Air Quality-Related Equity Implications of U.S. Decarbonization Policy

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ABSTRACT (150 words): We quantify potential air pollution exposure reductions resulting from U.S. federal carbon policy, and consider the implications of resulting health benefits for exposure disparities across racial/ethnic groups. We assess reductions in carbon dioxide (CO_2) emissions of 50% in 2030 relative to 2005 levels, comparable in magnitude to the 2022 Inflation Reduction Act. Using energy-economic scenarios and an air quality model, we find reductions in average fine particulate matter ($PM_{2.5}$) exposure across racial/ethnic groups under a carbon pricing policy, with greatest benefit for non-Hispanic Black and white populations. However, the average relative gap in exposure between white people and people of color widens. Alternative choices of sources that reduce a similar amount of CO_2 emissions also cannot substantially mitigate these disparities. Our results suggest that fully mitigating exposure disparities between white and non-white populations will require efforts beyond optimization of existing CO_2 policy strategies, including large-scale structural changes.

KEY WORDS: air quality disparities; environmental justice; U.S. climate policy; cap-and-trade; economy-wide decarbonization; air quality modeling; energy-economic modeling.

Emissions of greenhouse gases (GHG) that contribute to climate change are often associated with air pollutant emissions that lead to formation of fine particulate matter ($PM_{2.5}$), which causes upwards of ~200,000 premature deaths in the U.S. annually and disproportionally harms people of color and low-income populations (Burnett et al., 2018; Tessum et al., 2021). A growing body of literature has demonstrated how policies aiming to reduce GHG emissions can concurrently reduce air pollution and improve public health (Gallagher and Holloway, 2020). However, there remains disagreement on both the direction and magnitude of effects of such policies on disparities (Zhu et al., 2022). Addressing disparities in air pollution exposure and climate change risks are both closely tied to existing environmental justice (EJ) related policy goals. Here, we use energy-economic scenarios and an air quality model to quantify whether and how different policies that reduce carbon dioxide (CO_2) emissions by 50% in 2030 relative to 2005 levels simultaneously reduce racial and ethnic air pollution disparities at national scale. A 50% reduction by 2030 is consistent with the Biden-Harris administration's pledge under the Paris Agreement. Preliminary analyses of the recent Inflation Reduction Act (IRA) indicate it would make substantial progress towards this goal (42%), with measures that target specific sectors including electricity and transportation (Jenkins et al., 2022). We evaluate the extent to which carbon policies of comparable magnitude and sectoral scope can feasibly achieve reductions in air pollution disparities consistent with the administration's EJ related policy goals.

Air pollution exposure disproportionally harms people of color and low-income populations in the US, and disparities have persisted despite improvements in air quality (Colmer et al., 2020; Jbaily et al., 2022; Liu et al., 2021). Disparities by race/ethnicity are greater than disparities by income and exist across all income groups (Liu et al., 2021; Tessum et al., 2021). Tessum et al. (2019) estimated that in 2014, Black and Hispanic people were exposed to 56% and 63% more $PM_{2.5}$ than they were responsible for based on consumption; in contrast, non-Hispanic white people experienced 17% less. Another study showed that most sources of $PM_{2.5}$ disproportionately harm people of color (POC, defined here as all except non-Hispanic white people), except for coal-fired electricity generation and agriculture (Tessum et al., 2021). These disparities in part reflect systemic environmental racism, including the long-lasting consequences of discriminatory practices such as redlining (Lane et al., 2022).

Many studies have evaluated health benefits of climate and clean energy policies (sometimes referred to as "co-benefits"). Gallagher and Holloway (2020) review 26 such studies, including several that found that monetized air pollution related health benefits can exceed the estimated climate benefits as well as implementation costs of the policy alone (e.g., Dimanchev et al., 2019; Thompson et al., 2016). While the impact of carbon reductions is the same regardless of the location of emissions, the local nature of $PM_{2.5}$ exposure means that changes in air pollution-related health burdens due to policy can be unequally distributed. Communities affected by sources with lower marginal abatement costs will typically benefit more from policies that involve carbon pricing, and therefore equity outcomes depend on the characteristics of these communities (Burtraw et al., 2005; Hernandez-Cortes and Meng, 2020). Furthermore, reductions in one location may result in increased emissions outside of the policy coverage ("leakage") that could increase exposures (Thompson et al., 2016). This has led some EJ proponents to argue that market-based carbon policies will not address air pollution disparities, leading to efforts such as in California and Washington to adopt distinct and explicit EJ provisions as complements to carbon pricing (Roberts, 2021).

Much existing research evaluating air pollution equity impacts of climate policy has focused on retrospective analyses of existing policies, largely in California, finding limited but mixed effects on equity outcomes. For example, Cushing et al. (2018) estimate that California's 2013 GHG cap-and-trade program exacerbated inequities, finding that over half of covered facilities increased emissions (with total emissions remaining under the cap) and that areas within 2.5 miles of facilities with increased emissions had higher shares of people of color and low-income people than areas with decreased emissions. In contrast, Anderson et al. (2018) find limited equity impacts of the same program by comparing changes in emissions for disadvantaged counties. Hernandez-Cortez and Meng (2020) apply an atmospheric dispersion model to track transport of primary pollutants as well as a reduced-form chemical transport model including secondary $PM_{2.5}$ formation, finding that while disparities had been increasing before the cap-and-trade program, the program reduced disparities but did not eliminate them.

A few studies have considered equity impacts of future decarbonization scenarios focusing on selected regions or specific policies. Li et al. (2022), again focusing on California, apply an energy-economic optimization model and a chemical transport model (CTM) to evaluate low carbon energy scenarios in 2050, finding that reducing GHG emissions by 80% relative to 1990 levels could reduce racial/ethnic $PM_{2.5}$ disparities by up to 20%. Zhu et al. (2022) find in a study of California that the magnitude and distribution of health benefits varies among scenarios reducing economy-wide GHG emissions by 80%. Luo et al. (2022), for Texas, found that power sector decarbonization there yields health benefits but fails to address air pollution inequities. The report by Diana et al. (2021) constructs a national policy scenario that reduces CO_2 emissions by 20% and air pollution damages by 50% for Black, Hispanic, and low-income populations specifically. In another policy-focused report, Burtraw et al. (2022) evaluate distributional air quality impacts of reducing U.S. GHG emissions and energy-related CO_2 emissions by 51% and 35%, respectively, by 2030 (relative to 2005 levels), finding that total premature mortalities are reduced for each racial/ethnic group and income group, not quantifying disparities directly.

Here, we examine the underlying fundamental question of whether and to what extent national CO_2 policy with an ambition level comparable to near-term federal goals can mitigate racial/ethnic disparities in air pollution exposure. In contrast to studies focusing on selected regions or specific policy designs, our economy-wide approach allows us to identify the national-scale implications and trade-offs of carbon reduction strategies. We focus on reductions in economy-wide emissions by 50% below 2005 levels by 2030. We apply modeled energy-economic scenarios of a cap-and-trade program to estimate policy-induced emissions reductions, and use a reduced-form air quality model to evaluate $PM_{2.5}$-related equity outcomes including impacts of disparities in exposure, at county or census tract level. We then quantify the degree to which alternative distributions of CO_2 emissions reductions can better address air pollution exposure disparities, providing ranges of outcomes given modeling uncertainty. We conclude by discussing policy implications, identifying where complementary policy approaches would be required to address equity-related air pollution concerns.

Results

We first present our estimate of distributional air quality impacts of a carbon policy in 2030 ("*Cap 50%*") relative to baseline results in 2030 ("*Baseline*") and the historical year 2017 ("*Hist.*"). The policy design follows an energy-economic analysis conducted and described by Yuan et al. (2022) (see Methods). We quantify the potential range for exposure reduction and equity outcomes for this particular policy due to uncertainty in the distribution of sources, providing an upper and lower range for nationally averaged equity outcomes for each racial/ethnic group. We then present our analysis quantifying whether any alternative emissions distribution scenario can better mitigate $PM_{2.5}$ disparities while achieving the same total CO_2 reductions.

Distributional Air Quality Impact of Carbon Policy

National emissions by sector in *Hist.*, *Baseline* and *Cap 50%* are shown in Figure 1. The inputs and results of the underlying energy-economic model scenario were described previously (Yuan et al., 2022). CO_2 emission reductions relative to *Baseline* in 2030 are driven mostly by the electricity sector (77%), followed by transportation (10%), industry (7%), and residential and commercial sectors (6%). Changes vary regionally, with greatest absolute CO_2 reductions in Texas followed by the Alabama-Georgia-Tennessee region, and the largest reductions relative to *Baseline* in Idaho-Wyoming and West Virginia. In contrast, for states such as California and New York, ambitious state emission reduction targets are already in the *Baseline* and thus they experience few additional reductions under the federal policy. Regions and sectors with changes in CO_2 emissions also see changes in non-CO_2 emissions.

Changes in the electricity sector, with a near-elimination of coal-fired generation and additional reductions in other fuel combustion sources, drive reductions in sulfur dioxide (SO_2) and nitrogen oxides (NO_X), precursors to $PM_{2.5}$ formation in the atmosphere. Figure 1 shows that relative to *Baseline*, the policy reduces total emissions of SO_2 and NOx by 49% and 16%, respectively. For other pollutants where the electric sector is only a minor contributor to total emissions, reductions relative to the *Baseline* are smaller: 7% (primary $PM_{2.5}$), 1% (ammonia (NH_3)) and 5% (volatile organic compounds (VOC)). Emissions decrease under *Cap 50%* for each pollutant relative to *Baseline*. However, primary $PM_{2.5}$, NH_3, and VOC increase relative to their 2017 levels (*Hist.*).

Figure 1. National emissions (Billion metric tons (MT) for CO_2 and Million MT for non-CO_2 pollutants) by pollutant and sector in Hist. (2017), Baseline (2030) and Cap 50% (2030). Values are displayed above each bar.

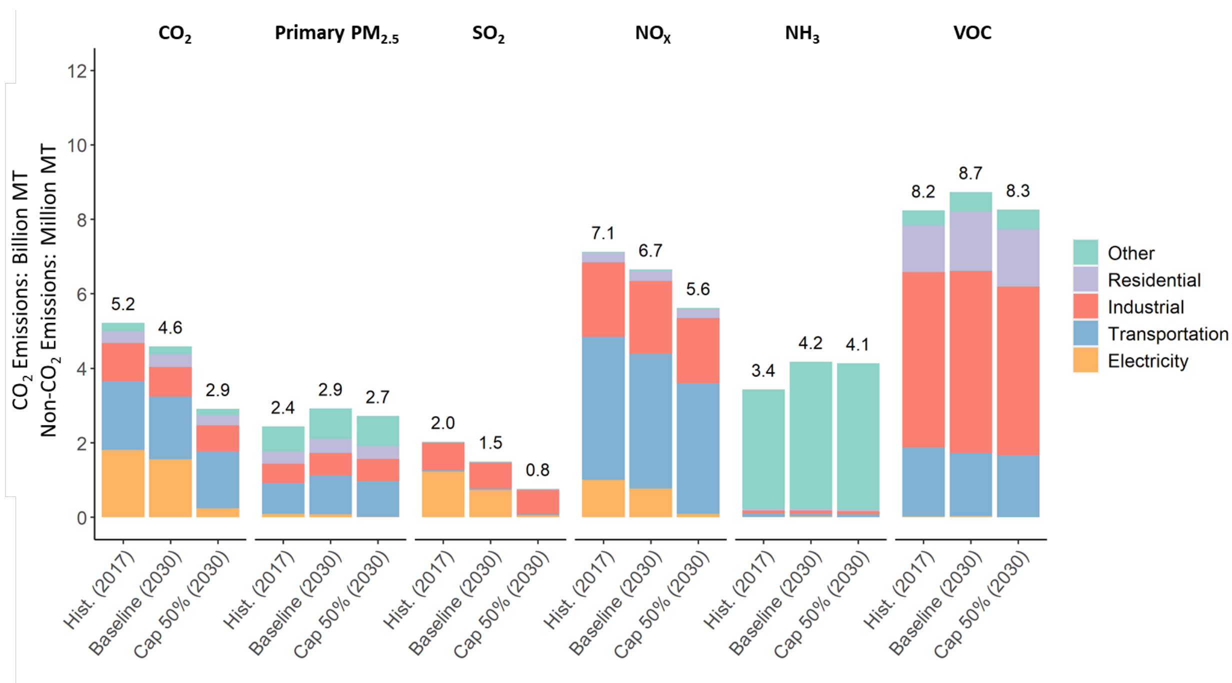
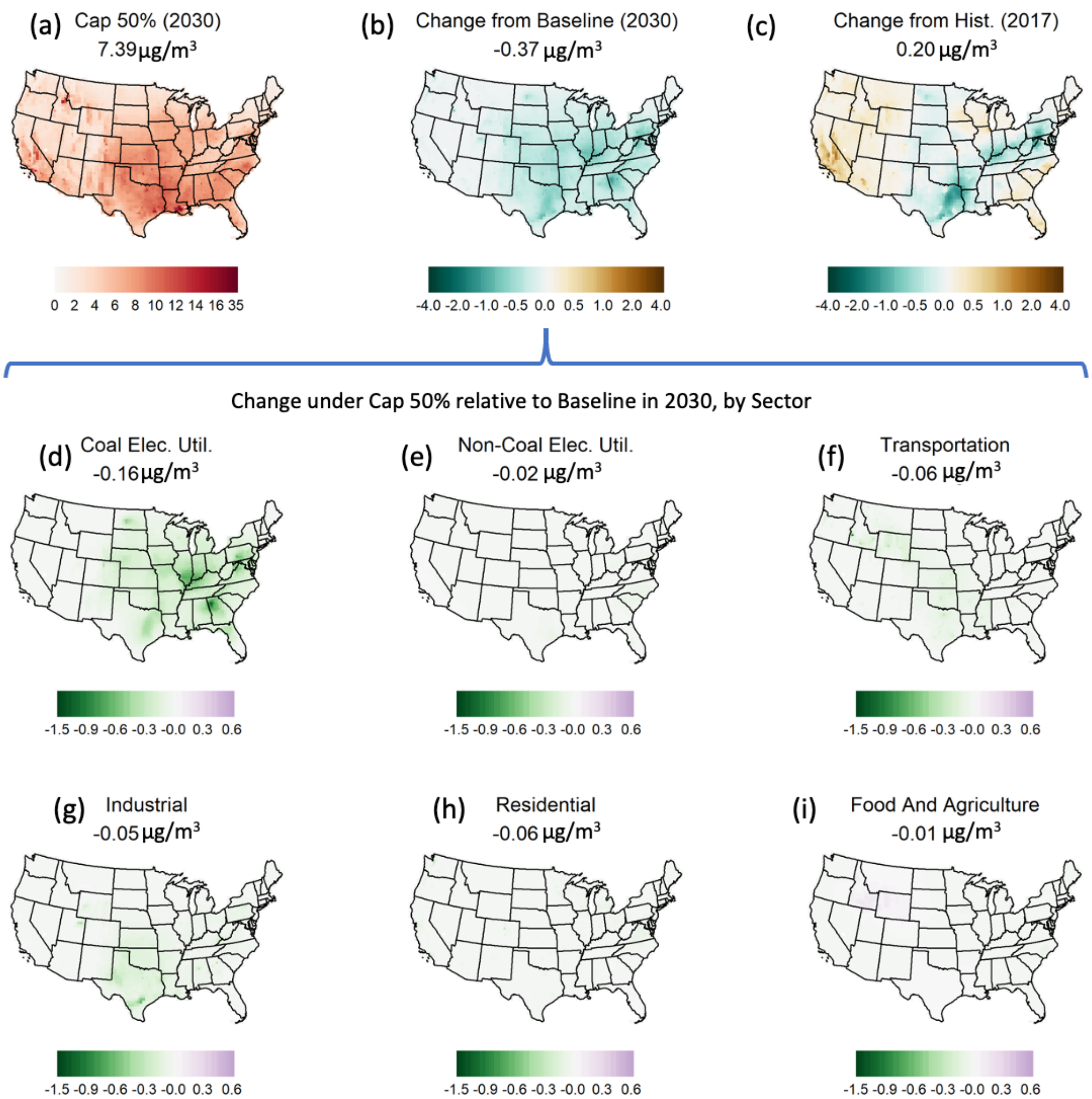


Figure 2 shows simulated $PM_{2.5}$ concentrations (including primary and secondary $PM_{2.5}$) for *Cap 50% (2030)* (panel a), changes from *Hist.* and *Baseline* (panels b-c), and contributions by sector to changes from *Baseline* (panels g-i). $PM_{2.5}$ is simulated using the Intervention Model for Air Pollution (InMAP), with emissions inputs for each sector-state/region combination scaled following energy-economic model output. Relative to *Baseline*, the policy drives a reduction in total population-weighted average concentration by 0.37 μg/m^3, with decreases in most, but not all counties and with changes ranging from -1.97 to +0.44 μg/m^3. Reductions are greatest from Texas through the Mid-Atlantic region, driven largely by coal electricity emissions (d) followed by industrial emissions (g). Coal electricity emissions account for nearly half of the reduction in total average exposure (-0.16 μg/m^3), with remaining reductions from transportation (-0.06 μg/m^3), residential (-0.06 μg/m^3), industrial (-0.05 μg/m^3), non-coal electricity (-0.02 μg/m^3), and food and agriculture (-0.01 μg/m^3). Although the *Cap 50%* scenario achieves reductions relative to *Baseline*, the average population-weighted concentration still increases relative to 2017 (c) due to increases in activity in other polluting sectors.

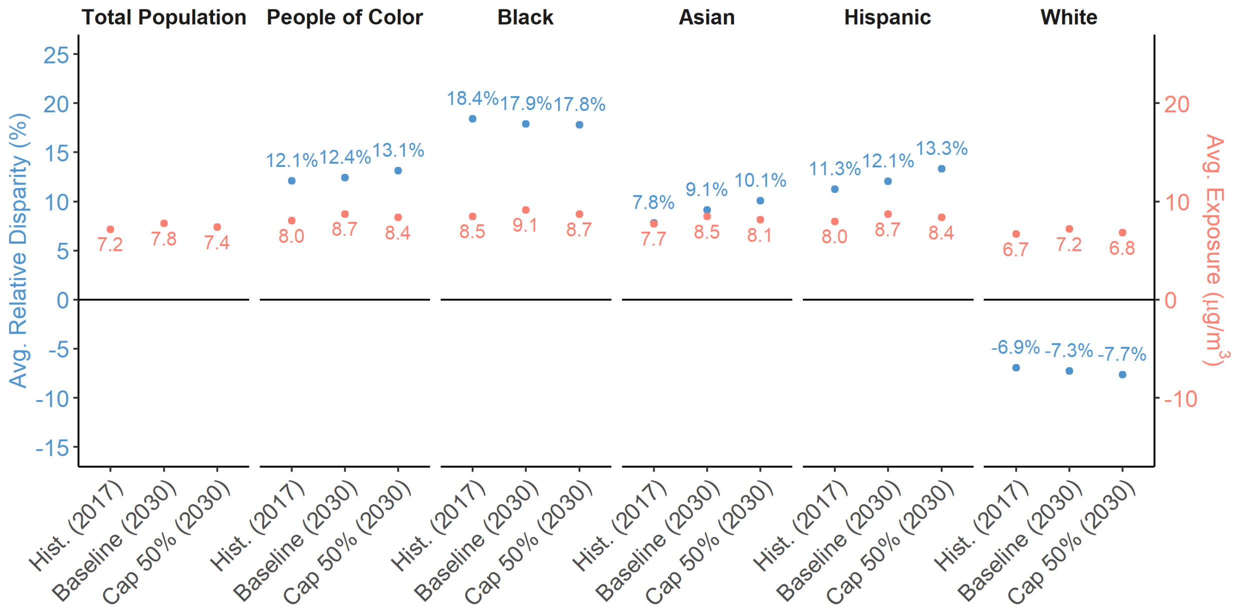
Figure 2. Row 1 (a-c): Annual average $PM_{2.5}$ concentrations (μg/m^3) under Cap 50% (2030) and changes relative to Baseline (2030) and Hist. (2017). Rows 2-3 (d-i): Change in concentrations under Cap 50% (2030) relative to Baseline (2030), by six sectors. National population-weighted averages are listed under each respective title. Color bar ranges in d-i are kept consistent to enable comparison of magnitudes of changes. For panels e, h, and i there is little change under the cap; a version of this figure with different color bar ranges is provided as Figure S1.



The policy decreases air pollution exposure across all racial/ethnic groups. Under *Hist.*, average exposure for the total population was 7.2 μg m^{-3}; people of color (including Black, Asian, and Hispanic populations) experience somewhat higher exposure (8.0 μg m^{-3}), and white populations slightly lower (6.7 μg m^{-3}), shown in red in Figure 3. Under *Baseline,* average exposures are slightly higher (7.8 μg m^{-3} for the entire population; 8.7 μg m^{-3} for people of color overall). In 2030 under *Cap 50%*, average exposures are lower than *Baseline* for all racial/ethnic groups, with the greatest reductions for Black (0.44 μg/m^3) and white populations (0.37 μg/m^3).

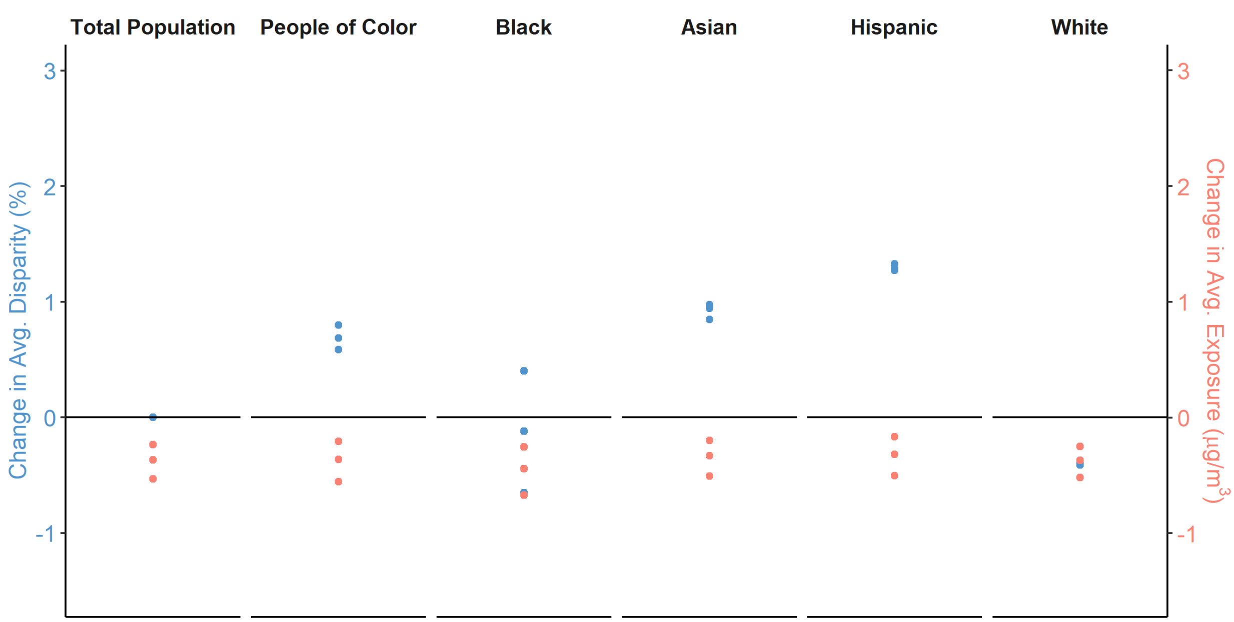
Despite the overall reduction in $PM_{2.5}$ exposure under the policy, it does not reduce exposure disparities at the national level. Relative exposure disparity (calculated as the percentage difference between the exposure for a given group and the total population) was 12.1% for people of color and -6.9% for the white population under *Hist.*, shown in blue in Figure 3. Relative disparities increase for Asian, Hispanic, and POC, and disparities for Black people and white people decrease on average, relative to 2017. Reductions in exposure for Black people and white people are greater than the reductions for the total population on average (0.37 $\mu g/m^3$), thus reducing the relative disparity for Black people (from 17.9% to 17.8%) and increasing the average relative benefit for white people (from -7.3% to -7.7%). In contrast, reductions in exposure for Asian (0.33 $\mu g/m^3$), Hispanic (0.32 $\mu g/m^3$), and POC (0.36 $\mu g/m^3$) are less than for the total population. As a result, the relative disparities increase for Asian (9.1% to 10.1%), Hispanic (12.1% to 13.3%) and people of color (12.4% to 13.1%), and the disparity gap between these groups and white people widens slightly. Thus, while each group benefits on average from the carbon policy with lower average exposures, relative disparities mostly persist (or even increase). Figure S2 shows the change in disparities by state between *Cap 50%* and *Baseline*, showing large regional variation in impacts, driven by the correspondence between the population of each group and the location of largest reductions (as shown in Figure S1). While the policy narrows disparities in some states, widening disparities in other states mean that there is limited aggregate impact at national scale.

Figure 3. National population-weighted average $PM_{2.5}$ exposure and relative disparity by race/ethnicity in Hist. (2017), Baseline (2030) and Cap 50% (2030). Disparity is calculated as the percentage difference between $PM_{2.5}$ exposure for the given group and the total population.


Total Population
People of Color
Black
Asian
Hispanic
White
Avg. Relative Disparity (%)
Avg. Exposure (μg/m³)
Hist. (2017)
Baseline (2030)
Cap 50% (2030)
7.2
7.8
7.4
12.1%
12.4%
13.1%
8.0
8.7
8.4
18.4%
17.9%
17.8%
8.5
9.1
8.7
7.8%
9.1%
10.1%
7.7
8.5
8.1
11.3%
12.1%
13.3%
8.0
8.7
8.4
6.7
7.2
6.8
-6.9%
-7.3%
-7.7%

Our primary modeling approach assumes that the emissions distribution for each sector within each of the underlying economic model's regions (see Methods) remains unchanged under *Baseline* and *Cap 50%*. However, emissions under carbon policies could change heterogeneously in ways that affect distributional outcomes. To assess the potential for different distributions within each state and sector to lead to different outcomes under the simulated carbon pricing strategy, we evaluate alternative emissions distributions for stationary point sources (see Methods/Uncertainty Analysis) to provide an upper and lower range for equity outcomes for each racial/ethnic group. Figure 4 shows resulting ranges of changes in exposure and disparities by group between *Cap 50%* and *Baseline*. For all groups except Black people, the impact of this change in distribution is relatively limited. For Black people, the disparity can either increase or decrease depending on emissions distribution, although the magnitudes of relative changes remain small (0.5% relative to 18.4%).

Figure 4. Uncertainty range for the change in $PM_{2.5}$ exposures (orange) and disparities (blue) by race/ethnicity between Cap 50% (2030) and Baseline (2030), based on a sensitivity simulation in which total reductions remain constant for each economic region and sector, but the distribution of these reductions among different point sources are allowed to vary.

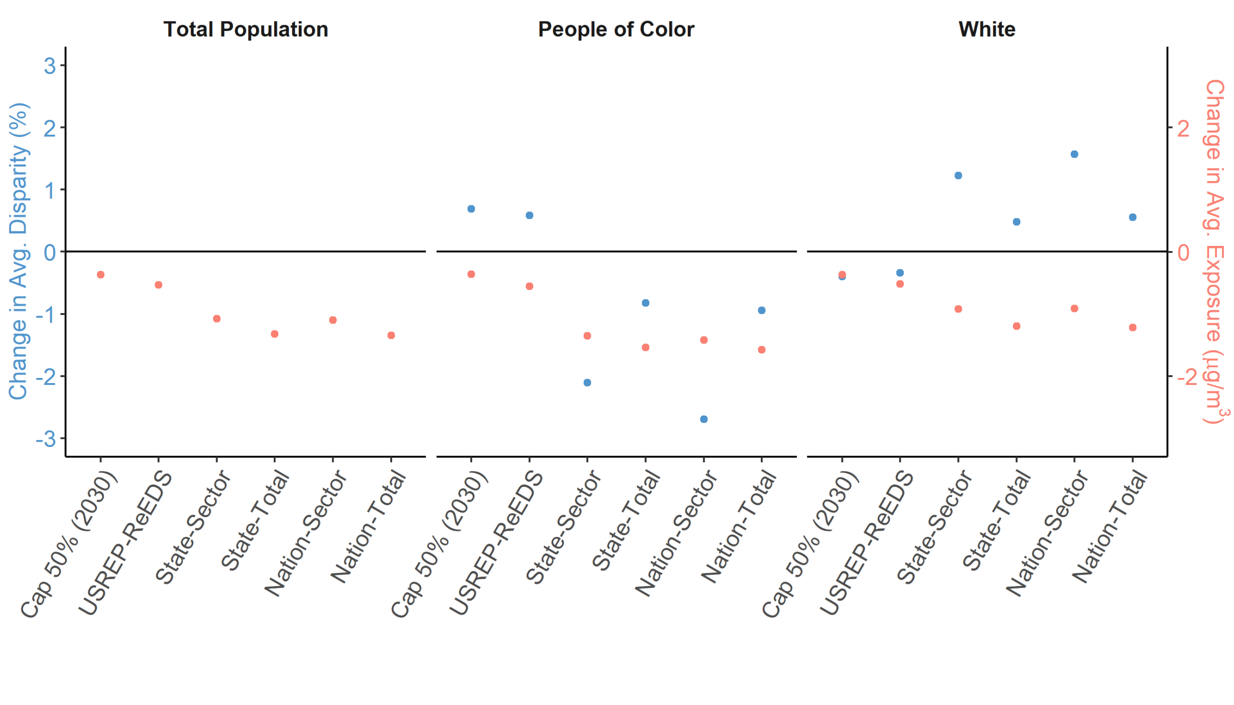


Potential for Disparity Mitigation through Alternative Carbon Reduction Distribution

We quantify the potential impact on disparities of reducing CO_2 from different regions and sectors than those that minimize CO_2 reduction cost, approximating different reduction prioritizations that might be achieved using either command-and-control or pricing mechanisms (see Methods/Optimization Approach). We explore the extent to which possible distribution scenarios of the same total CO_2 reductions can better mitigate $PM_{2.5}$ disparities. It shows the result of optimizations in which CO_2 reductions can come from different combinations of sources, minimizing $PM_{2.5}$ associated mortality for POC. The scenario "USREP-ReEDS" parallels the approach used for uncertainty quantification (Figure 4) in which the sectoral and regional totals are the cost-minimizing solutions from the economic model, but here the magnitude of reductions from all sources (including point and area sources) can vary for each sector-region combination. We also conduct optimizations, minimizing POC mortality, under four further sensitivity scenarios in which target CO_2 emissions reduction totals are distributed differently by sector or state, and individual sources are allowed to vary to achieve this in a way that minimizes POC mortality. Under "State-Sector", overall individual state and sectoral reductions are consistent with the "*Cap 50%*" policy but the distribution of reductions among sources within these can vary. "State-Total" maintains consistent reductions for each state, but allows reductions to come from different economic sectors. "National-Sector" maintains *Cap 50%'s* distribution of sectoral reductions but allows reductions from those sectors to come from anywhere in the country. "National-Total" sets a U.S.-wide cap and allows any source to reduce to meet it. The "State-Sector" and "State-Total" scenarios would correspond to efforts that states might introduce to prioritize CO_2 reductions in specific locations based on knowledge of sources that contribute the most to disparities. The least-constrained "National-Total" scenario reflects a conceptual upper limit of the potential for targeting individual sources through national-scale policy design under a carbon reduction scenario of comparable magnitude.

In Figure 5, we compare these sensitivity scenarios to the main impacts estimated for the *Cap 50%*. We find that further reductions in POC exposures are in principle achievable while still meeting the same CO_2 emissions reductions. The comparison between the USREP-ReEDS scenario and the additional scenarios in which reductions can come from alternate sectors and regions implies that the least cost reductions opportunities identified by the carbon policy do not produce the greatest improvements in $PM_{2.5}$ exposure. Prioritizing reductions in exposure for people of color also reduces exposure for white people and the total population on average, suggesting a win-win of absolute gains from reducing sources that minimize POC mortality. However, this means that the reduction in the overall disparity is limited, and substantial disparities remain. The sectoral contributions to this distribution are illustrated in Figure S3; the largest driver of additional reductions comes from the optimization constraint that allows for redistribution of emissions in the transportation sector, which is not substantially affected under the "*Cap 50%*" policy but which is both CO_2-intensive and a major air pollution source.

Figure 5. Change in average $PM_{2.5}$ exposure (relative to Baseline) and average disparities (%) under Cap 50% compared with sensitivity scenarios that identify alternative CO_2 emission reduction distributions for both point and area sources that minimize POC mortality associated with $PM_{2.5}$ exposure, while keeping overall CO_2 reductions constant for different region/sector combinations.



Discussion

We explored how federal decarbonization strategies might affect disparities in $PM_{2.5}$ exposure for different U.S. racial/ethnic groups, focusing on CO_2 policy of similar magnitude to current federal targets. We showed that a cap-and-trade policy instrument reduces exposure to $PM_{2.5}$ for all racial/ethnic groups relative to *Baseline*, but does not substantially mitigate relative disparities in exposure. Black, Hispanic, and Asian people continue to experience disparities, while white people experienced less exposure than the total population on average. This is because the carbon policy achieves most reductions in the coal-fired electricity sector. Previous studies have showed that this sector disproportionately harms only Black and white people more than average (Tessum et al., 2021). In contrast, the electricity sector contributes a relatively small fraction to population exposure overall, and key disparities arise from harder-to-decarbonize sectors with remaining emissions even under 50% cuts, such as industry and heavy-duty diesel transportation. These results are robust to assumptions about emissions reduction distribution, suggesting that the geographic distribution of source reductions under comparable policies do not drive substantial differences in outcomes with respect to disparities.

More broadly, we find limited opportunities to further reduce exposure and mitigate disparities at national scale while achieving the same CO_2 reduction goals. The extent of air pollution mitigation is limited in part due to the magnitude of the CO_2 reductions desired by 2030, where addressing only 50% of CO_2 emissions leaves many polluting sources unmitigated. At the same time, efforts to prioritize reductions for people of color benefit the entire population, including white people, on average. We conclude that while reducing CO_2 by 50% can yield air pollution and health benefits for all, and has the potential to provide targeted improvements in particular regions, climate policy alone is an insufficient tool to adequately address near-term air pollution disparities nationally.

This analysis considers reductions from sectors that are addressed in the IRA, which is expected to achieve U.S. carbon reductions through incentives targeted to clean energy and transportation. With an incentive-based approach, CO_2 reductions from these sectors will not be specifically targeted towards addressing individual sources. Because we consider a comprehensive range of possible distributions of CO_2 reductions, our results are applicable to a variety of the reductions that might occur when the IRA is implemented. Analysis of the provisions of the IRA would be needed to specifically project its anticipated impact on air pollution and equity for different regions. However, as the entire range of potential CO_2 reduction distributions we assessed reduced air pollution exposure overall and also had limited impact on disparities at national scale, we would expect a similar outcome for the IRA.

Our results suggest several ways forward for policy design. Even with the most targeted design, the emissions impacts of reducing CO_2 alone will not substantially change existing pollution disparities. This means that fulfilling policy goals associated with minimizing disproportionate impacts of air pollution on different racial/ethnic groups will require additional targeted interventions in the near term. More aggressive carbon policies than examined here, including those that ultimately remove all fossil fuel sources, could have larger effects, but the timescale of this transition would leave disparities unaddressed for more than a decade. Interventions to reduce both direct $PM_{2.5}$ and precursor emissions that are not directly associated with CO_2 sources, such as sectoral policies and community-focused mitigation measures, will be critical to improving air quality and public health equitably in the U.S. Taken together, this suggests that efforts fully mitigate the disparate impacts of pollutants will require efforts beyond optimization of existing CO_2 policy strategies, including large-scale structural changes.

Online Methods

In this section, we first describe the energy-economic modeling of the baseline and carbon pricing scenarios that produce the energy sector activity that we leverage. We then estimate future levels of emissions, using the energy modeling outcomes to scale historical U.S. emissions of CO_2, primary $PM_{2.5}$ and precursor gases that form secondary $PM_{2.5}$ in the atmosphere – sulfur dioxide (SO_2), nitrogen oxides (NO_X), ammonia (NH_3) and volatile organic compounds (VOC). Non-CO_2 emission factors are fixed at 2017 levels to enable consistent comparisons, as we do not have information regarding how non-CO_2 emission rates will change over time. Using these emissions, we then apply a reduced-form air quality model to estimate annual $PM_{2.5}$ concentrations and population exposures at a fine spatial scale and evaluate relative exposure disparities across racial/ethnic groups. Finally, we address uncertainty in the estimated emissions reductions under the policy as different distributions of CO_2 emissions could lead to different equity outcomes. Specifically, we produce alternative emissions distributions that are consistent with CO_2 emissions reductions in the energy modeling but provide an upper and lower range for equity outcomes for each racial/ethnic group.

Energy-Economic Scenarios

The analysis uses energy-economic modeling of two future scenarios for 2030, described in detail by Yuan et al. (2022): (1) a national CO_2 cap-and-trade program that requires a 50% reduction in U.S. economy-wide CO_2 emissions relative to 2005 levels by 2030, and (2) a baseline scenario without the program. Yuan et al. (2022) evaluated the impact of these scenarios, and others, on energy sector activity, CO_2 emissions, household welfare, and total net benefits accounting for climate and air quality-related health benefits as well as economic welfare costs of the policy. Yuan et al. (2022) deploy an economy-wide, energy-economic modeling tool (USREP-ReEDS) to evaluate the impact of potential CO_2 pricing policies on energy sector activity, CO_2 emissions, household welfare, and total net benefits. MIT's U.S. Regional Energy Policy (USREP) model is a computable general equilibrium model of the U.S. economy (Yuan et al., 2019), and in these simulations its electricity sector representation has been replaced by the Regional Energy Deployment System (ReEDS), a capacity expansion model of the U.S. electricity sector developed by the U.S. National Renewable Energy Laboratory (NREL) (Cohen et al., 2019). Relevant to air pollution projections in this paper, USREP represents states via 30 regions (including 18 individual states), while ReEDS spans 134 electricity balancing regions (with additional geographic representation of wind and solar resources across 356 regions); see Figure S4 for a map.

In the *Baseline* scenario ("*Baseline*"), results are calibrated to the Energy Information Administration's Annual Energy Outlook 2020 reference case and in addition, reflect NREL's Annual Technology Baseline 2019 Mid-Range electricity technology costs and performance characteristics, updated state clean energy policies, and a COVID-19 pandemic adjustment. The policy scenario ("*Cap 50%*") imposes on the *Baseline* a national CO_2 cap-and-trade program that covers energy and industry-related CO_2 emissions and allows national trading of emissions allowances without offsets or banking or borrowing across years. The scenario assumes that CO_2 emission allowances are distributed to states on a per-capita basis and that the state revenue raised from allowance sales are rebated to households on a per-capita basis. While other choices of allowance allocation schemes are evaluated by Yuan et al. (2022) affected economic welfare outcomes, they have negligible impact on emissions outcomes and therefore are not analyzed here.

Emissions Inventory and Projections

We construct emissions inventories for a base historical year (2017) and the modeled *Baseline* and *Cap 50%* scenarios in 2030, and take steps to make them compatible with the air quality model that we use (discussed in the following section).

Historical Emissions Inventory

We use the U.S. Environmental Protection Agency's (EPA) National Emission Inventory (NEI) 2017 containing annual emissions of CO_2, $PM_{2.5}$, SO_x, NO_x, NH_3, and VOC (EPA, 2021a) for 5,495 unique EPA Source Classification Codes (SCC). We use emissions spanning the continental U.S., allocating emissions spatially to grid cells and vertically to effective stack height (ESH) layers (reflecting the height of the emission plume that rises above the physical stack height). For point sources, we use the unique coordinates of each point source to assign the corresponding grid cell that each source is located in. We calculate ESHs for each point source using stack information (height, diameter, plume velocity, and plume temperature) applying the Holland formula (Turner, 1972), using ambient temperature and wind speed from the air quality model's atmospheric layer that corresponds to the emission source's stack height and location, and ambient pressure that we calculate as a function of sea level temperature and real stack height. If a source's stack height data is missing, we use the ESH layer of the nearest source within the same NEI Tier 2 category. For area sources, which are county-level and often overlap with multiple grid cells, we distribute emissions to grid cells using distributions in the NEI 2014 spatial modeling data prepared for use in Tessum et al. (2019), as 2017 emission spatial distributions were not available. NEI 2014 distributions reflect spatial surrogates unique to specific emission types (e.g., population for dry cleaning emissions and interstate highways for motor vehicle emissions), that are used in development of EPA emissions modeling platforms (EPA, 2022). We distribute state-level NEI 2017 emissions to grid cells based on the state-grid distribution for the corresponding NEI Tier 3 emissions in the 2014 dataset. For cases where there is not a Tier 3 match, we use Tier 2 or Tier 1 distributions to allocate remaining 2017 emissions. We then assign all area sources the ground level ESH. Finally, following Tessum et al. (2019), biogenic and wildfire emissions are from 2005 and held constant. The 2017 NEI includes CO_2 emissions for many point sources from the EPA's Greenhouse Gas Reporting Program (GHGRP) as well as for transportation area sources (calculated from EPA's MOVES model). While the GHGRP does not include all sources of emissions, it includes emissions from large facilities and in total covers approximately 85-90% of all U.S. GHG emissions (EPA, 2021b). We retain the CO_2 emissions for use in our sensitivity scenarios and optimization described below.

Emissions Scaling Methodology

For the two future scenarios, we scale 2017 emissions to 2030 based on projected outcomes modeled with USREP-ReEDS, assuming that non-CO_2 emission factors are fixed at 2017 levels. The scaling approach largely follows methods outlined by Dimanchev et al. (2019). All emissions – except power sector CO_2, SO_2, and NO_X pollutants from coal and gas fuel sources – are scaled within 29 USREP regions (Alaska is excluded) and using 20 USREP variables matched to NEI SCCs, producing 545 unique scaling combinations nationally (35 region-variable combinations have zero data). The scaling factor is calculated as the regional USREP value in 2030 divided by the value in 2017 (interpolated from 2015 and 2020 results). Then, the scaling factor is applied uniformly to emissions of each pollutant (including CO_2) within the region and emissions scaling category. The method differs from Dimanchev et al. (2019) for the electricity sector, where we scale coal and gas power plant emissions for CO_2, SO_2 and NO_X to match ReEDS emissions for 134 balancing areas. Furthermore, total CO_2 emissions are then adjusted by USREP region by broader sectors (electricity, transportation, industrial, and residential) to match CO_2 emissions output by USREP, reflecting modeled efficiency improvements over time.

$PM_{2.5}$ Modeling, Population Exposure, and Disparity Metric

We estimate annual average concentrations of $PM_{2.5}$ for each scenario using the Intervention Model for Air Pollution (InMAP), specifically the InMAP Source Receptor Matrix (ISRM) as described in and provided by Goodkind et al. (2019). InMAP is a reduced complexity air quality model (RCM) that reflects atmospheric chemistry and transport of particulate air pollution (Tessum et al., 2017). The model takes a set of emissions data (primary $PM_{2.5}$, SO_X, NO_X, NH_3, and VOC), among other inputs, and predicts annual average concentrations of total $PM_{2.5}$ and its components: primary $PM_{2.5}$, particulate sulfate (pSO_4), particulate nitrate (pNO_3), particulate ammonium (pNH_4), and secondary organic aerosols (SOA). InMAP provides relatively higher spatial granularity than other RCMs or CTMs, while reducing the temporal resolution to annual scale (among other simplifications) to avoid computational requirements from more complex CTMs. InMAP has been used and validated in numerous peer-reviewed analyses of air quality and equity impacts of emissions (Goodkind et al., 2019; Tessum et al., 2021, 2019; Thakrar et al., 2020). RCMs, including InMAP, have been evaluated against each other and more sophisticated CTMs by Gilmore et al. (2019). The reduced-form air quality modeling approach is limited by its largely linear chemical mechanism and its use of annual-averaged meteorology. However, previous studies have shown that regional nonlinearities are limited in the US (Holt et al. 2015), and that large-scale conclusions from InMAP modeling are comparable to those using more detailed chemical transport modeling (Qiu, 2021).

Given emissions inputs of primary $PM_{2.5}$, SO_x, NO_x, NH_3, and VOC, the ISRM provides the change in respective particulate concentrations (described above) in a “receptor” grid cell caused by a 1 unit increase in emissions of each pollutant in a “source” grid cell. The sum of particulate concentrations of primary $PM_{2.5}$, pSO_4, pNO_3, pNH_4, and SOA equals total $PM_{2.5}$ in each grid cell. The ISRM spatially consists of 52,411 grid cells with resolutions ranging from 1x1 km (in the most population-dense areas) to 48x48 km (in the least population-dense areas), and vertically distinguishes between three ESH layers: “ground” 0-57 m, “low” 57-379 m, and “high” > 379 m. Emissions inputs – allocated to ISRM grid cells and ESH layers - are multiplied by the respective pollutant source-receptor matrix to produce concentrations of final $PM_{2.5}$ in each of the grid cell. To employ the ISRM with our emissions input data, we create a shapefile of the ISRM grid using grid cell bounding box coordinates and the spatial projection provided by Goodkind et al. (2019).

The ISRM includes block-group level population data by race/ethnicity from the 5-Year 2012 American Community Survey (ACS) that have been allocated to grid cells. Following Tessum et al. (2021), we evaluate outcomes for several racial/ethnic groups: Asian, Black, Hispanic, people of color (POC), and non-Hispanic white groups. Here, Hispanic spans all races; Asian, Black, and white groups are non-Hispanic and correspond only to the specific race; and POC is everyone except non-Hispanic white people. The sum of POC and white populations therefore equals the total population. Using total population projections from UVA (2018), we scale population data to 2030 by applying state level growth rates for the total population to all populations in grid cells whose spatial centroids correspond to a given state. This dataset therefore allows us to estimate $PM_{2.5}$ exposure for each racial/ethnic group. We calculate a relative disparity metric at the national and state levels as the percentage difference between the average exposure for each group and the average exposure for the total population. We also calculate percentage point differences between the policy and baseline scenarios to evaluate how disparities change due to the policy.

Uncertainty Analysis

For our base case, we scale detailed NEI emissions uniformly at the USREP-ReEDS region and variable level – i.e., a top-down scaling approach. Emission sources would not scale uniformly in practice, and as a result this assumption could yield differing localized air pollution and equity impacts. To address this spatial uncertainty of estimated emissions reductions under the policy, we use the ISRM to produce alternative emissions distributions that are consistent with CO_2 emissions reductions in the energy-economic modeling but bound equity outcomes for each racial/ethnic group. Specifically, within each scaling region/variable set, we optimize point source emissions changes under the carbon policy to estimate upper and lower bounds on mortality by race/ethnicity, keeping total changes in CO_2 consistent with the primary scaling methods described in 2.2.2. This redistribution of emissions is applied to the policy case only to evaluate a range of impacts due to the policy; the baseline case remains the same. This approach aims to evaluate the robustness of the projected $PM_{2.5}$ exposures to inform environmental justice conclusions for each racial/ethnic group.

First, using the ISRM, we calculate marginal mortality values (total U.S. mortality caused per ton of emissions of primary $PM_{2.5}$, SO_2, NO_X, NH_3, and VOC) for emissions from each grid cell for each race/ethnicity, using the concentration response function from Krewski et al. (2009) and all-cause mortality incidence rates for the total population. By matching emissions to their respective marginal mortality values, we can then calculate the mortality across each race/ethnicity caused by each source and pollutant. Emissions that are eligible to vary are point sources that (1) have CO_2 emissions; (2) cause $PM_{2.5}$-related mortality; and (3) are non-zero in the 2030 baseline. Within each of the USREP regions (and ReEDS regions, for power sector coal and gas emissions) and scaling variable pairs and for each race/ethnicity group, the scaling factors for emissions sources are optimized to produce a range of mortality outcomes, subject to several constraints: (1) emissions of any pollutant cannot be less than 0 (lower bound); (2) emissions of any pollutant cannot double the higher of the value in the 2017 inventory or 2030 baseline (upper bound); (3) total CO_2 emissions within a region and scaling set remain constant. (The optimization is conducted using R version 3.6.3 and package *lpSolveAPI*.) The result are sets of emissions that capture a range of mortality outcomes for each race/ethnicity to provide upper and lower bounds. The redistributed emissions are then input to the ISRM to yield a range of exposures and disparities. The optimization formulation is presented below for a representative region and scaling variable set and racial/ethnic group.

Maximize or minimize:

$$objective\ function = \sum_i S_i TM_i$$

where:

- i = unique index of eligible emissions sources
- TM_i = total mortality (for a given racial/ethnic group) caused by emissions at source *i,* where emissions at source *i* for each pollutant are the higher of the value in the 2017 inventory or 2030 baseline.
- S_i = scaling factor (decision variable) applied to emissions of all pollutants at source *i*, allowed to range between 0 and 2. In other words, while in the uniform scaling method S_i is uniform across all emission sources within a region and scaling variable set, here S_i is unique to each emissions source *i* as determined by the optimization.

Subject to:

1. Total CO_2 emission within a region and scaling variable remain constant.

$$\sum_i S_i CO2_i = \sum_i CO2_i$$

2. Emissions of any pollutant cannot be less than 0 (lower bound) and cannot double the higher of the level in the 2017 inventory or 2030 baseline (upper bound).

$$0 \leq S_i \leq 2$$

Optimization Approach to Assess Alternative Carbon Reduction Distribution

We expand the optimization as described above to explore if emissions distributions that are different than those under the modeled carbon policy better mitigate national-scale air quality disparities while still achieving the same total CO_2 emissions reductions. To do this, we apply the above optimization methodology, expanding the eligibility of emission sources that can vary to include area sources in addition to point sources. Specifically, we minimize POC mortality while keeping CO_2 constant for respective emissions group combinations: “State-Sector”, “State-Total”, “National-Sector”, “National-Total.” The sectors considered here are electricity, transportation, industry, residential, and other.

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