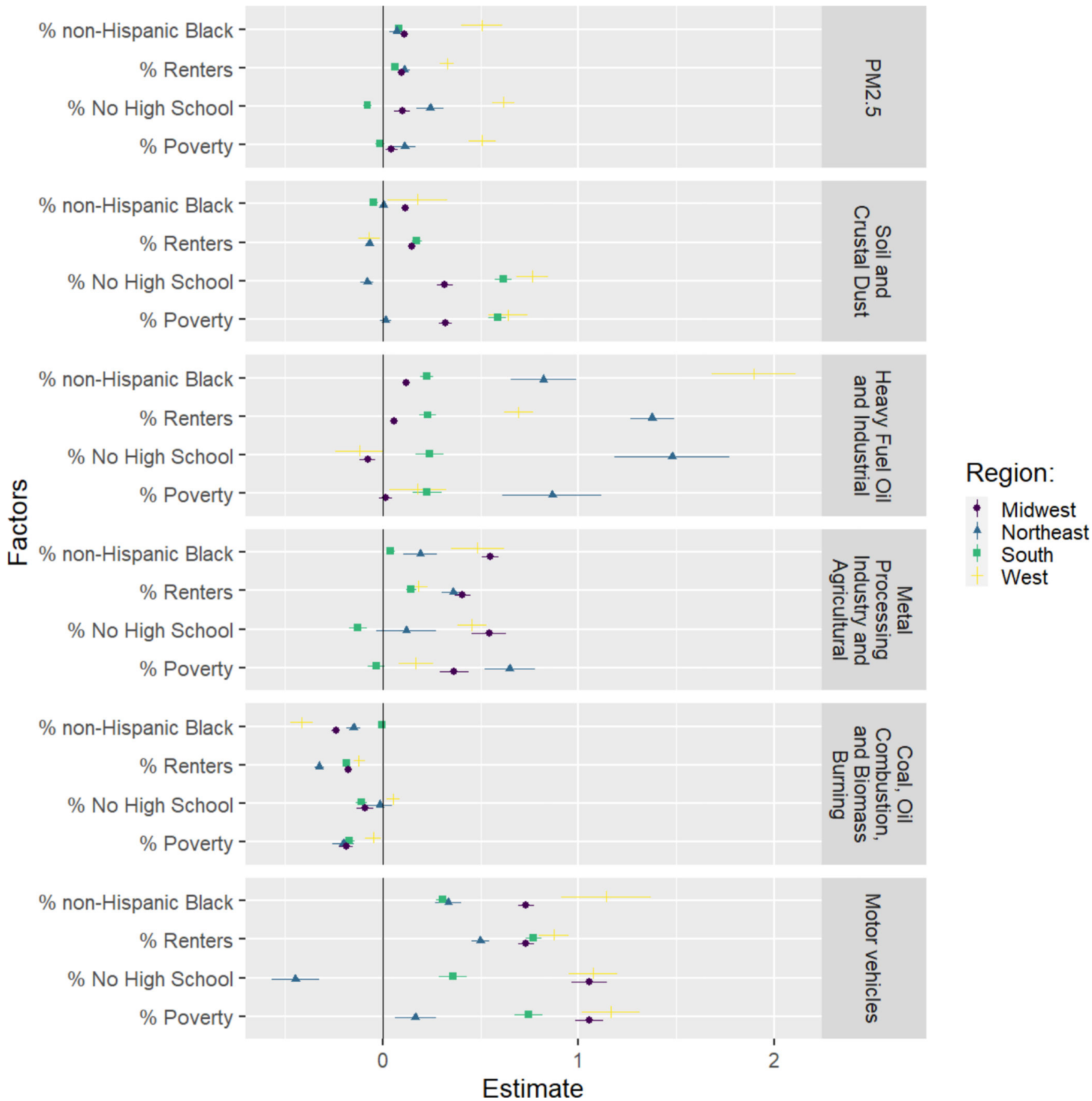

Figure 4:

The associations between 10% increase in zip code characteristics and $PM_{2.5}$ source categories, stratified by U.S. regions. We conducted generalized nonlinear models including each zip code characteristic separately to assess the independent associations with each source category. We adjusted for population density, RUCA, % population over 65, and % population female.

Table 1:

distributions of the socioeconomic characteristics and $PM_{2.5}$ levels of the 25,790 included ZIP codes.

Zip Code Characteristics (mean (SD))	Overall	25th Percentile	50th Percentile	75th Percentile
% Below Poverty Line	14.20 (9.16)	7.56	12.15	18.53
% No High School	16.34 (9.46)	9.46	14.52	21.44
% Renters	30.66 (18.55)	17.63	25.36	38.68
% Non-Hispanic Black	10.85 (17.94)	0.56	2.81	12.309
$PM_{2.5}$ μg/m^3	9.65 (2.45)	8.31	10.08	11.32