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Racial-ethnic exposure disparities to airborne ultrafine particles in the United States

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E-mail: apresto@andrew.cmu.edu and alr@andrew.cmu.edu**Keywords:** ultrafine particles, exposure disparity, people of colorSupplementary material for this article is available [online](#)**Abstract**

Ultrafine particles (‘UFP’; <100 nm in diameter) are a subset of fine particulate matter (PM_{2.5}); they have different sources and spatial patterns. Toxicological studies suggest UFP may be more toxic per mass than PM_{2.5}. Racial-ethnic exposure disparities for PM_{2.5} are well documented; national exposure disparities for UFP remain unexplored due to a lack of national exposure estimates. Here, we combine high-spatial-resolution (census block level) national-scale estimates of long-term, ambient particle number concentrations (PNC; a measure of UFP) with publicly available demographic data (census block-group level) to investigate exposure disparities by race-ethnicity and income across the continental United States. PNC exposure for racial-ethnic minorities (Asian, Black, Hispanic) is 35% higher than the overall national mean. The magnitudes of exposure disparities vary spatially. Disparities are generally larger in densely populated metropolitan areas. The magnitudes of disparities are much larger for PNC than for PM_{2.5}; PM_{2.5} exposure for racial-ethnic minorities is 9% higher than the overall national mean. Our analysis shows that PNC exposure disparities cannot be explained by differences in income. Whites of all incomes, including low-income Whites, have substantially lower average PNC exposures than people of color of all incomes. A higher proportion of traffic and other PNC sources are located near many minority communities. This means that the exposure disparities are structural and strongly tied to where certain subsets of the population live and that simply reducing PNC emissions nationwide will not reduce these disparities.

1. Introduction

Air pollution varies in space, which can create exposure disparities among different demographic groups. Past studies have shown that air pollution exposures for racial-ethnic minority populations (people of color, POC or non-White population) in the US are substantially higher than those of the White population [1–6]. This could contribute to the documented differences in health outcomes for different populations [7, 8]. Although exposures are higher for racial-ethnic minorities, their contribution to air pollution emissions is relatively low compared to other demographic groups [9]. There is growing

national interest, such as the Biden administration Justice40 initiative, to reduce exposure disparities. This requires an improved understanding of sources and factors that create these disparities.

Racial-ethnic exposure disparities for fine particulate matter (PM_{2.5}; particles less than 2.5 μm) are well documented in the US [2, 5, 10–15]. Ultrafine particles (UFP; particles smaller than 100 nm) are a subset of PM_{2.5}. However, little is known about racial-ethnic exposure disparities for UFP.

Although UFP is a subset of PM_{2.5}, they have different sources and spatial patterns. In the United States, PM_{2.5} mass concentrations are dominated by regional and long-range transported particles, which

is mostly secondary in nature. UFPs are dominated by fresh, primary emissions from local sources. Therefore, UFPs are much more spatially variable than $PM_{2.5}$. Toxicological studies suggest UFP may be more toxic than larger particles in $PM_{2.5}$ because of their smaller size, higher surface area, and distinct chemical composition [16].

A major challenge for large-scale population-based studies on UFP exposure disparities is the scarcity of exposure estimates [17]. Unlike $PM_{2.5}$ mass concentrations, spatially resolved UFP exposures estimates are rare because of the lack of routine monitoring data. Saha *et al* [18] developed high-spatial-resolution (census block level) outdoor concentration estimates for UFP (as total particle number concentration (PNC)) across the continental US. This is the first national-scale UFP exposure estimate in the US at high spatial resolution.

In this study, we combined our previously developed national estimates of UFP concentrations [18] with publicly available demographic data (census block-group level) [19] to examine racial-ethnic exposure disparities of UFP in the US. We apply our analysis to address the following questions: (a) How do the exposure disparities for UFP vary by race-ethnicity, income, and geographic location? (b) How do exposure disparities for UFP compare with $PM_{2.5}$? (c) What are the important factors driving the exposure disparities for UFP?

2. Materials and methods

2.1. Air pollution exposure estimates

We use total PNC as the exposure metric for UFP [20]. Here, the word exposure refers to ambient concentrations. The nationwide modeled PNC are from our previously published empirical land-use regression (LUR) model, described in Saha *et al* [18]. Model predictions are 2017-annual-average outdoor PNC estimates at ~ 6 million 2010-census block centroids across the continental US. Model estimates were made using 2010-census geographic boundaries.

The PNC LUR model was derived using intra-urban mobile sampling as well as urban and rural background fixed sites monitoring data across the continental US [18]. The model explained 77% of spatial variability of measured PNC using traffic and urbanicity-related predictor variables. Multiple evaluation approaches investigated model robustness, including random 10-fold holdout cross-validation ($R^2 = 0.72$) and evaluation against an independent dataset ($R^2 = 0.54$) [18]. Transferability of the PNC LUR model was assessed through systematic spatial holdouts ($R^2 = 0.66$), which demonstrated the model's ability to predict concentrations outside the training locations [18].

The focus of this paper is exposure disparities to UFPs. To compare to the results we present for PNC, we performed the same analyses using modeled

$PM_{2.5}$ and NO_2 concentrations from Kim *et al* [21]. Exposure disparities for these pollutants that have been explored in prior research [2]. The $PM_{2.5}$ and NO_2 estimates of Kim *et al* [21] are 2010-census block-level annual average estimates for 2015. These estimates are derived from empirical regression modeling using regulatory monitoring, satellite data, and land-use variables.

2.2. National demographic data

We used the 2010 census race, ethnicity, and household income data from the National Historical Geographic Information System (NHGIS) [19]. NHGIS reports population estimates in each census block group for eight racial categories and two ethnic categories (Hispanic or Latino and not Hispanic or Latino). Thus, there are a total of 16 combined racial-ethnic groups. For our analysis, we grouped these 16 racial-ethnic groups into five bins: (a) not Hispanic or Latino, White alone (hereafter: White; 65.4% of the total population), (b) not Hispanic or Latino Black alone (hereafter: Black; 12.1%), (c) not Hispanic or Latino, Asian alone (hereafter: Asian; 4.3%), (d) Hispanic or Latino from any race (hereafter: Hispanic; 15.5%), and (e) not Hispanic or Latino other racial minority including American Indian, Alaska Native, Native Hawaiian, Other Pacific Islander, Two or more races (hereafter: Other POC; 2.7%). Overall, racial-ethnic minority or POC is 34.6% of total population.

NHGIS also reports the total number of households in each census block group in 16 annual household income categories between ' $< \$10k$ ' and ' $> \$200k$ '. However, these block-group level household income data are not disaggregated by race-ethnicity. NHGIS reports the census tract level household income data disaggregated into eight racial and two ethnic groups. We used these census tract level data to investigate exposure disparities by both race-ethnicity and income together. For this analysis, we grouped the NHGIS data into four income bins (' $< \$15k$ ': Extremely low-income, '\$15k–\$50k': Low-Income, '\$50k–\$100k': Medium-Income, and ' $> \$100k$ ': High-Income) and five race-ethnicity bins (as discussed above), which gives a total of 20 combined racial-ethnic-income groups.

2.3. Exposure disparities analyses

We combined air pollution exposure estimates with demographic data to investigate exposure disparities by race-ethnicity, income, and both race-ethnicity and income. We used multiple metrics for characterizing absolute and relative exposure disparities. We compared (a) concentrations in locations (census block groups) binned by the proportion of racial-ethnic population, and (b) national- and state-level population-weighted mean concentrations for different race-ethnicity and income groups.

We used census block-level air pollution concentration estimates and block-group or tract level demographic data. To match air pollution and demographic data, we computed population-weighted mean concentrations of block centroids located within a block-group or tract spatial boundary. Our analysis included $\sim 210\,000$ census block-groups (average population 1400) and $\sim 70\,000$ census tracts (average population 4200) in the contiguous US.

3. Results and discussion

3.1. Association between spatial patterns of PNC and racial-ethnic minorities

Figure 1(A) shows the modeled outdoor PNC at census block centroids across the contiguous US. There is large urban-rural, intra-, and inter-urban PNC spatial variability on a national scale. The hotspots of PNC are in the city centers and near roadways [18, 22].

To illustrate the detailed spatial pattern over a metropolitan area, figure 1(B) shows a map for the Pittsburgh Metropolitan statistical area (MSA). An MSA typically centers around one big city (minimum population: 50 000), with multiple surrounding counties, townships, and suburban areas. PNC is highest in the city center and densely populated areas (figure 1(B)). PNC decreases as one moves away from the city center (figure 1(C)). Figure 1(D) shows the spatial pattern of the racial-ethnic minority population across the Pittsburgh MSA. The relative proportion of the racial-ethnic minority population is higher in the city center, where the pollution concentrations are also higher. As one moves away from the urban center, the proportion of the racial-ethnic minority population decreases (figure 1(E)) as well as PNC concentrations (figure 1(C)). Similar patterns exist in Oakland, CA, and Chicago, IL MSAs (see figure S1).

The magnitudes of PNC exposure disparities vary spatially and are generally more prominent in densely populated metropolitan areas. Figure S2 summarizes PNC exposure differences between POC and White group for 364 MSAs across the continental US. In 95% of MSAs, MSA-average population-weighted PNC exposures for the POC group are higher than for the White group. Exposure differences are about two times higher in high-populated MSAs (MSA total population >300 thousand) compared to relatively low-populated MSAs (MSA total population <100 thousand).

Figure 2 summarizes the data for the whole country, comparing PNC across locations (census block groups) based on the proportion of racial-ethnic population groups in census block-groups. For this analysis, we binned all census block groups nationwide

into 11 bins by the proportion of racial-ethnic population group (White, POC, sub-group of POC: Black, Asian, Hispanic, Other). The first bin contains all census block groups with 0% population of a racial-ethnic group. The remaining census block groups are divided into ten bins; each bin contains an equal total population, ranked by the proportion of racial-ethnic population.

Figure 2 shows that, on average, there is a clear trend. PNC levels are, on average, higher in census block groups with a higher proportion of POC. For example, the average PNC is $\sim 35\%$ lower than the overall national mean in the block groups with the lowest fraction of POC. PNC is 54% higher than the national mean in the block groups with the highest fraction of POC. This means that a larger fraction of racial-ethnic minority population lives in more polluted areas than the White population.

The trend is similar for most POC subgroups (Black, Asian, and Hispanic). However, there are some differences among subgroups. The largest PNC exposure disparity is for Asians, followed by Hispanics and Black (figure 2). The average PNC exposure curve for other POC groups (American Indian, Alaska Native, Native Hawaiian, Other Pacific Islander) is within 5%–10% of the overall national mean.

The racial-ethnic exposure disparities presented in figure 2 use the full range of the national PNC exposure distribution. We also investigated racial-ethnic disparities in PNC exposure for highest (block-groups those fall within 90–100th percentile range of national PNC distribution; dirtiest 10% of block groups) and lowest (block-groups those fall within 0–10th percentile range of national PNC distribution; cleanest 10% of block groups) PNC levels (figure S3). A disproportionately higher fraction of POC lives in census block groups with the highest levels of PNC. Comparing the cleanest versus dirtiest 10% of block groups, the POC fraction in the total population is 15% versus 70%, respectively.

Since the racial-ethnic exposure disparities for PNC shown in figure 2 use model estimates, we performed a similar analysis using PNC data experimentally measured in the ambient air at 118 locations across the US. These are the measurements that were used for LUR model development [18]. We assigned the measured PNC from these locations to the centroids of the nearest census block groups for spatial matching of air pollution and demographic data. We then ranked block groups by the fraction of minority residents, similar to the analysis in figure 2. The block groups with directly measured PNC data reveal a similar disparity pattern as the estimates based on the LUR model (figure S4). This analysis, based on measurements rather than models, suggests that the results above (PNC levels are higher for the

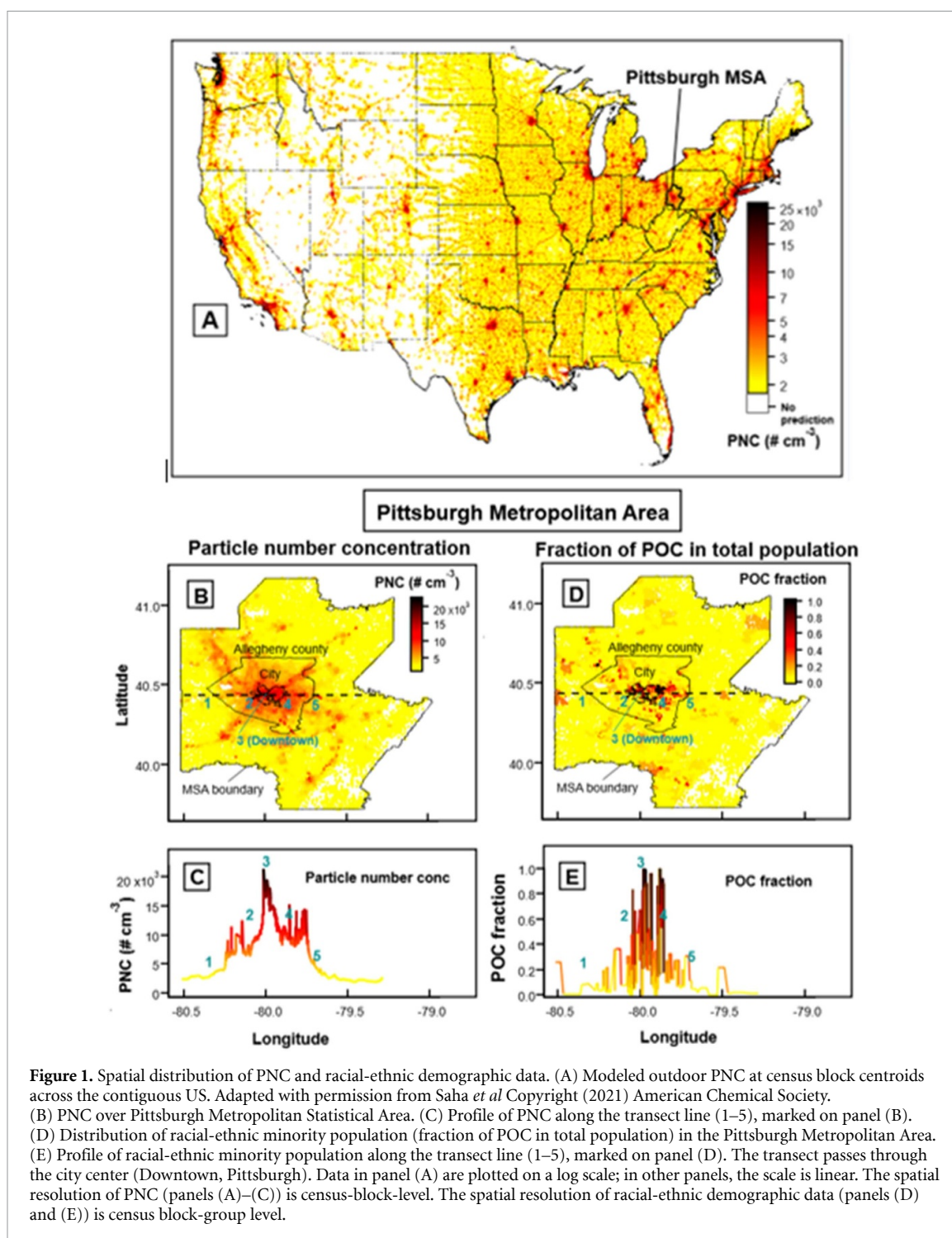


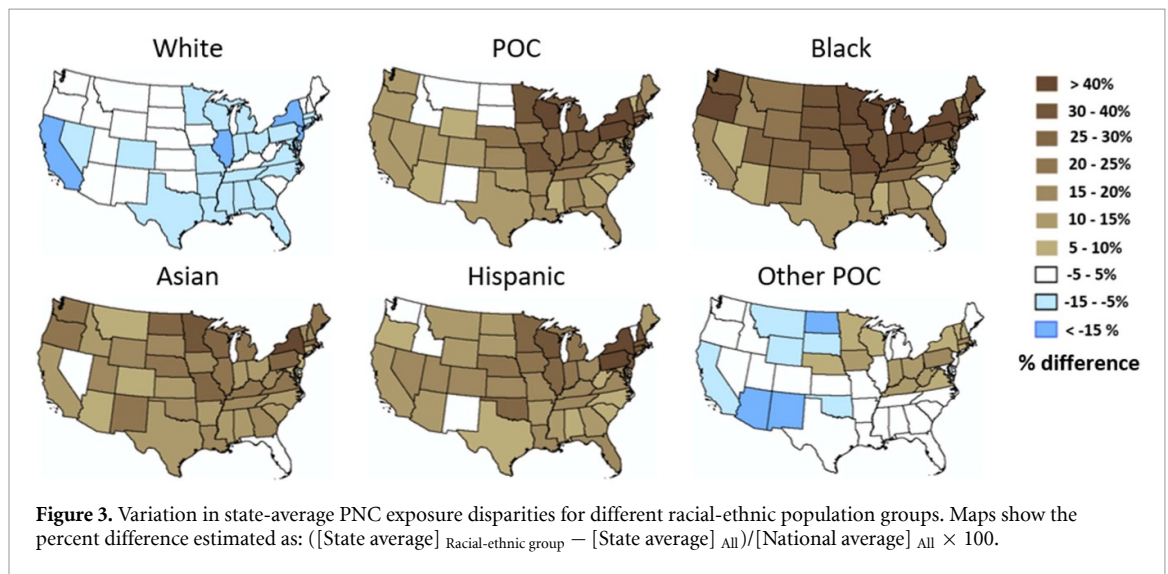
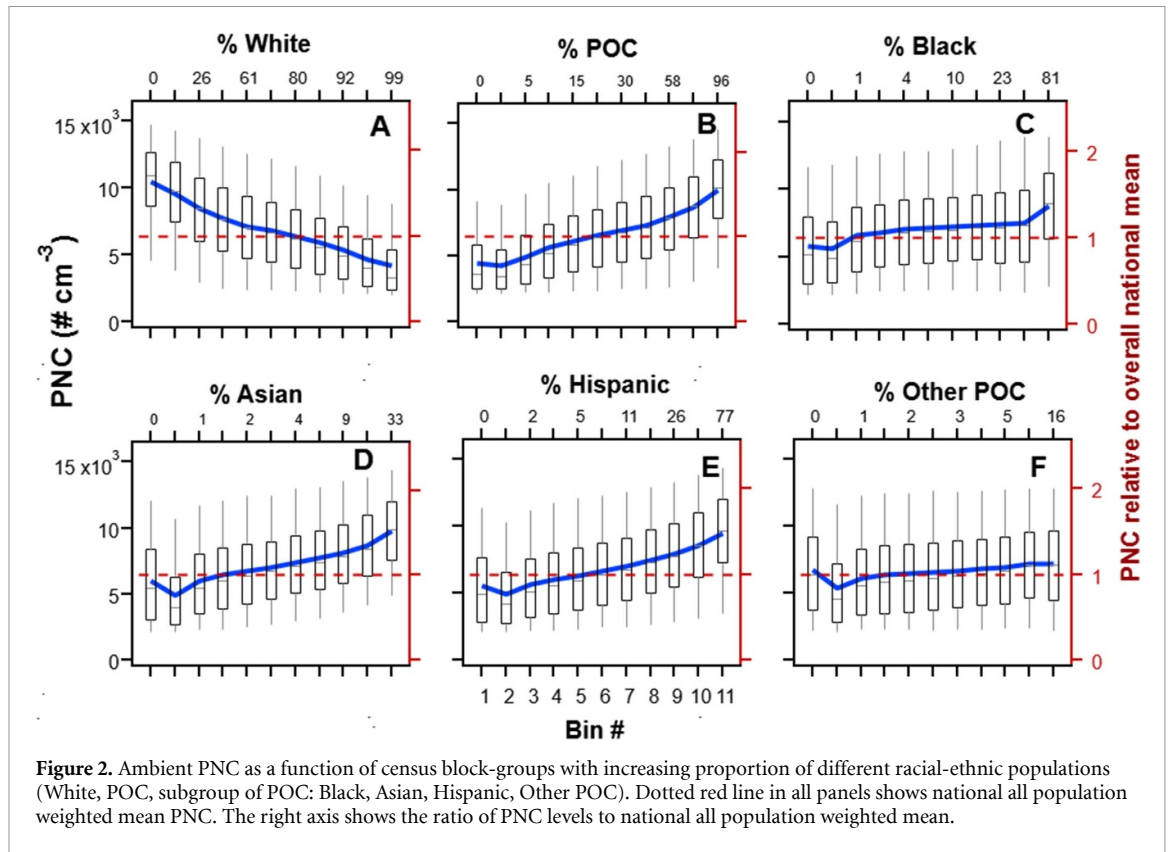
Figure 1. Spatial distribution of PNC and racial-ethnic demographic data. (A) Modeled outdoor PNC at census block centroids across the contiguous US. Adapted with permission from Saha *et al* Copyright (2021) American Chemical Society. (B) PNC over Pittsburgh Metropolitan Statistical Area. (C) Profile of PNC along the transect line (1–5), marked on panel (B). (D) Distribution of racial-ethnic minority population (fraction of POC in total population) in the Pittsburgh Metropolitan Area. (E) Profile of racial-ethnic minority population along the transect line (1–5), marked on panel (D). The transect passes through the city center (Downtown, Pittsburgh). Data in panel (A) are plotted on a log scale; in other panels, the scale is linear. The spatial resolution of PNC (panels (A)–(C)) is census-block-level. The spatial resolution of racial-ethnic demographic data (panels (D) and (E)) is census block-group level.

census block groups with a higher fraction of minority residents) are true observations about the real-world and not a reflection of error in the models.

3.2. State and national level mean PNC exposure disparities

In the United States, many air pollution regulations are implemented at the state level. Figure 3 shows PNC exposure disparities by state. For White people, in all states, PNC exposures are approximately equal or are lower than overall-state-average. For POC overall, and for the three largest subgroups (Black, Asian,

Hispanic), exposures are approximately equal or are higher than overall-state-average. The ‘other POC’ group includes American Indians, Alaska Natives, Native Hawaiian, and Pacific Islanders. Their exposures are equal or lower than overall-state-average in some states (e.g. west, and central US) and higher than overall-state-average in others (e.g. northeast). In many states, these ‘other POC’ population groups live in rural/remote locations, for example, Native American populations. Therefore, their exposures are expected to be lower. The highest racial-ethnic exposure disparities for PNC are in the northeast

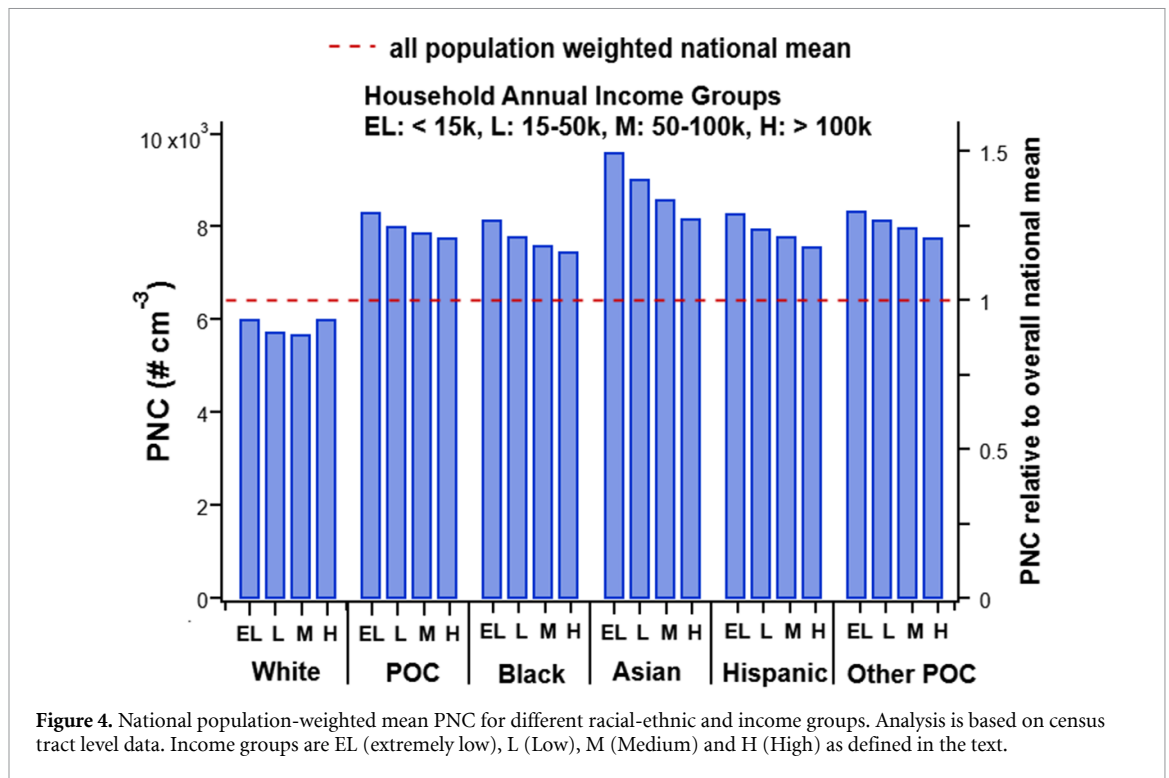


and mid-west. The top ten states are New York, New Jersey, Pennsylvania, Massachusetts, Connecticut, Rhode Island, Wisconsin, Illinois, Michigan, and Missouri. The intensity of PNC source-related land-use activities in proximity to the locations with a higher fraction of POC is comparatively higher in these states than in other states (figure S5).

Previous research has shown that air pollution exposure varies by race-ethnicity and income [1–3, 23]. Figure 4 presents national mean PNC for different demographic groups accounting for both race-ethnicity and income. Exposure differences between race-ethnic groups are much larger than

exposure differences based on income alone. For all racial-ethnic groups, exposure goes down as income goes up. However, the racial gaps are larger than, and are not ‘explained by,’ income differences (i.e. racial disparities persist even after accounting for income). Whites of all incomes, including low-income Whites, have substantially lower average exposures than POC of all incomes, including high-income POC. The analysis in figure 4 uses household income data in four bins. Analysis using household income data in 16 bins shows a similar trend (figure S6).

To quantify the relative influence income versus race-ethnicity, we calculated (a) the racial-ethnic



exposure disparities after controlling for income and (b) the exposure disparities by income after controlling for race-ethnicity. National mean racial-ethnic PNC exposure disparities ($PNC_{\text{most exposed race group}} - PNC_{\text{least exposed race group}}$), averaged across all income classes and normalized by the overall national mean, is 46%. National PNC exposure disparities among income groups ($PNC_{\text{most exposed income group}} - PNC_{\text{least exposed income group}}$), averaged across all racial-ethnic classes and normalized by overall national mean, is 12%, which is 4-fold smaller than the analogous value for race-ethnicity (46%). We also performed a similar state-level analysis (figure S7), which also shows that racial-ethnic exposure disparities after controlling for income differences are much higher than disparities among income groups after controlling for race-ethnicity. However, there are substantial state-to-state differences. Racial-ethnic disparities after controlling for income differences in the contiguous 48 states vary between 15%–75% of overall national mean (top five states with higher disparities: Wisconsin, New York, Pennsylvania, New Mexico, Rhode Island). Disparities among income groups after controlling for race-ethnicity vary between 5%–39% of the national mean (top five states with higher disparities: Pennsylvania, Rhode Island, Connecticut, Nevada, Colorado). The spatial distributions of state-level income and race-related PNC exposure disparities are also different (spearman correlation coefficient is 0.44).

3.3. Comparison with $PM_{2.5}$ and NO_2

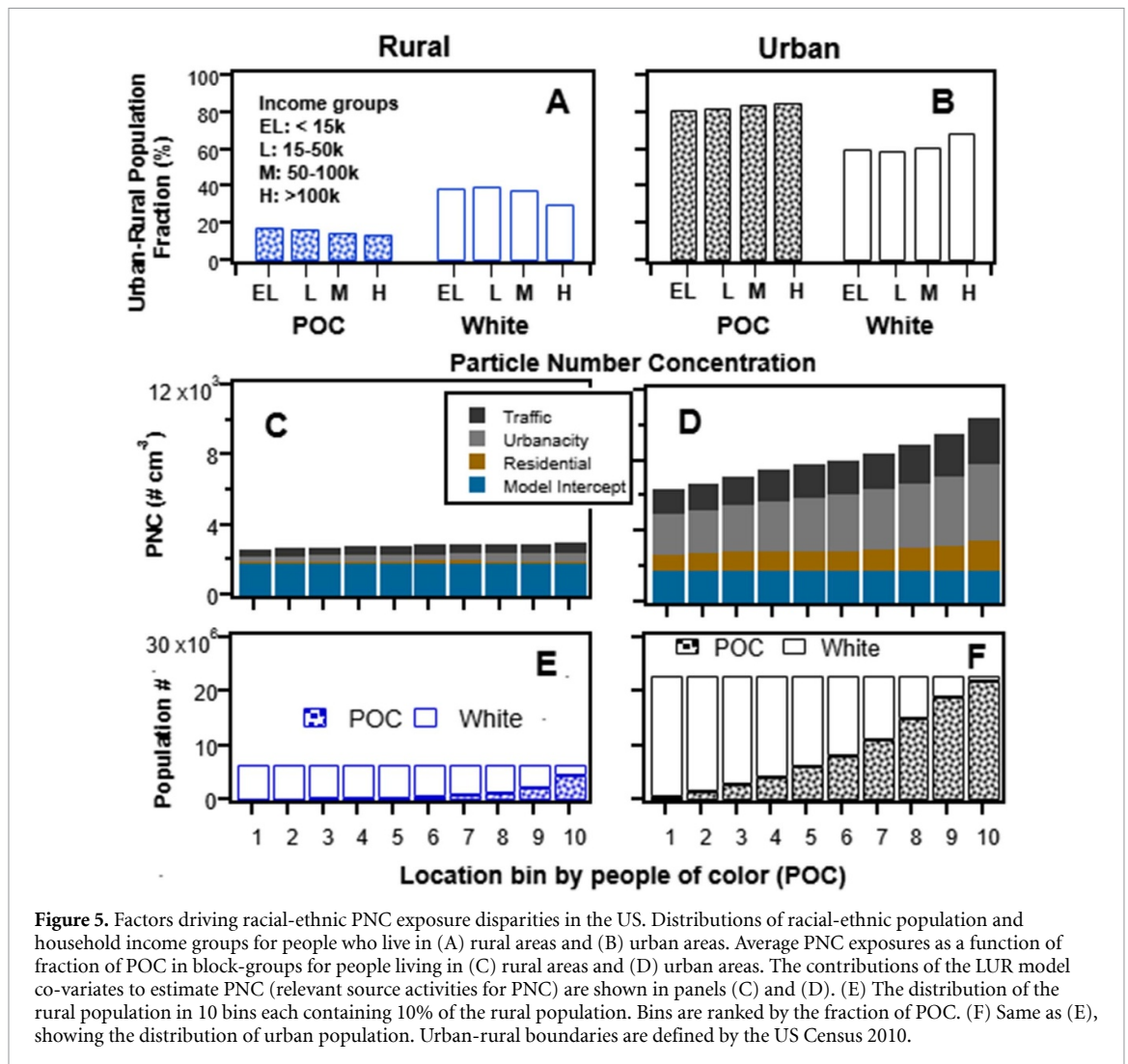
This section compares PNC exposure disparities to those of $PM_{2.5}$ and NO_2 . Results are shown in figure

S8 (block-groups concentrations binned by fraction of POC), figure S9 (state-level variations), figure S10 (national population-weighted concentrations) and briefly discussed below.

Exposure disparities for PNC are larger than for $PM_{2.5}$. While racial-ethnic minority and low-income groups are the most exposed groups for PNC and $PM_{2.5}$, the disparities are much larger for PNC. For example, national population-weighted exposure for POC is 35% higher than the national mean for PNC versus 9% for $PM_{2.5}$. The concentration differences (both relative and absolute) between block groups with the lowest and highest fraction of POC are much larger for PNC than $PM_{2.5}$ (figure S8). Inter-state variations in exposure disparities are larger for PNC than $PM_{2.5}$ (figure S9).

Exposure disparities for PNC are larger than $PM_{2.5}$ because PNC has more spatial variability, with high concentrations in urban areas and relatively low concentrations in rural areas. Traffic and various combustion emissions (cooking, biomass burning, industrial activities) drive the spatial variability in PNC [24–26]. Another source of PNC is nucleation, which is mainly a regional phenomenon [27, 28], which is more uniformly distributed in space [29] and therefore contribute minimally to intraurban exposure disparities. In contrast, $PM_{2.5}$ mass concentrations have less spatial variability because the majority of $PM_{2.5}$ mass is regional and secondary particles (sulfate, nitrate, ammonium, and secondary organic aerosol, which are formed in the atmosphere from oxidation of inorganic and organic precursor gases).

There are similar exposure disparity patterns for PNC and NO_2 at the block-group level



(figure S8), state-level (figure S9), and national population-weighted concentrations (figure S10). PNC and NO_2 are strongly correlated because traffic is an important source of both pollutants [16]. The common traffic source seems to be the underlying cause for the similarity between PNC and NO_2 exposure disparity patterns [30].

3.4. Factors driving exposure disparities of PNC

This section combines PNC, the PNC LUR model land-use covariates, and demographic variables to investigate the factors that contribute to racial-ethnic PNC exposure disparities in the US. Strong correlation between spatial patterns of PNC and racial-ethnic minorities is the key factor behind exposure disparities.

First, we consider the role of urban versus rural population demographics. Figures 5(A) and (B) shows the urban-rural distribution of the racial-ethnic population in the US. A greater proportion of POC lives in urban areas. Nationally, 82% of POC live in urban areas versus 60% of Whites. Since urban background PNC levels are 3–5 times higher than rural ones (figure 1) this results in higher population

exposures to POC than Whites. The urban-rural ratio of White versus POC does not vary much across income classes (figures 5(A) and (B)). This explains why the variation of household income is not a dominant factor in explaining exposure disparities in the US.

Figures 5(C) and (D) shows the distribution of PNC as a function of the proportion of POC in rural and urban areas. In urban areas, block groups with higher PNC have a higher fraction of POC (figure 5(D)). This indicates that many PNC sources (Traffic, restaurant, and commercial activities) are located near minority communities. This is presumably due to historical policies and planning decisions (e.g. redlining, eminent domain for freeway/industrial siting, etc). PNC also increase with increasing proportion of POC in rural areas, but this variation across rural block groups is much less than in urban areas (figure 5(C)).

3.5. Implications

Racial-ethnic exposure disparities are substantially higher for PNC than for $\text{PM}_{2.5}$ mass. Additionally, the spatial distributions of PNC concentrations are

different than for total PM_{2.5} mass. Current air pollution regulations in the US are based on total PM_{2.5} mass, not PNC. This suggests that regulation targeting only PM_{2.5} mass may not address the exposure disparities for PNC.

Our analysis provides insight into underlying causes and drivers of exposure disparities for PNC. We raise here a potential challenge, or perhaps conundrum. Traffic and localized urban emissions are the main drivers of racial-ethnic PNC exposure disparities in the US. Historically, many of these sources were located in minority communities. This means that the exposure disparities are structural and strongly tied to where certain subsets of the population live. Simply reducing emissions nationwide will not reduce PNC exposure disparities by race-ethnicity.

Exposure disparities due to traffic emissions are illustrative. Figure 5(D) shows that POC in urban areas are more likely to live in high-traffic areas than White residents. While traffic emissions have substantially reduced in the US over the past decade [31], POC still have higher average exposures to traffic-related PNC because they tend to live closer to highways and other heavily trafficked roads. Further reducing traffic emissions will reduce exposures for everyone, but POC will, on average, still suffer higher exposures unless near-zero conditions are achieved. The relative difference will exist due to the geographical distribution of racial-ethnic minority residents and sources that emit PNC. Future policies aimed at reducing these exposure disparities will need to explicitly address the spatial association between areas of high emission intensity and census blocks with a high fraction of POC.

Data availability statement

The PNC data that support the findings of this study are openly available at the following URL/DOI: www.caces.us.

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