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Article

Human Health Impacts of Energy Transitions across the United States among Sociodemographic Subpopulations for the Year 2050

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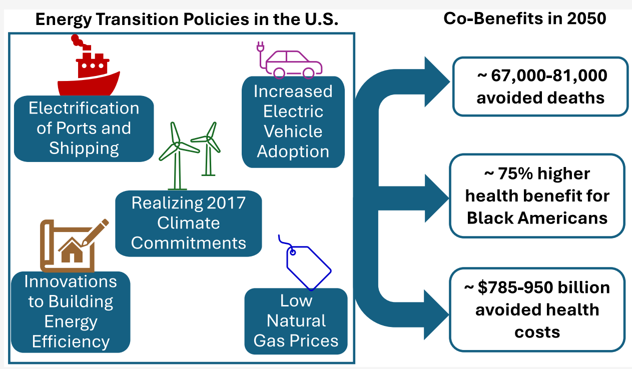
ABSTRACT: Strategies to reduce greenhouse gas emissions may provide health benefits through improved air quality, yet these benefits might not be equitably distributed. Understanding these cobenefits and who receives them can aid policymakers in prioritizing mitigation strategies. We investigated four future energy scenarios (port electrification, electric vehicles, natural gas, energy efficiency) and a business-as-usual scenario to determine how changes to ambient fine particle ($PM_{2.5}$) levels impact health within the contiguous United States (U.S.) by region, race/ethnicity, urbanicity, and income. We also investigated how methodological assumptions affect findings. Our projections of avoided mortalities from energy transition policies range from 67,011 (95% CI: 45,692, 82,397) to 81,003 (55,286, 99,532) in 2050. The monetized health benefits from avoided mortalities and hospitalizations range from $785.8 billion to $949.9 billion/year. These benefits vary by region and subpopulation, with Black, suburban, and less wealthy Americans experiencing higher percent avoided mortality across scenarios. Results were sensitive to assumptions for future concentration−response functions relating pollution levels to health, baseline incidence rates, and population projections. Our findings indicate energy policies transitioning from fossil fuel production in the U.S. provide substantial health and economic benefits that vary across populations and help reduce environmental health inequities in exposure and associated morality.



KEYWORDS: *PM2.5, co-benefits, energy policy, environmental justice, exposure disparities*

INTRODUCTION

Air pollution is a leading cause of death with 6.67 to 8 million premature mortalities per year worldwide.[1,2] Substantial evidence shows that exposure to fine particulate matter ($PM_{2.5}$) contributes to premature mortality and morbidity.[3−7] $PM_{2.5}$ is the leading contributor of global disease burden, totaling 8% of all disability-adjusted life years (DALYs)[8] and nearly 4.6 million deaths each year.[9]

United States (U.S.) cohort studies have shown differential mortality risk across subpopulations by age, race/ethnicity, education, income, and urbanicity/rurality.[10−12] Social deprivation and other measures of socioeconomic status have been identified as independent risk factors for $PM_{2.5}$-mortality in the U.S.[13−15] Previous work indicated that concentration−response functions (CRF) vary by location, season, and time period.[16,17] This is attributed to differences in overall concentrations, population characteristics and particulate composition.[18−22]

Economy-wide fossil fuel combustion is a major $PM_{2.5}$ contributor, thus future projections of overall $PM_{2.5}$ levels and subsequent health outcomes depend greatly on assumed emissions levels and their patterns across regions and subpopulations. These emissions may drastically alter due to climate mitigation, air quality, and economic strategies. Strong evidence of such includes coal electricity generation displacement by gas-fired and renewable power over the past decade. Simultaneously, climate change could impact air pollution levels through changes in dispersion, dry and wet deposition, and photochemical reactions (e.g., secondary pollutant generation), which are related to meteorological patterns. Numerous studies estimate future health impacts of $PM_{2.5}$ from both energy policy changes and climactic changes.[23−31] A meta-analysis of 36 studies across 17 countries identified positive coimpacts (often called cobenefits) to human health from greenhouse gas emission reductions across energy use domains, with possible multiplicative impacts across sectors.[32] Several studies also researched regional differences across the

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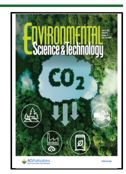

U.S. and globally for health coimpacts from proposed and enacted energy policies.[24,29,33−40]

However, few health studies on ancillary air quality and health impacts of energy policies examined differential impacts across demographic and social factors of affected populations. Other studies showed disparities related to $PM_{2.5}$, both for exposure and subsequent health response, across the U.S. by race/ethnicity and socioeconomic status, but most such studies are for the present day with few investigating how environmental health disparities are affected by coimpacts from energy policies into the future.[41−48] A 2016 review of air quality policies and future health coimpacts in Europe highlighted only three studies that investigated a component of equity.[49] Some more recent studies investigated future energy, transportation, or carbon-pricing policy projections and health equity include analysis stratified by income in New York City,[50,51] by race/ethnicity in Boston,[52] by disadvantaged neighborhoods in California,[53,54] by race/ethnicity across the U.S.,[55,56] and by region in China.[57] While these studies provide critical evidence that coimpacts are not shared equally, existing research is limited in policy exploration and subpopulation inequity.[42,49,51,52] Understanding the health cobenefits of energy policies is critical to addressing climate change and understanding whether such policies exacerbate or lessen disparities. Complicating such research is the wide range of methodologies and assumptions applied.[31]

By linking energy-economy, air quality and climate change modeling; epidemiology; and economic analysis, we estimate how projected changes to $PM_{2.5}$ from different energy transition scenarios would affect human health for the contiguous U.S., including by regions and subpopulations under various selected health impact assessment (HIA) model assumptions. Our goal is to estimate how public health benefits differ across energy transition strategies and evaluate how the distribution of benefits differs. In other words, a scenario under which population health is improved overall may not be the most beneficial scenario for all subpopulations. As secondary analysis, we examine how methodological assumptions impact results.

■ METHODS

An HIA framework was developed to investigate overall health impacts and disparities from air quality changes in 2050 across energy policy projections based on a business-as-usual (BAU) emissions scenario of U.S. policies in place at the beginning of 2017 and four scenarios of sector-specific changes in policy. We combined engineering-economic energy simulations; air quality modeling; epidemiology; and economic analysis. Figure S1 presents a flowchart of the methodology.

Energy Emission Scenarios. Five energy policy scenarios represent the culmination of research and extensive communication with state-level air quality policymakers.[58] It was determined that traditional scenarios modeled in cobenefits research (e.g., net zero emissions) are useful but did not match what policymakers felt most impactful. This is the impetus for selection of our energy policies: 2017 National and Subnational Policy Scenario (BAU), inclusion of all energy and climate policies passed through 2017;[59] Marine Shipping and Port Electrification Scenario (Port), including electrification in ports, emissions control areas, and of all associated fuels;[59] High Electric Vehicle Uptake Scenario (HighEV), assuming a 60% adoption rate by 2040;[60] Low Long-Term Natural Gas Pricing Scenario (HighNG), assuming high utilization of unproven U.S. gas reserves;[61] and Innovations in Building Energy Efficiency Scenario (HighEE), assuming 16% overall energy reductions through efficiency.[62] We use versions for each sector that align with the most ambitious scenarios we found among industry analysts from the government or private sector. Detailed information on these policies and their modeling approaches[58−64] can be found in Supporting Information.

Air Quality Modeling for $PM_{2.5}$. $PM_{2.5}$ levels, along with $PM_{2.5}$ precursors, were modeled previously for current and future concentrations using the WRF-Chem air quality modeling platform, with the surface layer results used for analysis.[65] $PM_{2.5}$ predictions were generated at 36 × 36km resolution for the contiguous U.S. for the baseline year 2010 (5 year 2008−2012 average) and five policy scenarios in 2050 (5 year 2048−2052 average). This model computes hourly $PM_{2.5}$, and these data were aggregated across each five-year period. Concentration data were area-weighted to county averages.[66] The 5 year average $PM_{2.5}$ predictions were evaluated using observations from the US EPA surface monitoring network. Normalized mean biases and errors are within ± 15 and ± 22%, which are considered high performing. These results are being analyzed for a separate journal publication.

Population Characteristics. Demographic data were retrieved from the 5 year 2016−2020 U.S. Census American Community Survey (ACS) county-level data and include the 18+ population by race (White, Black, Asian and Pacific Islander, Native American, Two or More, Other), ethnicity (Hispanic, Non-Hispanic), age (18−64, 65−74, 75+ years), and annual income (<\$35,000, \$35,000−\$49,999, \$50,000−\$74,999, ≥ \$75,000).[67] Urban status was defined by the 2013 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties by population size (Large Central Metro, Large Fringe Metro, Medium Metro, Small Metro, Micropolitan, and Non-Core).[68] Population characteristics were chosen based on availability to incidence rates and CRF in the literature. Age groupings and income mirror CRFs from the literature,[7,10,12] while race/ethnicity followed availability of groupings in the Census ACS data[67] and urban status with the more nuanced NCHS data than a simplistic urban/rural demarcation.[68]

Projected Population Characteristics. Population projections from the 2017 U.S. Census Bureau National Projections were used to estimate 2050 18+ populations, consistent with the energy policy modeling. An increase ratio of 1.169201 from the U.S. Census 5 year ACS data[69] was used to estimate the population overall and by subpopulation (U.S. Census region, income, urbanicity). Race/ethnicity subpopulation projections were determined through the 2017 U.S. Census Bureau National Projections using population rate change multipliers of: Hispanic (1.6015599), non-Hispanic (1.0695383), White (1.0758291), Black (1.2680511), Asian and Pacific Islander (1.6290942), Native American or Alaskan Native (1.262051), and Two or More Races, nondifferentiated (2.1368861).[69] The Other race category in the ACS data was not represented under the U.S. Census projections and was assumed to follow the overall population change rate.

Incidence Rates. Baseline incidence rates for mortality were determined from county-level, race/ethnicity- and age-stratified data from the CDC WONDER mortality data set (2015−2019).[70] Cardiovascular and respiratory hospital admissions rates were determined using Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost and

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Utilization Project (HCUP) National Inpatient Sample (NIS) data, which include ICD-10-CM diagnoses across the contiguous U.S. and District of Columbia, covering 97% of the U.S. population, except for Delaware and New Hampshire in 2016 and New Hampshire in 2017.[71] Incidence rates for morbidity were grouped from 2016 to 2019. County-specific incidence rates were calculated by age (18−64, 65−74, ≥ 75 years) for overall population and race/ethnic-specific subpopulations matching the 5year ACS population data for each age grouping and available CRFs. County-level data were unavailable for 54 counties for which state-wide incidence rates were substituted.

Concentration−Response Functions. CRFs link air pollution exposure change and risk of health outcome. CRFs were identified from an epidemiological literature review for associations between long-term $PM_{2.5}$ exposure (≥1 year average) and mortality or hospitalization (including all-cause, respiratory, and cardiovascular hospitalizations) in large, representative U.S. cohort studies. CRFs were selected from published papers based on data collected within the last 15 years for mortality[7,10,12] and cardiovascular and respiratory hospitalizations.[72] An alternate mortality CRF was also considered.[7] For mortality, we considered separate CRFs by age, income (<$35,000, $35,000-$49,999, $50,000-$74,999, ≥ $75,000/year), urbanicity (Urban, Rural), U.S. Census Region (Northeast, Midwest, South, West)[12] and race/ethnicity for White, Black, Two or more races, Other Race, Non-Hispanic, and Hispanic 18+ populations[12] and Asian/Pacific Islander and Native American 65+ populations.[10]

Health Impact Functions: Deaths and Hospitalizations. Estimation of changes in the number of avoided premature deaths for a given scenario was determined through a health impact function corresponding to differences in pollution levels between the reference (2010) and each of the five (BAU plus four alternative) policy scenarios across subpopulations, as well as comparison between the 2050 BAU projections against the four alternative policy projections

$$\Delta y_{ati} = y_{0_{ati}} \times P_{ati}(e^{\beta_a \times \Delta x_{ti}} - 1)$$

$$\Delta y_{at} = \sum (\Delta y_{ati} | t)$$

where y_{0ati} is the baseline incidence mortality rate for population P_{ati} for subgroup a, energy policy t, and county i; b_a is the CRF for subpopulation a; and Δx_{ti} is change in $PM_{2.5}$ concentration for policy t and county i.[22,73−79]

Change in hospitalizations were calculated as follows

$$\Delta HA_{ati} = HA_{0_{ati}} \times P_{ati}(e^{\beta_a \times \Delta x_{ti}} - 1)$$

$$\Delta HA_{at} = \sum (\Delta HA_{ati} | t)$$

where HA_{0ati} is the baseline cause-specific hospital admission rate for subgroup a, energy policy t, and county i. Other terms are described above.

These equations were applied to each county, using the corresponding incidence rate, population projection, CRF, and $PM_{2.5}$ concentration changes for 2050. We use the 95%CI values from CRF inputs as our projected 95%CI in the results.

Health Impact Function Model Assumptions. Our main analysis considers race-specific population projections; baseline incidence by age, county, and race; and subpopulation-specific (race/ethnicity, urban/rural, income, U.S. Census region) CRFs to account for the known differences across these factors. We explored the impact of various methodological assumptions for: population projection (overall population projection vs allowing population growth to differ by race), baseline incidence (single value overall vs county-specific vs county- and age-specific), and CRF (single association for the whole population vs different CRFs by subpopulation). By combining these assumptions, we investigated how results were affected by a higher degree of methodological sophistication. Table S1 shows combinations of methodological assumptions underlying the main analysis (Main Approach) and six alternative analyses (Alternative Approach 1−6).

Economic Analyses of Health Outcomes. The U.S. Environmental Protection Agency (EPA) Value of Statistical Life (VSL) metric was used to estimate economic impacts of death. VSL provides an estimate for the aggregate amount society is willing to pay to avoid one additional death.[79] The current EPA VSL quantifying death risk reduction benefits is $11.5 million using 2024 USD adjustments to the $7.4 million 2006 EPA value.[80,81] Hospital inpatient admission cost (HOSP) was estimated at $18,531 (95% CI: $10,028, $27,034) per hospitalization in 2024 USD, adjusted from 2017 USD.[80,82] Economic valuation of deaths and hospitalizations is estimated as

$$F_{at} = \sum_{n=1}^{a} \Delta HA_{at} \times HOSP + \sum \Delta y_{at} \times VSL$$

where Δy_{at} is the change in premature mortality avoided for subpopulation a for policy scenario t; and ΔHA_{at} is the change in premature hospitalization for population a for policy scenario t.[83,84]

Inequality Metrics. Social disparities in impacts of air pollution can have various causes. Here we focus on disparities in exposure and health response to a given level of exposure. To evaluate exposure inequality, population-weighted averaging of exposure by subgroup was used. Population-weighted average $PM_{2.5}$ exposure was calculated for each subpopulation as

$$PW_a = \frac{\sum_{j=1}^{n} P_{a,j} C_j}{\sum_{j=1}^{n} P_{a,j}}$$

where $P_{a,j}$ is subpopulation a in county j, and C_j is $PM_{2.5}$ for county j.[85] This was done using 5 year ACS population counts for each subpopulation and county plus the total county population for three age groupings (18−64, 65−74, ≥ 75 years). Exposure estimates were generated for each policy scenario and subpopulation of interest and averaged for country-wide and Census region-wide values.

The use of different CRF by race, income, urban status, and region incorporates differences by subpopulation in their response to a given level of air pollution. We calculated both absolute and relative difference. Relative difference was calculated as

$$RD = \frac{(A_{at} - B_t)}{B_t} \times 100\%$$

where A_{at} is the avoided death rate for subpopulation a for policy t and B_t is the overall, group specific (i.e., all income level groups combined) population avoided death rate for policy t.[86,87] We chose this measure of inequality for its ability to differentiate, by percentage, from the average population

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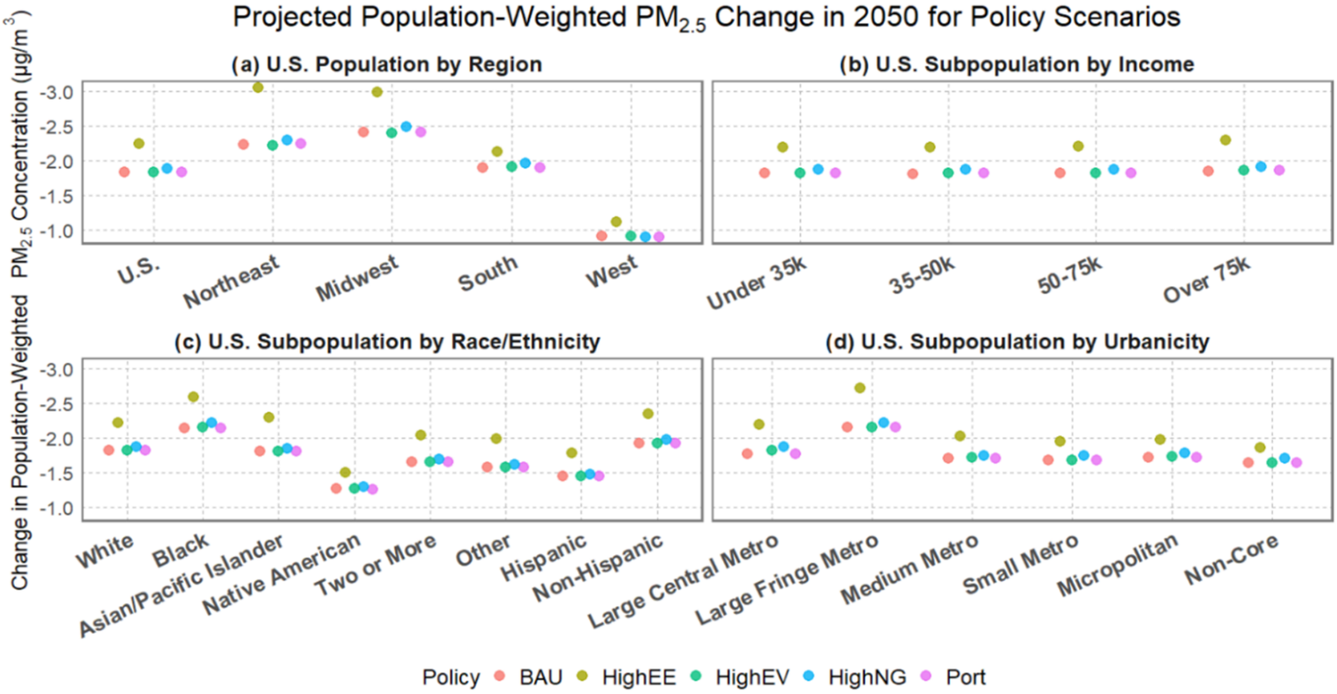

Figure 1. Policy-specific projected population-weighted $PM_{2.5}$ concentration changes in 2050 from the 2010 reference for by (a) region, (b) income, (c) race/ethnicity, and (d) urbanicity.

thus not comparing between racial groups, while also presenting more readily interpretable differences for policy relevance.

Analyses were conducted using the R statistical program version 4.2.0.

RESULTS

Pollution Reductions. Energy policy scenarios involving full implementation of sector-specific regulations are projected to result in overall population-weighted U.S. $PM_{2.5}$ reductions in 2050 of 1.83 $\mu g/m^3$ for Port, 1.89 $\mu g/m^3$ for HighNG, 1.84 $\mu g/m^3$ for HighEV, and 2.24 $\mu g/m^3$ for HighEE, compared to 2010 modeled averages (9.08 $\mu g/m^3$ U.S.-wide) (Figure 1 and Table S2). In comparison, full implementation of the BAU policy in 2050 is estimated to result in 1.83 $\mu g/m^3$ reduction in $PM_{2.5}$. Regionally, average ambient $PM_{2.5}$ concentration changes varied greatly, with the largest reductions across scenarios observed in the Midwestern and mid-Atlantic states, with lower reductions across the western half of the U.S. (Figure 2).We analyzed how disparities in pollution levels differ among policy scenarios. On average, every subpopulation experiences the largest $PM_{2.5}$ reductions under HighEE (Figure 1). Reductions were second highest under the HighNG scenario, except for the Western U.S. for which the BAU scenario projects the second highest concentration reductions. By county, HighEE has the largest $PM_{2.5}$ reductions for 98% of counties (3060 of 3108 counties) (Figure S2). On the other hand, the policy with the lowest county-level $PM_{2.5}$ reductions was most frequently the Port policy scenario (37.1%, 1153 counties), followed by the HighEV policy (30.1%, 937 counties), the BAU policy (25.2%, 784 counties), and the HighNG policy (7.5%, 234 counties).

Disparities in Pollution Levels by Subpopulations. While the general transition toward more renewable power means that all policy scenarios reduce $PM_{2.5}$ concentrations in 2050 compared to the 2010 reference scenario, some subpopulations are estimated to benefit more than others. By race/ethnicity, the Black subpopulation is projected to experience the largest $PM_{2.5}$ reductions across all policy scenarios, compared to 2010 reference concentrations (Figure 1). This holds true for the contiguous U.S. and all four U.S. regions. The second largest reductions are projected for the White subpopulation averaged across the entire U.S. for each policy scenario, but this projection varies across U.S. regions (Table S2). The Asian/Pacific Islander subpopulation is projected to experience the lowest $PM_{2.5}$ reduction in concentration across all policy scenarios for the Northeast and South regions, and across all policies aside from the HighEE scenario in the Midwest.

By income, the richest group (≥$75,000/year, 2020USD) is projected to experience the highest decrease in $PM_{2.5}$ from every policy scenario across the U.S. and all four regions (Figure 1 and Table S2). The largest difference in overall $PM_{2.5}$ reductions across income levels is for the HighEE scenario, with a difference of 0.10 $\mu g/m^3$ between reductions for the highest and second to lowest ($35,000−$50,000/year) groups.

Across urban gradients, the Large Fringe Metro areas have the highest $PM_{2.5}$ reductions, with Large Central Metro areas having the second highest concentration reductions across all policies (Figure 1). The most rural areas (Non-Core) are projected to experience the lowest $PM_{2.5}$ reductions under each scenario.

Overall Health Benefits. Compared to the 2010 baseline scenario, we estimate that BAU will avoid 67,011 (45,692, 82,397) deaths in 2050 across the contiguous U.S. (Table 1). When compared to the fully actualized BAU policy scenario in 2050, the Port, HighNG, HighEV, and HighEE scenarios are projected to avoid (i.e., beyond 2050 BAU projections) 65 (44, 79), 2,104 (1,442 2,577), 153 (104, 186), and 13,992 (9,594, 17,136) additional deaths in 2050, respectively (Table S2). The BAU policy scenario projects 11,577 (1,332, 19,918)

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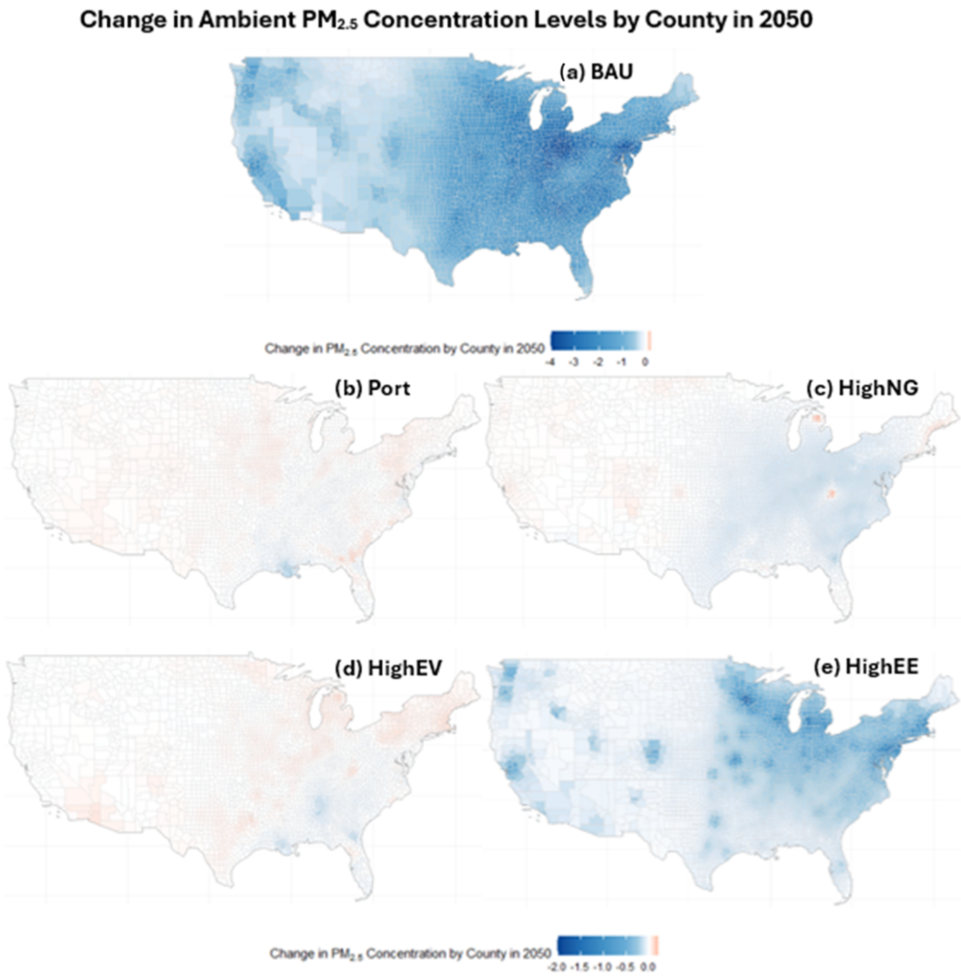

Figure 2. County-level ambient $PM_{2.5}$ concentration changes in 2050, compared to 2010 reference concentrations, for the (a) BAU policy scenario, and the county-level ambient PM2.5 concentration changes in 2050, compared to the BAU scenario in 2050, for each sector-specific policy scenario (b) Port, (c) HighNG, (d) HighEV, and (e) HighEE. Note that (a) BAU has a different scale than (b) Port, (c) HighNG, (d) HighEV, and (e) HighEE to allow for these scenarios to better display concentration changes from the 2050 BAU scenario comparison, where blue is additional reductions from BAU and red is lower reduction than BAU.

fewer cardiovascular and respiratory hospitalizations across the U.S. compared to the 2010 baseline scenario (Table S4). The Port, HighNG, HighEV, and HighEE scenarios project an additional 7 (1, 11), 429 (50, 736), 22 (3, 37), and 1,976 (228, 3,385) avoided hospitalizations than the 2050 BAU projections (Table S5).

Disparities in Health Benefits across Policies Overall and by Region. Health benefits were calculated based on subpopulation-specific exposures, CRFs, incidence rates, and population projections as well as location-specific exposures, CRFs, and incidence rates. Due to these differences, not all U.S.-wide health benefits sum exactly when compared across subpopulations. For example, overall avoided deaths under the BAU scenario are 67,011, but 62,645 under BAU when summing the avoided deaths across all race subpopulations.

We estimate that the HighEE scenario generates the most avoided deaths and hospitalizations in 2050 for every subpopulation nationally and regionally, which is also seen across subpopulations for avoided deaths per 100,000 persons (Figure S3). For overall avoided deaths compared to BAU in 2050, results were mixed by region across the four sector-specific scenarios. The Port scenario projects to have additional avoided deaths compared to BAU for the Northeast and South regions, but fewer avoided deaths in the Midwest and South (Table S3). The HighNG and HighEV scenarios also project fewer avoided deaths in the West compared to BAU, with BAU projecting additional avoided deaths in the Northeast and Midwest compared to the HighEV scenario (Table S3).

Disparities in Health Benefits across Subgroups. Differences in overall health benefits are projected for all sociodemographic subpopulations under all energy policies (Table S6). While absolute differences in avoided mortality rate can be found in (Table S7), relative rates are focused on for their comparability in magnitude across population groups. The Black subpopulation has the highest projected health benefits across all policies. Avoided mortalities in the Black subpopulation are estimated to be 72.3−74.5% higher than the overall U.S. population across energy policies (Table S6). All other racial/ethnic groups fare worse than the overall population average for avoided mortalities, with the Asian/Pacific Islander population projected to have 56.7−59.1% lower avoided mortality benefit than the overall population in 2050 (Table S6). The Black subpopulation is estimated to have 18.1−20.1% higher reduction of hospitalizations than the overall population average (Table S6). The Other racial

Table 1. Projected Avoided Deaths (95% Confidence Intervals) in 2050 for Five Energy Policy Scenarios across U.S. Subpopulations (Results of the Five Energy Policy Scenario Projections in 2050 Compared to the 2010 Baseline)[a]

death co-benefits in 2050	avoided deaths for each projected policy scenario in 2050 vs 2010 baseline				
	BAU	Port	HighNG	HighEV	HighEE
overall	67,011 (45,692, 82,397)	67,075 (45,736, 82,476)	69,114 (47,134, 84,974)	67,162 (45,796, 82,583)	81,003 (55,286, 99,532)
race					
White	38,998 (27,769, 56,904)	39,022 (27,786, 56,939)	40,235 (28,654, 58,699)	39,065 (27,817, 57,002)	47,069(33,540, 68,604)
Black	14,696 (5,187, 24,834)	14,742 (5,203, 24,912)	15,214 (5,372, 25,697)	14,782 (5,217, 24,978)	17,608 (6,231, 29,673)
Asian/Pacific Islander	2,003 (1,624, 2,394)	2,005 (1,625, 2,396)	2,044 (1,658, 2,443)	2,005 (1,625, 2,395)	2,535 (2,057, 3,028)
Native American	321 (203, 431)	321 (203, 431)	330 (209, 443)	321 (203, 432)	374 (237, 503)
two or more	4,461 (−2,197, 11,371)	4,463 (−2,198, 11,377)	4,584 (−2,259, 11,679)	4,468 (−2,201, 11,389)	5,445 (−2,699, 13,824)
other	2,166 (−1,429, 5,525)	2,166 (−1,429, 5,525)	2,215 (−1,426, 5,6446)	2,166 (−1,429, 5,524)	2,713 (−1,798, 6,887)
ethnicity					
Hispanic	12,860 (7,414, 18,371)	12,860 (7,414, 18,870)	13,149 (7,582, 18,778)	12,870 (7,420, 18,385)	15,768 (9,110, 22,477)
non-Hispanic	46,830 (−30,953, 119,226)	46,881 (−30,987, 119,354)	48,349 (−31,979, 123,013)	46,945 (−31,031, 119,515)	56,523 (−37,518, 143,333)
income level					
less than $35,000	20,509 (12,978, 26,246)	20,536 (12,998, 26,281)	21,185 (13,411, 27,106)	20,568 (13,019, 26,322)	24,480 (15,509, 31,298)
$35,000 to $49,999	10,215 (4,978, 15,019)	10,225 (4,991, 15,034)	10,548 (5,146, 15,503)	10,243 (4,999, 15,060)	12,213 (5,970, 17,624)
$50,000 to $74,999	17,926 (10,838, 26,005)	17 941 (10,849, 26,029)	18,495 (11,187, 26,823)	17,968 (10,863, 26,067)	21,511 (13,028, 31,144)
over $75,000	17,273 (0, 37,546)	17,287 (0, 37,587)	17,791 (0, 38,660)	17,331 (0, 37,609)	21,203 (0, 45,987)
region					
northeast	12,173 (1,284, 22,010)	12,178 (1,285, 22,019)	12,509 (1,320, 22,611)	12,108 (1,277, 21,893)	16,352 (1,731, 29,465)
midwest	41,695 (29,148, 53,169)	41,639 (29,108, 53,097)	43,091 (30,134, 54,932)	41,554 (29,048, 52,990)	50,987 (35,722, 64,887)
south	24,970 (9,450, 41,310)	25,078 (9,492, 41,490)	25,976 (9,834, 42,961)	25,263 (9,562, 41,793)	27,950 (10,589, 46,191)
west	4,770 (2,706, 7,235)	4,747 (2,693, 7,200)	4,738 (2,688, 7,186)	4,756 (2,698, 7,214)	5,880 (3,337, 8,913)
urbanicity					
large central metro	18,669 (14,603, 23,890)	18,674 (14,607, 23,896)	19,135 (14,969, 24,483)	18,692 (14,621, 23,919)	23,388 (18,310, 29,894)
large fringe metro	19,923 (15,589, 25,484)	19,960 (15,617, 25,530)	20,540 (16,073, 26,268)	19,952 (15,611, 25,520)	24,980 (9,563, 31,915)
medium metro	14,986 (11,720, 19,180)	15,002 (11,733, 19,201)	15,464 (12,096, 19,790)	15,051 (11,771, 19,264)	17,698 (13,849, 22,635)
small metro	6,910 (5,404, 8,845)	6,917 (5,409, 8,854)	7,156 (5,597, 9,158)	6,929 (5,419, 8,869)	7,971 (6,237, 10,197)
micropolitan	5,736 (1,792, 9,886)	5,737 (1,792, 9,889)	5,955 (1,861, 10,261)	5,750 (17,96, 9,910)	6,562 (2,052, 11,296)
non-core	4,157 (1,298, 7,171)	4,161 (1,299, 7,177)	4,320 (1,349, 7,448)	4,167 (1,301, 7,186)	4,686 (1,464, 8,074)

[a]An analogous table for hospitalizations can be found in the Supporting Table S4. Note: Positive values indicate avoided deaths; negative values indicate additional deaths.

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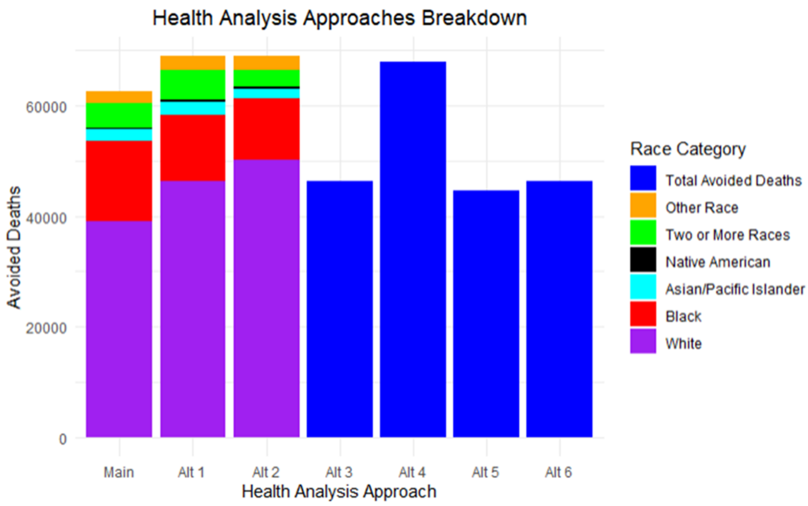

Figure 3. Total avoided death projections in the year 2050, compared to 2010 reference ambient $PM_{2.5}$ concentrations under different methodological assumptions (assumptions detailed in Table S1). The Main Approach (Main) and Alternative Approach 1 and 2 (Alt_1 and Alt_2) include breakdowns by racial/ethnic groups, where Alternative Approaches 3–6 only include overall avoided deaths.

subpopulation is projected to have the highest avoided hospitalization rate across racial groups, 57.6–57.8% higher than the overall population average (Table S6).

When comparing across income levels, the highest earners (>$75,000/year) project to have 39.3–40.5% lower avoided mortality benefit than the overall population. All three lower income subgroups (<$35,000, $35,000–$50,000, $50,000–$75,000/year) project to have a higher magnitude of avoided deaths and hospitalizations than the overall population across all energy policies, with the $50,000–$74,999/year group having the highest mortality benefit, at 58.0–58.6% further reduction in deaths compared to the overall U.S. population. For hospitalizations, the lowest benefit was for the highest income group and the highest benefit for the lowest income group (Table S6).

The largest difference in health benefits spans across the two most urban categories. The most urban (Large Central Metro) subpopulation projects to have 11.6–15.0% lower mortality benefits and 13.6–14.4% lower hospitalization benefits compared to overall population averages across policy scenarios. The second most urban (Large Fringe Metro) subpopulation projects the highest death and hospitalization benefits across policy scenarios (12.7–16.7% increase in avoided mortalities and 11.6–13.6% increase in avoided hospitalizations compared to the overall population) (Table S6).

Avoided Health Costs by Energy Policy. Monetization of avoided deaths and hospitalizations across the five policy projections in 2050 indicates cost savings of $785.8 billion to $949.9 billion (Table S8). Comparing the four sector-specific policy scenarios against BAU in 2050, an additional $750 million to $164.1 billion in avoided health impacts is estimated. These cost estimations consider deaths and hospitalizations totals, not other health impacts, lost productivity, ecological impacts, or cost of implementation of energy policies.

Analysis of the Impact of Methodological Assumptions. The calculated totals in Table 1 and S3 are based on our most detailed consideration of health response assumptions for the given sociodemographic populations of interest. This includes race-, age-, and county-specific incidence rates, race-specific CRFs, county-specific exposures, and race- and county-specific population projections.

The importance of these methodological assumptions can be observed through changes to incidence, population projections, and CRF inputs on population-wide avoided deaths projections (Figure 3). These results are most influenced by using age-tiered incidence rates, which yielded 21,598 additional projected deaths compared to overall mortality incidence (Table S9). Use of race-specific subpopulation CRF, incidence rates, and population projections also impacted the total projected avoided deaths, but to a lesser extent. Use of race-specific CRFs (Main Approach) rather than an overall CRF (Approach 1) led to 7279 fewer projected avoided deaths for the White population in the main approach, while increasing projected avoided deaths by 2742 for the Black population in the main approach (Table S9).

DISCUSSION

While many studies have investigated health cobenefits of renewable energy policies in the U.S., few focused on differential exposure and health impacts by race/ethnicity, socioeconomics, or urbanicity.[42,50,52,54,86,88] The three major takeaways from our research are as follows.

(1) Every considered future energy policy projection that transitions away from fossil fuels, including the BAU policy projected to 2050, is estimated to provide substantial exposure and health cobenefits for all populations in all regions of the U.S.

(2) Some sociodemographic subpopulations (Black, lower income) that are considered environmental justice communities, but not all (Hispanic, Native American) were estimated to experience higher relative mortality cobenefits across energy policy projections than other communities. This indicates that the anticipated energy transition can improve environmental disparities with respect to avoided deaths due to changes in future $PM_{2.5}$ exposure as well as subpopulation health vulnerabilities (mortality incidence and concentration–response rates) in some cases.

(3) The choice of HIA model inputs, while they all involve assumptions, can influence results when investigating overall cobenefits as well as subpopulation-specific deaths, with more

specificity providing better clarity into impacts on health disparities.

These general findings are particularly important given the existing disparities in air pollution exposures and associated health outcomes, combined with the need for climate change mitigation strategies.[13,89] This study advances the literature by providing evidence on how different sector-specific energy policy scenarios and subsequent $PM_{2.5}$ concentrations affect future exposures and health effects across the U.S. and regionally, including by subpopulation. All the considered ambitious energy policies, based on sector-specific analyses and regulatory feasibility, are estimated to improve air quality. However, which subpopulations experience the most cobenefits vary. This follows previous research findings that broader goals of reducing air pollution, improving health, and improving equity across populations would benefit from more granular analysis than simply quantifying aggregate pollution reductions.[42,84,90,91]

First, we found universal reduction in $PM_{2.5}$ and health burden for every county across all five energy policies compared to the 2010 baseline except for a 0.02 $\mu g/m^3$ $PM_{2.5}$ increase under both the Port and HighEV scenarios in Yuma County, AZ, providing further evidence that climate action in the energy sector provides substantial cobenefits. The substantial cobenefits for the fully realized BAU scenario in 2050, compared to 2010 baseline emissions, highlight positive steps that have already been taken by U.S. federal and state governments. Further benefits are estimated for the sector-specific energy transition scenarios in 2050 with lower overall $PM_{2.5}$ than projected 2050 BAU $PM_{2.5}$ concentrations for at least one sector-specific policy in every county, indicating that most sector-specific policy projections provide additional benefit to the full actualized BAU scenario. The magnitude of $PM_{2.5}$ reduction and number of avoided deaths and hospitalizations differ across counties for a given policy as well as across policies for a given county, including significant but small differences in concentration reduction across some sector-specific energy policies, such as the BAU, Port, and HighEV scenarios in the eastern U.S.

A comparison of avoided deaths between the 2050 BAU projections and the sector-specific policies highlight the extensive additional benefits of the HighEE policy. Previous research done in California and New York City corroborates these findings, showing higher total health benefits for building decarbonization over transportation decarbonization, although equity benefits prove to be more nuanced.[50,54] These higher overall cobenefits are likely due to changing emissions patterns from household heating and cooling, as most U.S. households rely on fossil fuel combustion.[92] Shifting to renewable sources, while reducing the amount of energy needed to provide comfortable household temperatures through more efficient HVAC systems and building envelopes, further reduces the overall emissions of fossil fuels.

Another policy-specific conclusion arises from the fact that natural gas combustion emits less particulates than other fossil combustion sources, such as coal.[93] Thus, we observe the HighNG scenario was the second most beneficial U.S.-wide. The Port scenario and the HighEV scenario also both saw large health cobenefits compared to the 2010 baseline but were more like overall avoided death projections observed under the BAU scenario. Adoption of electric vehicles has been shown to provide varied air quality and health impacts globally due to cleanliness of electricity[94] with U.S.-centered research showing both widespread positive effects[95] and mixed effects of such adoption based on U.S. geographic location and population.[96] Our research backs the previous work that has provided evidence of positive health benefits, albeit less than HighEE or HighNG cases. The smaller effect of the Port scenario, compared to the BAU scenario, is because ports are in relatively few U.S. counties, providing less overall benefit inland. However, electrification of shipping and on-site port infrastructure has shown to reduce $PM_{2.5}$ concentrations from 0.3 $\mu g/m^3$ in Seattle and 0.6 $\mu g/m^3$ in New Jersey[97] to 2.57 $\mu g/m^3$ in California,[98] aligning with the positive benefits we see from this transition. Significant health cobenefits were also observed in many previous studies investigating energy transitions across sectors.[36,99−101]

In the second set of nuanced conclusions, we found that disparities in $PM_{2.5}$ reductions and health cobenefits for each energy policy varied across U.S. region and subpopulations. For instance, the Black subpopulation projects substantially higher percent avoided mortality than the overall population or other racial groups. This is due to the combination of high $PM_{2.5}$ reductions, incidence rates, and CRFs compared to other racial/ethnic groups. These higher exposure, incidence, and CRF rates relate to complex interconnected environmental, social, and economic systems (e.g., historical redlining, siting of fossil fuel combustion activities), as observed in previous research.[46,102]

Turning to disparities among regions with different densities of population, more urban areas are projected to experience higher $PM_{2.5}$ reductions compared to less urbanized areas across policy scenarios. This is expected due to the higher overall concentrations for the 2010 baseline in urban areas and concentration of many energy production activities in more urban areas.[103] Interestingly, the most urbanized areas are projected to have the lowest percent avoided mortality of all six urbanicity classifications. Meanwhile, among income subpopulations, the highest group (≥$75,000/year 2020USD) is projected to experience the highest $PM_{2.5}$ reductions across policies which relates to a larger proportion of these individuals in urban areas (47.9% in Large Fringe Metro compared with 29.8% in Non-Core), although they experience the lowest percent avoided deaths across income groups.

Our research indicates a range of differences in magnitude of avoided deaths and hospitalizations within a given policy scenario for every subpopulation. Large differences are found among various race/ethnicity and urbanicity groups, but only smaller differences among income subpopulations. These findings provide important insight into the relative equity of energy policies, showing that some of the most underserved populations (e.g., lower income, Black) are projected to benefit most across policies. Recent research has found similarly large differences in equity patterns by race across U.S.-focused decarbonization policy, with universal improvement in disparity for Black populations[55,56] and larger general disparity for Hispanic and Asian populations.[55]

Third, we conducted our health analyses by incorporating the highest degree of information available by race, location, and age for population projections, baseline incidence, and CRFs, while investigating how numerous methodological assumptions in the health impact function model affected estimated health outcomes. We found that including race-specific population projections reduced overall avoided mortality projections, mainly due to lower avoided mortalities for the White population. Application of race-specific incidence rates resulted in little difference in total avoided mortality, but we found an observable difference when applying age-specific incidence rates. Alternatively, race-specific CRFs did not substantially change overall population mortality projections compared to the overall CRF, but did result in changes for estimates across racial groups specifically. Our alternative CRF projected far less avoided mortality than the main overall CRF, indicating the importance of CRF choice within health impact function models.

While most previous research used U.S.-wide CRFs that do not differentiate by subpopulation,[34,50,84,104] several studies examined subpopulation granularity for incidence rates and CRF inputs.[42,105] For example, Fann et al. Considered more granular assumptions of incidence rate and population growth, stratifying by 10-year and 5-year age bins, respectively.[105] Another study found a substantial difference in avoided deaths for the Black population using a race-specific CRF compared to population-level CRF, which we also observed.[42] Our work builds on these findings to explore how methodological assumptions can drive estimates of cobenefits in relation to CRFs, population projections, and incidence rates, as the highest level of detail can provide greater accuracy, although such information is not always available. This specificity is essential for decisionmakers who prioritize equity and justice in policymaking as it allows for fuller determination of local scale benefits by subpopulation.

This study makes several contributions, including detailed analyses on various subpopulations, real-world energy policy projections, and determination of how health model assumptions impact results. Few previous studies investigated distribution of cobenefits among subpopulations,[42,50−52,88] and none, to our knowledge, have provided the level of detail of this study across race/ethnicity, income, urbanicity, and geographical region. This provides scientific evidence on how energy transition policies may differentially impact subpopulations including those known to be vulnerable to air pollution.[13,15,106,107] Additionally, our findings can inform policymakers and communities regarding the benefits of energy transitions within a given location and across locations, including how different scenarios impact environmental inequality. The policies examined focus on sector-specific, politically relevant energy transitions, thereby better informing prioritizations of energy strategies and populations, focusing on improving air quality, public health, and/or equity. We investigated how different health impact model assumptions influence results, which is unaddressed by most cobenefits studies. Finally, we applied state-of-the-science air quality, climate, and energy economic modeling to generate pollution estimates and considered energy scenarios developed in collaboration with decisionmakers.

This study has several limitations. Our selection of 95%CI was done through CRF uncertainty values obtained from the literature, although the other HIA model inputs could also be used for confidence bands. While we incorporated different baseline incidences at the county level and allowed the CRF to differ by subpopulation, we did not incorporate differences by location for the CRF, although earlier work shows existence of such differences.[12] Inclusion of these differing inputs also causes slight summation disparities compared to the overall avoided deaths as they incorporate different CRF rates. Further, we did not consider higher spatial resolution (e.g., neighborhood level) due to lack of available health data, finer exposure resolution, and long-term epidemiological studies that investigate such fine locational differences. Thus, our predictions of $PM_{2.5}$ did not capture neighborhood-level heterogeneity. County-level data has been shown to underestimate disparities seen at a finer spatial resolution among racial and ethnic groups, thus more research is needed on greater spatial resolution to better understand subpopulation disparities.[90] Since heterogeneity exists within our subpopulation categories, inclusion of other subpopulations is warranted, including additional racial/ethnic groups, persons with disabilities, people experiencing homelessness, immigrants/migrants, 2SLGBTQIA+ populations, and more.[107,108] Another limitation is our $PM_{2.5}$ predictions were generated using one three dimensional (3D) air quality model. While two models were used to predict $PM_{2.5}$, we use only one given the results were similar. While all 3D air quality models are subject to uncertainties in their inputs, model configurations, and model representations, quantification of such uncertainties is beyond the scope of this work.

Also, our exposure projections assume a stable climate from the 2010 baseline period of comparison, and did not consider the effects of climate change on projected $PM_{2.5}$ concentrations. Thus, our analysis isolates the effect of energy policy choices, not climate change. Not only are there complex interactions between suspended particles and meteorological variables that shape concentration levels, but also climate-induced factors such as increased wildfire intensity and duration that are not captured in our modeling. Wildfires specifically produce extensive $PM_{2.5}$ and are projected to increase.[109] We considered $PM_{2.5}$ and did not address other air pollutants relevant to human health (e.g., O_3),[110−112] although they would likely shift from energy policy changes.[32,37] Thus, our projections of avoided deaths and hospitalizations likely underestimate the health benefits from the presented energy transitions. Energy policies are shifting rapidly, and the BAU policy may not represent up-to-date emissions strategies including local efforts, which are constantly evolving. For example, the BAU scenario utilizes national and state energy commitments from 2017, whereas only Hawaii has made a 100% renewable energy commitment. An additional 22 states, along with Puerto Rico and Washington, DC, have passed laws or executive orders for some iteration of a 100% clean/renewable energy goal.[113] Additional analysis is needed to explore a wider range of energy transition policies, including the implementation of multiple policies simultaneously and stronger or weaker transition scenarios under evolving policy landscapes.

To conclude, numerous studies investigating energy transitions identified substantial health cobenefits by shifting away from fossil fuels. We add further evidence on cobenefits of energy policies, finding that some subpopulations benefit more than others for all policies, although the magnitude of benefit varies. HIF modeling assumptions, such as whether race-specific incidence rate or CRF are applied, can change the specific results. However, we still found that large estimates of cobenefits are obtained regardless of what methodological assumptions are made in the health impact model. In addition, this study showed how different population groups can be disproportionately impacted by energy policy decisions across the U.S. and locally. Overall, we found that energy transition policies could contribute to addressing environmental inequity. The outcomes of this research can lead to better targeted policymaking driving energy emissions reductions in the areas of most need, both regionally and for specific U.S. populations.

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ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.4c14326.

Energy models used for analysis, a project flowchart, and exposure and health projections (PDF)

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Notes

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