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Just decarbonization? Environmental inequality, air quality, and the clean energy transition

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Abstract

Environmental inequalities are often large and consequential, exacerbating vertical inequalities of income and class and horizontal inequalities along lines of race and ethnicity. Climate policies can widen these inequalities as well as mitigate them, depending on their design. Decarbonization of the US electricity sector illustrates these possibilities. A strategy narrowly focused on carbon reduction alone is likely in some regions to increase disparities in exposure to localized co-pollutants emitted by fossil fuel combustion and, in some cases, to increase exposure in absolute terms. Strategies that in addition explicitly mandate improvements in air quality, both overall and specifically for frontline communities, can couple decarbonization with remediation of environmental inequalities and broad-based gains in public health.

JEL Classification: Q53, Q56

1. Introduction

Environmental inequalities, in the form of unequal exposure to bads such as air and water pollution, proximity to polluting facilities and roadways, and unequal access to natural resources and goods such as green space, are often quite large in comparison to other dimensions of inequality such as income, health, and education. In general, environmental inequalities reinforce rather than offset other inequalities, including vertical inequalities of class and horizontal inequalities of race and ethnicity. Moreover, environmental inequalities are consequential, with growing evidence that unequal exposure to environmental bads impairs the health, education, property values, and work opportunities of people excluded from the full enjoyment of a clean, healthy, and safe environment (Boyce *et al.*, 2016).

Decarbonization of the economy offers a rare opportunity to confront problems of environmental equity and justice in the core of the economy and society. It would be hard to overstate how importantly the energy system gives structure to the entire society. The decarbonized energy system that will come into being in the present century can reshape society as profoundly as did the previous transition to fossil fuels. With careful assessment, forethought, and innovation, the coming reshaping can embed equity and justice directly into this transition.

This paper examines the current pollution configuration in the US electricity sector and how it can be affected by the application of decarbonization policy. First, we examine the potential for environmentally disequalizing consequences if decarbonization policy ignores the damage done by localized co-pollutants emitted along with greenhouse gases (GHGs). We then show that systematic consideration of the opportunities to reduce co-pollutant impacts can provide large, immediate, and egalitarian benefits.

Beginning with a baseline program that minimizes the cost of generation subject only to meeting electricity demand, we compare three alternative decarbonation scenarios: a "carbon-alone" program that focuses exclusively on a 20% reduction in carbon dioxide emissions; a "carbon plus air quality" program that targets the dirtiest power plants by reducing health damages from co-pollutants by 50%; and a "carbon and air quality plus environmental justice" (EJ) program that additionally requires attainment of a 50% reduction in co-pollutant damages for Black, Hispanic, and low-income populations that tend to be on the frontlines of exposure to air pollution from power plants (Boyce and Pastor, 2013).

The inclusion of air quality and EJ constraints substantially changes the profile of electricity generation compared to the baseline and "carbon-alone" scenarios. Differences arise because natural gas-fired power plants, which are heavily favored in the carbon-alone scenario, often are located in more densely populated areas than the coal-fired plants they replace and are closer to minority neighborhoods. In the carbon-alone scenario, health damages to minority neighborhoods often increase relative to other neighborhoods, and in some regions of the country, notably California, it can increase absolute exposures of EJ populations. That is, in some cases, the carbon-alone strategy can both exacerbate environmental disparities and actually worsen pollution exposure in minority communities.

Decarbonization policy that explicitly incorporates the objectives of improving air quality and advancing EJ sharply reduces co-pollutant damages. These gains are achieved partly through greater reliance on renewable energy sources and partly through reallocating co-pollutant emissions from natural gas facilities to lower-damage locations.

The addition of clean air and EJ targets modestly increases the cost of decarbonization. With the goal of a 20% reduction in CO_2-equivalent (CO_2e) emissions, the additional co-benefits of meeting air quality and EJ targets are more than twice as large as the additional cost. Adding clean-air and EJ targets increases costs over the carbon-alone scenario by no more than 5%, and the additional cost percentage declines as the decarbonization target becomes more ambitious.

2. Decarbonization in the electricity sector

In response to the climate crisis, decarbonization over the coming decades is likely, and necessary, with a trajectory towards net-zero emissions by 2050. Electric power generation composes approximately 30% of US GHG emissions, and so the reduction in the GHG emissions of the electricity sector is a crucial component of a decarbonization program. Here, we examine how decarbonization policies can be designed effectively and efficiently to pursue the goals of improved air quality and EJ by targeting emissions reductions across electric power plants to achieve these goals.

As a type of pollution that threatens the entire planet, GHGs are a global public bad. No matter where carbon dioxide, methane, or other GHGs are emitted, the consequences for Earth's climate are the same. In contrast, the impacts from emissions of hazardous co-pollutants such as NO_x, SO_x, and particulate matter are localized.

Accounting for the local air quality co-benefits of emission reductions in climate policy introduces critical challenges for public health and distributive justice, challenges that an exclusive focus on GHG emissions neglects. Where and how decarbonization occurs will profoundly affect both the magnitude and the distribution of co-benefits. Shifts in the location of activities that emit GHGs—for example, shifting electric power generation towards power generation facilities that produce less carbon per kilowatt hour—could exacerbate co-pollutant hotspots and harm populations living near sites of increased activity.

Fitting into a well-established pattern of environmental injustice in the United States, people of color and low-income communities bear disproportionate exposure to air pollution, including co-pollutant emissions from electrical power plants (Ash *et al.*, 2009; Boyce and Pastor, 2013; Richmond-Bryant *et al.*, 2020). Well-designed shifts in activity could maximize local health gains, contribute to the political popularity of decarbonization programs, and protect populations that have been disproportionately exposed.

Decarbonization creates an opportunity to improve public health significantly and to advance EJ by reducing emissions of hazardous co-pollutants. But these gains will not result automatically from decarbonization; they must be pursued deliberately. Policies narrowly focused solely on the objective of reducing carbon emissions are likely to fail to take full advantage of opportunities to improve public health and advance EJ in the process. It is worse that in some instances, decarbonization policies that are blind to co-pollutants and their inequitable distribution may increase exposures in specific localities and exacerbate environmental injustice. There is good evidence that such outcomes occurred in California, which has pursued one of the most ambitious decarbonization policies in the United States (Boyce and Ash, 2018; Cushing *et al.*, 2018).

The risk of exacerbating co-pollutant hotspots, or creating new ones, derives in part from differences between the locations of older coal-burning facilities and newer natural gas-burning facilities. While natural gas facilities tend to be much cleaner than coal facilities in terms of carbon and co-pollutants released per unit electricity, they also tend to be located in more densely populated areas and in places with higher concentrations of EJ populations.

Tables 1 and 2 provide a profile of US electricity generation from fossil fuels. Table 1 compares coal and natural gas plants in terms of the composition of the population living within 5 km of the facilities. While the population surrounding the average coal plant (8.1% Black) roughly replicates the Black population share of the average county, the Black population share around natural gas generation facilities (13.4%) is substantially higher.

Table 2 compares the co-pollutant damages of plants sorted by fuel type. Plants with high carbon emissions per unit electricity are disproportionately coal-fired, whereas those plants with low carbon emissions per unit electricity generally burn natural gas. (Oil-fired plants, which have poor carbon and co-pollutant performance and high costs per unit electricity, are increasingly

Table 1. EJ population shares near electrical generation facilities, by fuel type

	Black share within 5 km		Hispanic share within 5 km		Low-income share within 5 km	
Fuel	Mean (%)	95th percentile (%)	Mean (%)	95th percentile (%)	Mean (%)	95th percentile (%)
Coal	8.1	34.9	6.1	22.4	32.3	59.2
Gas	13.4	53.4	19.8	64.3	34.8	59.0
Oil	13.1	53.3	10.0	31.6	28.9	48.7
Nuclear	8.5	30.6	5.7	17.4	27.3	42.7
US counties	9.1	42.4	11.4	53.0	36.0	54.0
US population	12.7		18.7		28.9	

The table shows the demographic composition within 5 km of fossil fuel electrical generation facilities by fuel type. The mean values describe the average facility. The 95th percentile values describe facilities that are up the upper end of the distribution of representation of EJ populations. The demographic composition around nuclear facilities is shown for comparison as are the composition of US counties and the entire US Population. *Source*: US EPA eGRID (2018) and US Census.

Table 2. Co-pollutant damages for all and EJ populations, by fuel type

	Co-pollutant damages			
Fuel	All	Black	Hispanic	Low-income
Total ($ billion)				
Coal	55.3	4.0	3.6	17.5
Gas	6.6	1.1	1.4	2.2
Oil	1.2	0.3	0.1	0.4
Per megawatt-hour ($/MWh)				
Coal	47.3	3.4	3.0	14.9
Gas	4.8	0.8	1.0	1.6
Oil	72.1	14.6	8.1	23.6

The table presents co-pollutant damages (total and per megawatt-hour estimated damages in dollars from SO_2, NO_x, and $PM_{2.5}$ using the APEEP model) by fuel type for the total population and for three EJ groups.

rare and often limited to meeting peak loads with low annual generation; they are not central to this analysis.) Monetized damages, computed using the Air Pollution Emission Experiments and Policy (APEEP) model, provide further evidence of the differential impacts. Coal combustion is more locally toxic, both in total and specifically for EJ populations, than natural gas combustion. For the population as a whole, the impact of coal is roughly eight times greater than that of natural gas, but for Blacks, it is less than four times larger and for Hispanics less than three times larger. The demise of coal unquestionably will bring substantial health co-benefits, but if the replacement energy source is natural gas, it is likely that not all will benefit proportionately.

Some studies on the decarbonization of the electric power sector have tallied health co-benefits as a by-product of meeting carbon goals, but only a few have targeted health benefits in designing a decarbonization program (Thompson *et al.*, 2014; Schucht *et al.*, 2015; Nock and Baker, 2019).

Much of the literature on decarbonization policies operates at a high level of aggregation, examining, for example, the national energy source mix under alternative policy scenarios. There are two shortcomings to the aggregated approach. First, the generation of energy is spatially and temporally constrained due to challenges of transmission and storage in a system that must meet consumer electricity demand at all times and places. Unit commitment models like those employed by Anjos and Conejo (2017) provide a technique to analyze the timing of output by generating unit to meet electricity demand.

Second, attention to local co-pollutants in energy generation also requires a spatially specific model. Proximity and local geographic and physical features, such as wind speed and direction, stack height, the combustion process, and volume of activity are key determinants of the exposure of nearby populations. The unit commitment model combined with detailed unit-specific data on carbon and co-pollutant intensity per unit electricity makes it possible to capture the impact on local populations of the activity of each plant in a regional or national electrical system.

In pioneering work that uses an optimization model, Sergi *et al.* (2020) analyze a single maximand that adds monetized health benefits, monetized decarbonization benefits, and conventional generation costs to compute an optimal generation program for the US power sector. While the authors do not include EJ as either an objective or a constraint, they do assess the EJ profile of the optimized program and find that the inclusion of a public health component in the maximand disproportionately benefits counties with lower minority population shares. This raises concerns about EJ even in a co-pollutant-sensitive decarbonization model.

A limitation of the Sergi *et al.* (2020) study is its reliance on monetization of diverse non-priced elements of the maximand, i.e., the benefits of carbon reduction and the co-benefits of co-pollutant reduction, including the Value of a Statistical Life (VSL). This makes the results dependent on the choice of techniques for monetization of the non-priced health and environmental benefits. Similar problems arise in estimates of the Social Cost of Carbon, which can vary by a factor of 40 or more (Nordhaus, 2017; Boyce and Bradley, 2018).

Here, we develop an alternative approach that is also built on a cost minimization unit commitment model of the electricity sector. Our model limits cost minimization to the operation and maintenance cost of generators. We treat decarbonization, population health, and EJ as constraints, defined as percentage reductions in CO_2-e emissions and mortality and morbidity resulting from exposure to local co-pollutants. Although the APEEP assessment model that we use presents mortality and morbidity as monetized values, our approach does not rely on the accuracy of monetization methods (such as VSL) since the constraints could equivalently be expressed in physical terms, such as lives or life years. This constraint-based approach is closer to a science-based safety standard rather than an efficiency standard derived from cost–benefit analysis (Boyce, 2018). The constraint approach does, however, generate the monetized shadow prices of improving performance in any of the targeted domains, i.e., reduced carbon emissions, improved overall public health, and improved public health specifically for EJ populations.

3. Model

We assess alternative programs for energy generation, GHG emission reduction, and co-pollutant reduction by modeling a for-profit (or at least business cost-minimizing) electric power sector that meets electricity demand subject to technical and regulatory constraints. We assume that the electrical generation sector, which is largely private and for-profit, will choose the least expensive way to meet electricity demand subject to regulatory constraints. This assumption lets us apply optimization methods to model how the sector will respond to different constraints (Anjos and Conejo, 2017).

A unit commitment program is a systemwide, technically feasible cost-minimizing assignment of electricity generation for every available electrical facility that meets the demand of customers and the regulatory goals specified by public or private decision makers. A constrained optimization assigns non-negative electrical generation to each potential generator in a fleet of generation units to minimize the cost of operations and maintenance while meeting technical, demand, and regulatory constraints. The regulatory constraints include GHG reduction obligations and co-pollutant exposure limits.

We operationalize the program with a linear programming optimization using publicly available facility-specific parameters and data on capacity, operations and maintenance costs per unit electricity, and the intensity of GHG and co-pollutant emissions per unit electricity. The business cost for a facility is the operation and maintenance cost, including fuel, for all of the electricity it generates. The systemwide cost of a program sums the cost for each plant based on the amount of electricity that each plant produces.

We require that electrical energy demand be met around the clock by specifying times of day in which renewable energy sources, i.e., wind and solar, are not available. Solar is not available when the sun is not shining; wind energy is not available when the wind is not blowing. The problems of providing baseload and confronting the intermittency of renewable sources are sometimes managed by modeling hourly energy production on an annual basis. The data we use do not permit year-round hourly modeling. We instead divide each day into four periods reflecting the availability of renewable resources. These assumptions, based on expert consultation, reflect a conservative stance with respect to the intermittency problem and the imperative of meeting electrical energy demand and avoiding blackouts or brownouts.

The model also assumes, again conservatively, that no GHG reductions will be effected via energy efficiency. Shortfalls in energy production are made up with a backstop technology that has a higher cost per kilowatt hour because of the additional capital cost of creating the new source. In our optimization, we apply a linear programming model without start-up or ramping costs or modeling of transmission systems. The development of more sophisticated unit commitment models that apply non-linear programming to capture greater realism is a potential direction for future research.

We first compute a baseline program for the universe of generation facilities that minimizes cost per unit of energy while meeting energy demand. We then extend the model to minimize cost while achieving a specified reduction in total CO_2-e GHG emissions from generation activity. Our model analyzes a 20% reduction in CO_2-e GHG emissions as a near-term goal that is consistent with more ambitious reductions by 2050. We compute the collateral benefits of this decarbonization program in terms of reduced chronic human health damages from localized pollutants associated with the reduction in GHG emissions even if no special effort is made to maximize or to target these benefits. Because minimizing cost per unit of energy without a constraint on co-pollutant reductions is the sole objective of this program, there may be well-missed opportunities for co-pollutant reductions at low cost.

We then compute an alternative decarbonization program that, in addition to minimizing cost while achieving the specified reduction in total CO_2-e GHG emissions, adds a constraint of a 50% reduction in co-pollutant impacts overall. Finally, we compute a program that adds the additional constraints of a 50% reduction in co-pollutant impacts for Black, Hispanic, and low-income people.

A formalization of the model follows. For each facility, indexed by i, c_i is a fuel-specific cost per unit of energy expressed in dollars per megawatt-hour. The North American Electric Reliability Corporation identifies 10 subregions of the US electrical grid, which we index s, and the four daily periods are indexed by q. E_{qis} is the total annual net electrical energy generation in megawatt-hours at time of day q for the plant i in subregion s, and E_{is} sums the electrical generation over periods of the day (over the year) to express the total annual energy generation of facility i. In addition to existing plants 1 to I_s, each region can add new renewable capacity, effectively, an additional plant $I+1_s$ that will, at a relatively high cost of installing and operating the new capacity, enable the regional energy system to meet regional demand. In this way, we ensure that the electrical energy plans meet regional demand at all times, i.e., without brownouts or blackouts. Regional demand is defined as the 2018 electrical use for the region. This guarantee is conservative in the sense that we assume no reduction in energy demand from conservation or pricing measures. Each of the energy programs we analyze guarantees full provision of electricity to users at historical levels.

M_{qis} is the nameplate capacity expressed in megawatt-hours per year of facility i in subregion s at time-of-day q. The EIA data reports capacity in terms of power, i.e., in megawatts. We convert power capacity to annual energy capacity in megawatt-hours with assumptions concerning operation by time of day, uptime and downtime, e.g., for nuclear facilities, and physical constraints for hydroelectric facilities. No plant can exceed its time-of-day capacity for the amount of energy produced at that time of day throughout the year.

G_i is the total plant CO_2-e GHG emissions in metric tons for facility i , and $g_i = \frac{G_i}{E_i}$ is the plant i average rate of CO_2-e GHG emissions in kilograms per 2018 plant unit of electrical energy generation in megawatt-hours computed from 2018 totals for CO_2 and electrical generation. We assume that the marginal rate of CO_2-e GHG emissions per electrical energy generation is equal to the historical average rate of plant-specific CO_2-e GHG emissions per electrical energy generation.

P_i is the total potential chronic human health damage from local pollution exposure for the entire population living within 50 km of the facility. $p_i = \frac{P_i}{E_i}$ is the total potential chronic human health damage per unit of electrical energy generation. As with GHGs, we assume that the marginal rate of local pollution per electrical energy generation is equal to the plant's historical average rate of pollution per unit of electrical energy generation. P_i^j is the total potential chronic human health damage from local pollution exposure for the facility for specific community j.

The full model is expressed below with the business cost minimization problem and up to four constraints:

$$\min_{E_{qi}} \sum_{i=1}^{I} c_i \cdot E_{qi}$$

subject to

$$\sum\nolimits_{i=1}^{I_{q,s}} E_{qi} \geq E_{q,s}{}^{2018} \forall s, q \tag{1a}$$

which shows 2018 demand by region and time of day;

$$M_{qi} \geq E_{qi} \geq 0 \tag{1b}$$

which shows facility non-negativity and capacity;

$$\sum\nolimits_{i=1}^{I} g_i \cdot E^*{}_i \leq G \tag{2}$$

which shows the GHG target;

$$\sum\nolimits_{i=1}^{I_s} p_i \cdot E^*{}_i \leq P_s \forall s \tag{3}$$

which shows the co-pollutant damage target by region;

$$\sum\nolimits_{i=1}^{I_s} p_i^j \cdot E^*{}_i \leq P_s^j \ \forall j, s \tag{4}$$

which shows the EJ co-pollutant damage target by region and group.

We establish the baseline with constraints 1a and 1b. The optimized program yields an energy output $E^*{}_{qi}$ for each facility i (in region s) at each time of day q, with the times of day corresponding to capacity varying because of fuel-specific intermittency. Summing over the four times of day yields $E^*{}_i$, the optimal energy output for each facility. The linear programming approach finds the most efficient way, in terms of minimizing costs, to meet the full set of constraints (Gurobi Optimizer Reference Manual, 2021). As a cost-minimizing method, the program will first mobilize the lowest cost energy source available within the region and time of day, then the next lowest cost available source, and so on, until the demand constraint is satisfied.

Every facility can then be analyzed in terms of its optimal, i.e., business cost-minimizing, energy output $E^*{}_i$, the cost of generation $c_i \cdot E^*{}_i$, the output of GHGs $g_i \cdot E^*{}_i$, and the population exposure from local pollutants $p_i \cdot E^*{}_i$. The total energy, cost, GHG emissions, and local pollutant exposure from operating the electrical generation system, stratified by region, fuel, or ownership, are the sum of the facility-level results.

We then successively add constraints (2) for GHG reduction, (3) for population exposure to local co-pollutants, and (4) for the exposure of EJ populations to local co-pollutants. In constraint (2), G is the total GHG emission target for the entire electrical system. We specify the target as a percentage of 2018 emissions, with $G := (1-\tau) \cdot \sum_{i=1}^{I} g_i \cdot E^{2018}{}_i$, where τ is the targeted percent reduction in GHG emissions. In this analysis, τ is set to 20%, targeting emissions to 80% of their 2018 value. In terms of the optimization problem, the addition of the GHG constraint complicates the selection basis of the next source from the available set of generators from a merit order based on least cost per unit electricity to the least cost per unit electricity subject to the GHG constraint. The addition of co-pollutant and EJ constraints similarly adds new consideration to the minimization problem.

4. Data

The fuel-specific cost of generation is compiled from Klein and Whalley (2015), Nock and Baker (2019), and Lazard (2020). In general, we use the operation and maintenance cost per unit electricity to characterize the cost of generation at existing facilities and a levelized cost-of-energy measure to express the cost of generation at newly constructed renewable energy facilities.

The capacity figures are taken from the US EPA eGRID 2018 database, which, in turn, draws on data from the Energy Information Administration (United States Environmental Protection Agency (EPA), 2021). We assume hydro and geothermal facilities to be currently operating at maximum potential. Solar and wind can produce at their maximum wattage (power), but their effectiveness varies over the time of day. We constructed a 24-hour day, extended over the year, in which both solar and wind are available for 3 hours per day, solar but not wind is available 2 hours per day, wind but not solar is available for 3 hours per day, and there are 16 hours per day when neither wind nor solar is available. These assignments were based on consultation with experts in the field of energy economics and policy (Frank, 2014). Regional demand and average rates of CO_2-e GHG emissions are also taken from the US EPA eGRID 2018 database.

The information on the impacts of local pollutants comes from the APEEP model (Muller and Mendelsohn, 2006). The APEEP model is a peer-reviewed integrative assessment model that provides damage estimates in dollars for the electrical generation sector, using standard methods (also used by the US EPA) to value impacts on mortality and morbidity. We use eGRID data on each of three leading pollutants (SO_2, $PM_{2.5}$, and NO_x) released by each facility, multiplied by the APEEP-estimated damages in dollars per ton for the pollutant released, which varies based on which county the facility is located. We express damages in monetized terms in order to collapse three pollutants to a single metric, but the approach could be applied pollutant-by-pollutant in physical terms.

Finally, we introduce EJ into the analysis by computing the demographic shares within a 15 km radius of facilities, using Tract-Level Summary File data from the American Community Survey 5-year Estimates for 2014–2018 (United States Census Bureau, 2019). We assume that the demographic distribution of non-health damages mirrors that of health damages. We apportion these estimated countywide health impacts from the APEEP model to EJ populations on the basis of population shares within 5 km (and 15 km in robustness checks) of the generating facility.

Table 3. Comparing decarbonization scenarios

Outcome	Fuel	2018	Baseline	Carbon alone	Carbon plus air quality	Carbon and air quality plus EJ
Electrical generation		100	100	100	100	100
	Coal	**28.5**	**25.6**	**15.0**	**14.1**	**14.2**
	Gas	**33.6**	**31.3**	**41.9**	**41.6**	**41.5**
	Other	**22.3**	**21.3**	**21.3**	**21.5**	**21.5**
	Clean renewable	**15.7**	**21.8**	**21.8**	**22.8**	**22.8**
CO_2 emissions		100	100	80	80	80
	Coal	**67.4**	**66.4**	**35.9**	**35.5**	**35.6**
	Gas	**32.6**	**33.2**	**43.8**	**44.0**	**43.9**
Co-pollutant damages		100	100	66.7	50	48.1
	Coal	**89.3**	**89.3**	**53.5**	**36.4**	**36.5**
	Gas	**10.7**	**10.7**	**13.2**	**13.5**	**11.6**
Co-pollutant damages for EJ population (Black)		100	100	**66.8**	**55.0**	47.9
	Coal	**79.0**	**78.2**	**40.6**	**28.2**	**23.8**
	Gas	**21.0**	**21.8**	**26.1**	**26.8**	**24.1**
Co-pollutant damages for EJ population (Hispanic)		100	100	**73.7**	**67.1**	47.9
	Coal	**71.4**	**73.0**	**41.6**	**33.4**	**22.7**
	Gas	**28.6**	**27.0**	**32.1**	**33.8**	**25.1**
Co-pollutant damages for EJ population (low-income)		100	100	**65.9**	**51.5**	48.5
	Coal	**88.6**	**88.5**	**51.9**	**37.2**	**36.2**
	Gas	**11.4**	**11.5**	**14.0**	**14.3**	**12.4**

The table shows the results of simulated carbon reduction and co-pollutant-sensitive carbon reduction programs in the key domains of electrical generation by fuel, CO_2 emissions, co-pollutant damages in total and for EJ groups, and generation costs. The decarbonization target in all of the decarbonization columns is a 20% reduction from 2018 levels. Except for the electrical generation fuel mix and cost, the results are limited to coal and natural gas. The values are expressed relative to a baseline of no decarbonization. The values in bold face are model results; the values in standard font are imposed goals. The 2018 values are shown to establish that the baseline is broadly calibrated to actual values.

5. Results for pollution in alternative decarbonization scenarios

Table 3 gives an overview of the results for the alternative scenarios in terms of nationwide fossil fuel use, CO_2 emissions, and co-pollutant damages for different populations. Our focus here is on the relative contributions of coal and natural gas to each of these outcomes.

A decarbonization program that is focused on carbon alone leads to a major shift away from coal in favor of natural gas. The share of coal-fired plants in electricity generation falls from 25.6% to 15%, while the share of natural gas plants increases from 31.3% to 41.9%. Renewables do not grow substantially because in this scenario most of the 20% decrease in CO_2 is accomplished simply by means of this shift among fossil fuels.

The shift from coal to natural gas reduces co-pollutant damages overall by one-third. But there is an increase in co-pollutant damages from natural gas electricity generation units, which rise by around 30%, along with the roughly 30% increase in the share of natural gas in the electricity generation mix. As a result, Hispanics, many of whom live near gas-fired plants, see a smaller decrease in total co-pollutant damages than other groups. Moreover, as discussed later, our results indicate that some regions of the country, notably California, actually would experience *increased* co-pollutant damages in the wake of the carbon-alone policy.

The other decarbonization scenarios, which incorporate the additional constraints of achieving 50% reductions in co-pollutant damages overall (in the second scenario) and also in frontline EJ communities (in the third), have little further effect on the shares of coal and gas in the electricity mix.[1] But by reshaping decisions as to *which* gas-fired plants are tapped for more

1 The co-pollutant constraints here result in only a modest increase in the share of clean renewables, reflecting our conservative assumptions as to the scope for increasing their output and reducing their cost. With more optimistic assumptions, this effect would be stronger.

power generation, they do have major effects on the magnitude of air quality co-benefits and their distribution.

In the second (carbon plus air quality) scenario, the 50% reduction in co-pollutant damages overall is almost matched for the low-income subgroup of households, but the reductions for Blacks and Hispanics fall short of that mark. Incorporating the EJ constraint (the third scenario) results in further changes in the locations where gas-fired generation is ramped up, again with little impact on the overall mix of coal and gas in the nation's electricity supply.

6. Costs of incorporating air quality and EJ constraints

Decarbonization has costs as well as benefits. A key question from the standpoint of air quality and EJ is what will be the additional cost of doing decarbonization "right" by including these objectives in policy design. The answer is that it is fairly inexpensive to do so. What is more, the more ambitious the decarbonization program in terms of its carbon reduction goals, the lower the additional cost of incorporating these additional constraints.

Adding the objective of a 50% reduction in co-pollutant damages to a 20% reduction in carbon raises the total cost of electrical generation, that is, the target of the optimization problem, by 5%. Adding the further objective of reducing the co-pollutant damages by 50% specifically for EJ communities results in virtually no extra cost beyond 5%. With a 50% decarbonization, i.e., a substantially more ambitious and somewhat more expensive decarbonization goal, the additional cost of a 50% reduction in co-pollutant damages is essentially nil, and the additional cost of reducing the burden for EJ communities commensurately is on the order of 1%.

Table 4 compares the additional co-benefits and additional costs of the co-pollutant-sensitive carbon reduction programs to the 20% decarbonization-alone program. The additional co-benefits (as valued by the APEEP model) are more than twice as large as the additional costs, yielding a total net benefit of $4.75 billion per year when including the air quality target and a total net benefit of $5.77 billion per year when including the EJ target as well.

In other words, the inclusion of co-pollutant reduction objectives that will make a substantial contribution to improvements in public health, both overall and for vulnerable communities, is a fairly low-cost modification of the decarbonization program, with health benefits that substantially exceed the costs.

7. Regional variations in the carbon-alone scenario

Although a carbon-alone policy would reduce co-pollutant damages (albeit not by as much as in the scenarios that incorporate air quality and EJ as explicit policy goals), there are pronounced variations in its effects at the regional level. These are shown in Table 5, with the regions defined by the US EPA's Emissions & Generation Resource Integrated Database (eGRID) and shown in the accompanying map (Figure 1).

Most striking is the perverse impact of the carbon-alone scenario in the state of California (roughly corresponding to the CAMX region), where co-pollutant damages increase by a whopping 156%, in other words by a factor of roughly 2.5. The increase is even greater for EJ communities: in this scenario, co-pollutant damages for Blacks in California more than triple.

Table 4. Annual benefits and costs of including air quality and EJ in the decarbonization program

	Adding air quality	Adding air quality and EJ
Additional benefit	$9.56 bn	$10.61 bn
Additional cost	$4.81 bn	$4.84 bn
Net benefit	$4.75 bn	$5.77 bn

The table compares the additional benefits and additional costs of simulated co-pollutant-sensitive carbon reduction programs to those of a 20% decarbonization-alone program. Benefits are estimated damages avoided from SO_2, NO_x, and $PM_{2.5}$ emissions (based on the APEEP model using standard EPA valuation methodology). Costs are the extra cost of supplying electricity so as to achieve the co-pollutant reduction goals.

Table 5. Regional changes in co-pollutant damages from all fossil fuel electrical generation facilities

Region	Percent change in co-pollutant damages from a 20% decarbonization program relative to baseline (%)			
	All	Black	Hispanic	Low income
CAMX	156.7	219.8	186.5	168.0
MROE	5.7	5.2	5.6	5.7
MROW	−6.1	−1.5	−8.2	−7.7
RFCW	−9.9	−28.9	−14.0	−9.6
SPNO	−13.0	−9.4	−4.4	−16.5
SRVC	−15.4	−12.3	−11.7	−12.1
RFCE	−18.0	10.6	58.8	−22.1
ERCT	−22.0	−16.5	−27.4	−35.0
SPSO	−28.5	−64.2	−4.2	−31.1
NEWE	−37.3	−41.9	−31.4	−34.5
SRMW	−46.7	−17.6	−45.0	−39.1
NYUP	−48.2	−1.7	−35.2	−45.7
SRSO	−52.4	−30.6	−64.5	−48.3
NYCW	−62.8	−62.1	−65.1	−63.1
SRTV	−66.2	−51.7	−73.1	−60.9
FRCC	−67.2	−63.6	−61.1	−69.9
AZN	−72.9	−0.3	−35.2	−75.3
SRMV	−80.3	−63.2	−38.8	−82.3
RMPA	−86.2	−77.6	−86.8	−89.9
NWPP	−88.1	−19.4	−83.4	−82.1
RFCM	−90.0	−79.9%	−88.4%	−88.9%
NYLI	−91.5	−96.0	−92.2	−92.9

The table shows the percent change in damages from co-pollutants from all fossil fuel electrical generation facilities for a 20% decarbonization program relative to baseline damages from co-pollutants from these facilities for all people, for Black people, for Hispanic people, and for people living below 200% of the federal poverty line. A positive value indicates that the co-pollutant damages from natural gas facilities increase under the 20% decarbonization program. The change in damages is based on a linear programming simulation of a 20% decarbonization program. See Figure 1 for Map of Electricity Subregions.

A smaller increase in co-pollutant damages is also found in the MROE region, which includes Milwaukee and other cities in eastern Wisconsin.

This finding is consistent with the *ex post* study of the impact of California's cap-and-trade policy by Cushing *et al.* (2018), which concluded that co-pollutant emissions increased in certain locations and that the increases were concentrated in communities with higher percentages of people of color. The facility-level data confirm that some gas-fired plants and refineries experienced substantial increases in both GHG and co-pollutant emissions in the first 5 years of the cap-and-trade policy and were located in densely populated areas with high concentrations of people of color (Boyce *et al.*, 2023).

In several other regions, including much of the Midwest and also the Carolinas and Virginia, the 20% reduction in carbon is not accompanied by an equivalent reduction in co-pollutant damages.

Table 6 reports the regional impacts of the carbon-alone scenario specifically for co-pollutants from natural gas power plants. These results explain the co-pollutant findings for California. But increased co-pollutant damages from this source also occur across much of the country.

The regional results underscore the perils of relying on a carbon-alone strategy and further strengthen the case for incorporating explicit air quality and EJ goals into climate policy design.

8. Discussion

This study has examined how incorporation of local air quality and EJ objectives into the design of decarbonization policy would affect the course of decarbonization in the US electric power

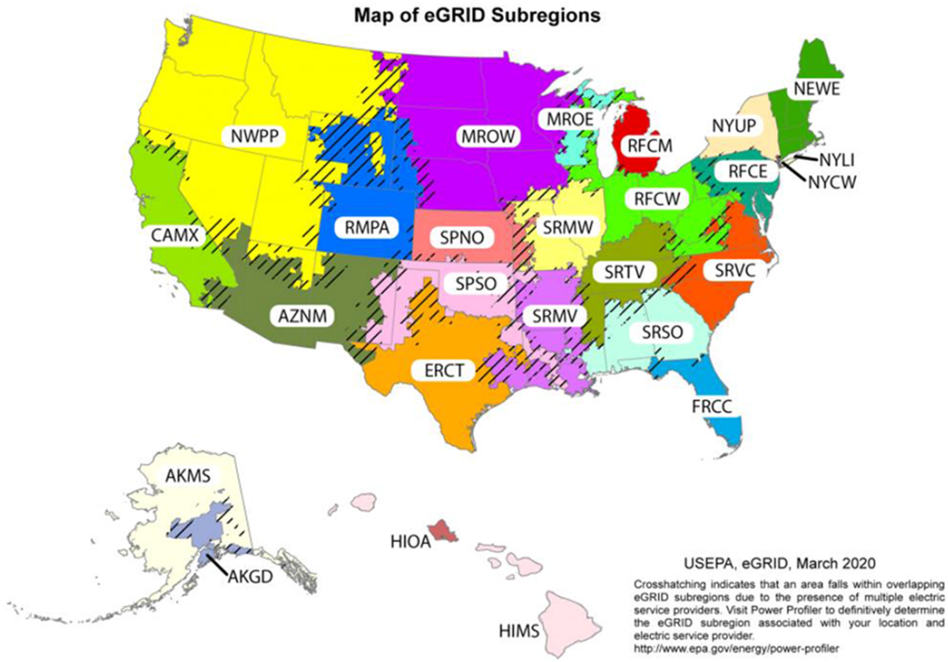

Figure 1. Map of eGRID subregions

sector. The results show substantial differences in the pattern of decarbonization between the carbon-alone scenario and scenarios that incorporate co-pollutant reduction objectives. Overall, the damages from hazardous co-pollutants decrease even in the carbon-alone scenario, thanks to the phasing out of coal. The results vary substantially across regions, however. California, in particular, sees substantially increased co-pollutant damages overall and even more so for Blacks and Hispanics. The explicit incorporation of air quality and EJ objectives into the design of decarbonization policy results in a substantial reduction in the co-pollutant damages from gas-fired power plants compared to the carbon-alone scenario.

The fulfillment of the clean air and EJ goals does not radically increase the cost of decarbonization. Meeting these additional goals increases costs on the order of 5% more than the cost of a policy focused exclusively on carbon alone, and the additional cost declines as the decarbonization target is tightened. Moreover, the public health benefits substantially exceed this modest cost.

It is both feasible and cost-effective to adhere to these principles in designing climate policy. This will require moving beyond an exclusive focus on carbon to embrace clean air and EJ as complementary policy objectives in the design of decarbonization strategies.

Environmental inequalities are an important feature of the broader inequalities, both vertical and horizontal, that characterize not only the United States but also other societies. By bearing these in mind when advancing the clean energy transition and tackling other environmental problems, policy makers can help to secure an environment that is safer and healthier for all.

Table 6. Regional change in co-pollutant damages from natural gas electrical generation facilities

Region	Percent change in co-pollutant damages from a 20% decarbonization program relative to baseline (%)			
	All	Black	Hispanic	Low income
CAMX	155.9	219.6	186.1	166.9
SRTV	105.0	230.2	79.4	116.0
NWPP	104.4	99.3	61.7	125.8
RFCE	101.0	88.6	169.8	105.9
AZNM	57.0	69.9	34.3	22.6
RMPA	51.8	31.9	53.4	49.2
SRMV	51.0	43.6	56.4	49.5
SRMW	48.4	46.7	56.9	49.5
SRVC	47.8	44.0	43.5	39.7
SRSO	35.1	38.9	17.4	39.9
RFCM	25.3	10.6	17.2	22.1
SPSO	21.8	36.1	27.8	23.8
RFCW	18.7	20.3	31.9	20.0
MROW	17.8	19.1	10.1	14.1
NYUP	17.4	3.2	−23.7	14.8
ERCT	17.2	20.8	16.7	16.7
MROE	16.1	7.9	−1.2	13.6
FRCC	11.0	−3.7	−7.2	4.9
SPNO	−3.3	−19.7	−7.2	−3.4
NEWE	−19.1	−26.6	−14.5	−17.8
NYCW	−62.8	−62.1	−65.1	−63.1
NYLI	−91.5	−96.0	−92.2	−92.9

The table shows the percent change in damages from co-pollutants from natural gas facilities for a 20% decarbonization program relative to baseline damages from co-pollutants from natural gas facilities for all people, for Black people, for Hispanic people, and for people living below 200% of the federal poverty line. A positive value indicates that the co-pollutant damages from natural gas facilities increase under the 20% decarbonization program. The change in damages is based on a linear programming simulation of a 20% decarbonization program. See Figure 1 for the Map of Electricity Subregions.

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