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Article

CABOT-O_3: An Optimization Model for Air Quality Benefit-Cost and Distributional Impacts Analysis

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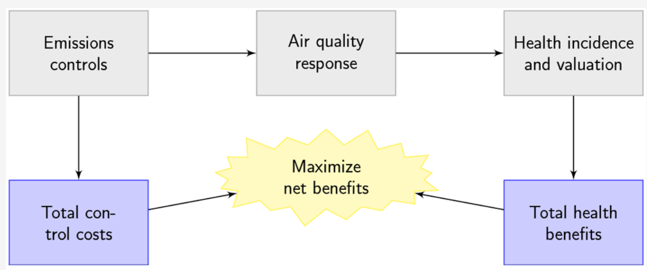
ABSTRACT: Macpherson et al. (2017) presented a mathematical programming model that identifies minimum-cost control strategies that reduce emissions regionally to meet ambient air quality targets. This project introduces the Cost And Benefit Optimization Tool for Ozone (CABOT-O_3), which extends the previous model by updating emissions and air quality relationships, adding a health impacts module, and quantifying distributional impacts. The tool draws upon source apportionment photochemical air quality modeling to characterize the contribution of emissions reductions to ambient ozone concentrations across the contiguous United States. The health impacts analysis module estimates the change in the number and economic value of premature deaths using modeled changes in ozone levels resulting from the application of emission control strategies. These extensions allow us to evaluate strategies to attain ozone air quality standards at minimum cost or to maximize net benefit, while assessing the change in the distribution of health impacts. In a case study applied to stationary pollution sources, we find that, when compared to minimizing costs to meet a uniform ozone standard, maximizing net benefits results in greater emissions and ozone concentration reductions in some parts of the country and fewer in others. Our results highlight potential equity-efficiency trade-offs in designing air quality policies.



■ INTRODUCTION

From Kohn's model of particulate matter and sulfur dioxide emissions in the St. Louis, Missouri area[2] to present, mathematical programming models have served as tools for identifying least-cost control strategies for air pollution planning. In previous work, we presented a mathematical programming model that identifies minimum-cost multi-pollutant emissions control strategies to meet ambient air quality targets.[1] That model combined detailed emission control information and relationships between state-level emissions and ozone at individual monitor locations to evaluate alternative attainment planning scenarios, test regional emissions control strategies, and identify monitors that may significantly influence strategies to attain ambient air quality targets.

Macpherson et al.[1] presented a literature review of models using optimization approaches to identify least cost strategies for controlling source-specific emissions to manage impacts on ambient air pollution concentrations at receptor locations. While this literature is well-developed,[2−12] these models have not incorporated the ability to simultaneously estimate projected changes in the incidence and economic value of health impacts resulting from modeled air quality changes. Although there are tools in the literature and available to the public that estimate the health impacts and monetized benefits of emissions reduction strategies via a reduced form air quality model,[13−15] they do not link spatially- and technologically explicit emission control information to health impacts within an optimization framework. Recently, attention has turned toward approaches that incorporate health impacts of emissions changes into the detailed planning models.[16,17] The key in this emerging literature is the integration of comprehensive and spatially detailed information on emissions sources and control costs, air quality, demographics, and exposure into a platform useful for policy analysis.

This project extends Macpherson et al.[1] to introduce the Cost And Benefit Optimization Tool for Ozone (CABOT-O_3). In CABOT-O_3, we update emissions and air quality relationships, add a new module for estimating health impacts, and incorporate the ability to assess the distribution of air quality and health impacts among population subgroups. The tool draws upon source apportionment photochemical air quality modeling to characterize the contribution of statewide emissions reductions to ozone design values, the regulatory metric based on the fourth highest 8-h daily maximum (MDA8) ozone value across 3 years, at locations of air quality

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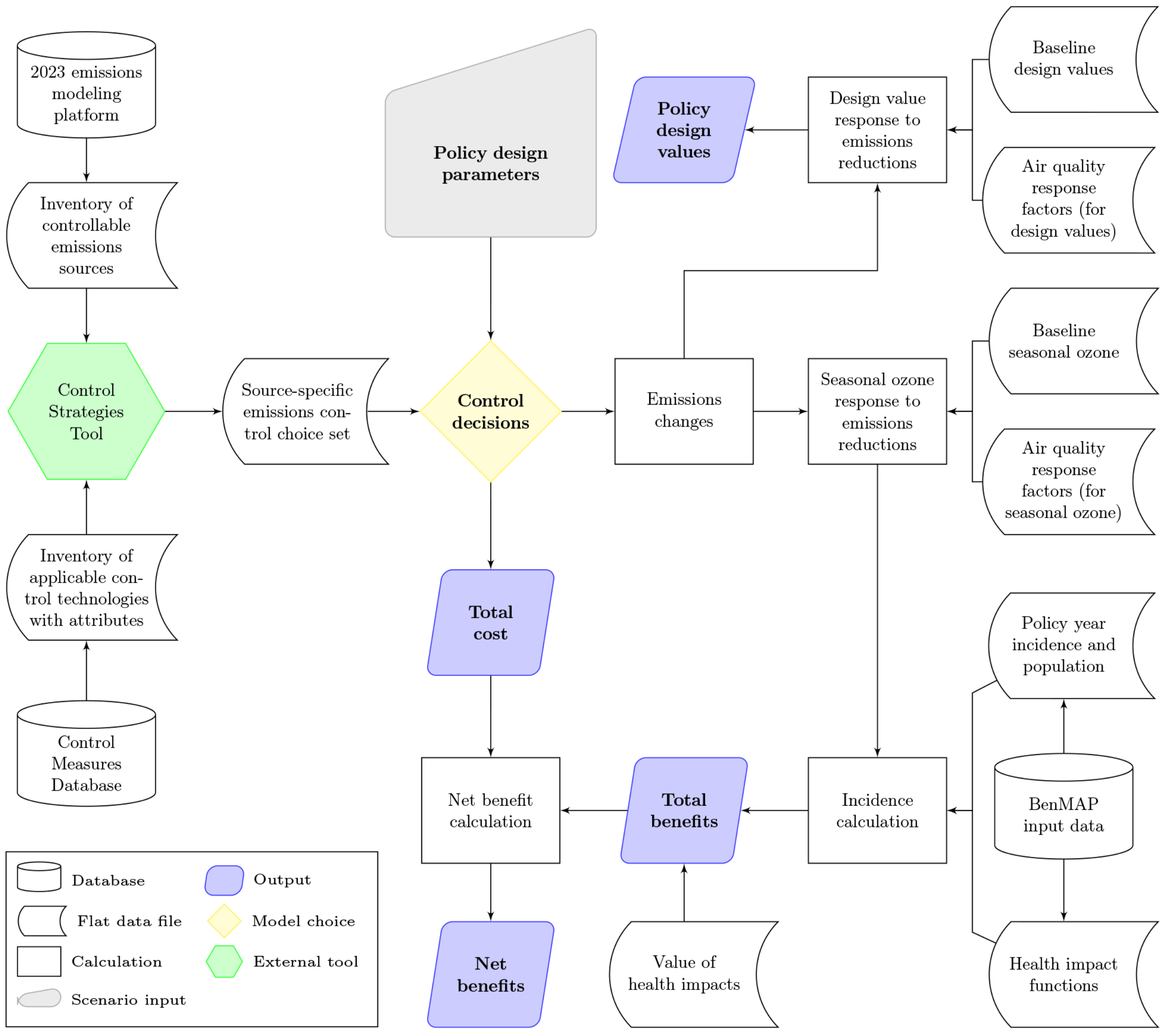

Figure 1. Data inputs and net benefit optimization model.

monitors and May−September ("summertime") MDA8 in 12 km-by-12 km grid cells across the contiguous United States. The health impacts analysis module estimates the change in the number and economic value of premature deaths and illnesses using modeled changes in the summertime mean of MDA8 ozone levels resulting from the application of emission control strategies.

These improvements allow us to evaluate control strategies to achieve hypothetical ozone air quality objectives, including achieving air quality standards at minimum cost, maximizing net benefits of emissions reductions, or achieving a more equitable distribution of health impacts. The model presented in this work advances the optimization and air quality planning and management literature by connecting spatially and technologically detailed emissions control information, a series of reduced-form air quality models, and detailed health and distributional impacts assessment to enable rapid regional- and national-level policy analysis. To our knowledge, the only application that jointly models emissions control costs, emissions-to-concentration changes, and health impacts is the Air Benefit and Cost and Attainment Assessment System, which has been used to analyze air quality planning and management issues in China.[18]

Model Structure, Data Inputs, and Scenarios. In this section, we summarize the basic structure of CABOT-O_3, the data inputs used to parametrize the model, and the scenarios for our case study. A detailed mathematical representation of the model is provided in the Supporting Information (SI) accompanying this manuscript.

Model Structure. CABOT-O_3 consists of two modules: a control cost module and a health impacts module. The control cost module leverages information on the costs and emissions reductions associated with a set of possible control measures. It also calculates changes in air quality by mapping emissions reductions from controls into changes in ambient pollutant concentrations by way of air quality response factors. These response factors define linear relationships between emissions reductions from a source location to changes in ambient pollutant concentration in a receptor location, with the full set of response factors containing entries for all source−receptor pairs. In the health impacts module, changes in ambient pollutant concentrations are mapped to changes in monetized health impacts.

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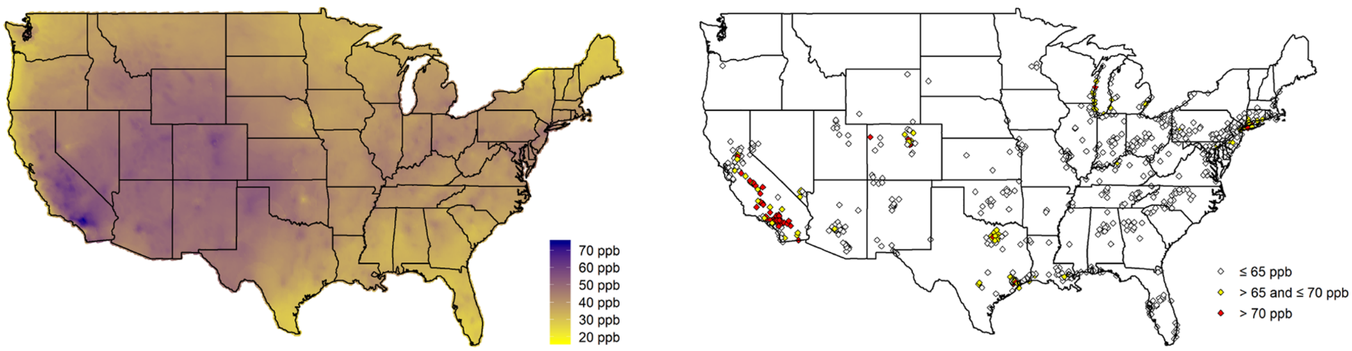

Figure 2. Projected 2023 summertime average MDA8 ozone concentrations at all grid cells (left) and projected 2023 ozone design values at monitoring stations (right).

The novelty of CABOT-O_3 resides in the integration of the two modules into a unified framework. The control cost module alone can be used to identify least-cost control strategies targeted at achieving ambient air quality standards, where control decisions on specific pollution sources are represented by binary variables and use of a backstop control at each source location is represented by a non-negative continuous variable. By incorporating the health benefits module, CABOT-O_3 can identify control strategies that maximize net benefits, which are defined as the sum of monetized health benefits across the entire geographic scope of the model less the sum of all control costs. Health benefits are calculated by applying concentration−response functions drawn from the epidemiological literature.[19]

An additional feature embedded into the CABOT-O_3 framework is calculation of the Atkinson Index (AI). The AI measures inequality on a scale of 0 to 1, with higher values indicating greater inequality. In our application, we calculate this measure as a postprocessing step to quantitatively assess the degree to which air pollution attributable risks are shared unequally throughout the United States. In principle, inequality metrics such as the AI can be incorporated into the objective function or constraints in CABOT-O_3, though we do not pursue that approach in the case study presented here.

Data and Scenarios. To conduct policy simulations, the mathematical model is parametrized using data from several sources. A summary of the key elements of the model and how they interact is depicted in Figure 1. Below, we also introduce the scenarios for our case study analysis. We choose the year 2023 for our case study because it has been extensively used for planning of cross-state air quality ozone control programs.[20,21]

Emissions Sources and Control Measures. The left region of Figure 1 corresponds to emissions sources and control technologies. Most emissions sources are drawn from the EPA's 2023 emissions modeling platform, which represents all stationary sources of air pollutants that are expected to be operating in the contiguous U.S. in 2023, excluding electricity generating units (EGUs).[22] Sources include both point sources, which are composed primarily of larger emissions sources for which we have facility-specific emissions data, and nonpoint sources, which are composed of county-level aggregates of more diffuse emissions sources. In addition, we supplement the non-EGU data with information on coal-fired power plants from the Air Markets Program Data (AMPD) and National Electric Energy Data System (NEEDS) v5.[23,24] The key information from the source data for our modeling simulations are the source category, the geographic location of each source, and the magnitude and species of emissions.[25]

As depicted in the diagram, the emissions sources are combined with information on emissions control technologies. For non-EGUs, the control technologies are drawn from the Control Measures Database (CMDB), which are merged within the Control Strategy Tool (CoST) for each source to generate appropriate source-specific emissions control choice sets.[26] For EGUs, NO_x control technologies include selective catalytic reduction (SCR) and selective noncatalytic reduction (SNCR). Key parameters for each source-control measure combination include total annualized engineering costs and tons of emissions reductions by precursor pollutant. EGU costs and emissions reductions are developed using the Retrofit Cost Analyzer,[27] assuming fixed capacity factors of 0.53 for units that install SCR and 0.48 for units that install SNCR.

Air Quality Response Factors and Pollutant Concentrations. The air quality dimension of the model is depicted in the top-right region of Figure 1. There are two parallel tracks for which we require air quality data: projected ozone design values at monitors and projected summertime averages of MDA8 ozone values at 12 km-by-12 km resolution grid-cells covering the contiguous United States. In both cases, the model uses 2023 baseline values for ozone concentrations and air quality response factors to map state-level changes in precursor pollutant emissions to changes in ambient pollutant concentrations.

The 2023 baseline values and air quality response factors are derived from state-level source apportionment modeling performed using the CAMx model in conjunction with 2009−2013 ambient ozone data;[28] see the SI for details. The modeled ozone design values and summertime average MDA8 concentrations are illustrated in Figure 2. The left panel illustrates how summertime average concentrations are predicted to vary across the contiguous U.S. in 2023, with the highest values projected in southern California. Other regions with higher concentrations include the Southwest and Rocky Mountain states. The right panel illustrates projected design values at locations of ozone monitors. Outside of California, most monitors are predicted to be below 70 parts-per-billion (ppb), which is the standard set by EPA's 2015 ozone NAAQS rule.[29] Monitors with design values projected to be above 65 ppb in 2023 are concentrated in California, along the Eastern seaboard, and in several major cities including Denver, Las Vegas, Dallas, Houston, and Chicago.

Health Incidence and Valuation. The health impacts dimension of the model is captured in the bottom-right region

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of Figure 1. Data for population and baseline incidence projections for the 2023 policy year and information for health impact functions are pulled from the database underlying EPA's Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE). The population and baseline incidence data are applied at the same 12 km-by-12 km grid resolution as the MDA8 concentrations. By combining the population and baseline incidence data, MDA8 concentration changes, and health impact function information, we estimate health incidence due to the policy. Total monetized benefits are estimated by applying health impact value estimates to the incidence estimates.

For our case study, we focus on monetizing changes in premature mortality due to changes in ozone concentrations. We rely on estimates from Smith et al.[30] to translate changes in ozone concentrations into changes in premature mortality, using a concentration response function parameter β (as defined in the SI) of 0.000322. To calculate monetized benefits, we apply a value of statistical life (VSL) parameter of \$10.3 million. The VSL estimate of \$10.3 million is derived by adjusting the base VSL of \$8.7 million for income growth to 2023 (see Appendix H in U.S. EPA[31]). In addition, as a postprocessing step, we calculate the health cobenefits from reductions in $PM_{2.5}$ concentrations associated with the chosen control measures using benefit-per-ton estimates developed in Fann et al.[32] The $PM_{2.5}$ benefits estimates are not used in the objective function of the net benefits-related scenarios described in the next section.

Policy Inputs and Scenarios. The final set of inputs represented in Figure 1 pertain to the policy design choices used to represent various scenarios. These inputs include the geographic scope of controls and monitors, the cost of backstop control measures, the choice of objective function (cost minimization or net benefit maximization), and the level of the design value target (or, in the case of net benefits maximization, whether the design value target constraint is activated or not). In this analysis, our geographic scope for controls, monitors, and MDA8 grid cells in all scenarios is the contiguous United States. For the cost of backstop controls, we assume an average annual cost of \$15 000 per ton for NO_x or VOC reductions. The central value of \$15 000 per ton is based on an assumption from the 2015 Ozone NAAQS RIA;[29] Section 4.2 of that document describes the development of that value and what it represents in detail. To summarize, backstop controls are assumed to represent control measures not captured by the Control Strategies Tool (CoST) or SCR/SNCR at coal-fired EGUs, including mitigation possibilities in the transportation sector and energy efficiency and fuel switching opportunities in stationary source sectors.

The central focus of this analysis is to demonstrate how the optimal control strategies change with different policy designs. We solve three general versions of the model: cost minimization subject to design value target constraints, net benefits maximization subject to design value target constraints, and net benefits maximization without design value target constraints. For the first two model versions, we solve the model for gradually decreasing ozone targets from 70 to 65 ppb with one ppb decrements. Therefore, our analysis consists of 13 scenarios: 6 versions of the cost minimization model using design values from 65−70 ppb, 6 versions of the net benefits maximization model using design values from 65−70 ppb, and 1 version of the unconstrained net benefits maximization model. We denote scenarios by the type of objective function followed by the ozone target level, e.g., *CostMin-65* or *BenMax-70*. The net benefits maximization without design value constraints is denoted as *BenMax-Free*. Hereafter, we refer to the scenarios, whether cost minimization or net benefits maximization, as the *constrained* scenarios. This is not to imply that the *BenMax-Free* scenario is solved without constraints, rather that it is solved without a set of design value constraints.

The model is implemented in the General Algebraic Modeling System (GAMS) version 25.2. Software and computational details are provided in the SI following the model formulation.

Limitations and Uncertainties. There are key limitations and uncertainties of CABOT-O_3 that arise from the simplifying assumptions needed to operationalize the model. One choice that affects all modules is the analysis year (2023); we expect that the results should be somewhat sensitive to the year chosen as the emissions, ozone chemical regime, and health incidence all are expected to change in the future. Additionally, we do not rigorously model the interdependence of ozone and $PM_{2.5}$ in characterizing optimal mitigation strategies, a limitation we will address in future work.

Within the cost and health benefits modules, we draw attention to three key sources of uncertainty in our analysis. On the cost side, the ambitious geographic and sectoral scope of our case study requires assigning control measures and estimating costs to point and nonpoint emissions sources for which we often do not have much of the information needed to produce highly certain engineering cost estimates. In addition, the cost of backstop controls in CABOT-O_3 is highly uncertain. Analysis of regional NO_x offset markets in nonattainment areas in the 2015 Ozone NAAQS RIA suggested that \$15 000 per ton is a plausible, albeit conservative, value. On the health benefits side, for simplicity of presentation, we focus the analysis here on a single concentration response function and VSL parameter value, although analysts often use different parameter values to generate a range of possible outcomes or pooling techniques to combine multiple parameter estimates.

Likewise, there are several key simplifications in the application of source apportionment-based air quality response factors in CABOT-O_3. First, we assume that the ozone response to NO_x and VOC emissions reductions is linear and additive between regions and pollutants, even though ozone can respond nonlinearly to emissions changes, especially when emissions changes are large or in VOC-limited chemical regimes. In VOC-limited regimes, ozone may increase in response to small to moderate NO_x decreases, a phenomenon we cannot represent with the current source apportionment-based response factors. The linear representation was employed in this application due to computational challenges in deriving air quality response factors (or higher-order sensitivities) that represent nonlinear interactions among emissions from all 48 contiguous states. Additionally, in NO_x-limited areas, past studies have suggested that changes in NO_x emissions less than 30% can be approximated with linear response factors.[33−37] Most areas of the U.S. are NO_x-limited in the summer and trending toward becoming even more NO_x-limited in the future.[38,39] While the linear air quality response coefficients are a reasonable approximation for this proof-of-concept of the CABOT-O_3 model, we nevertheless acknowledge the shortcomings of this approach. Another simplification is the application of source apportionment results that

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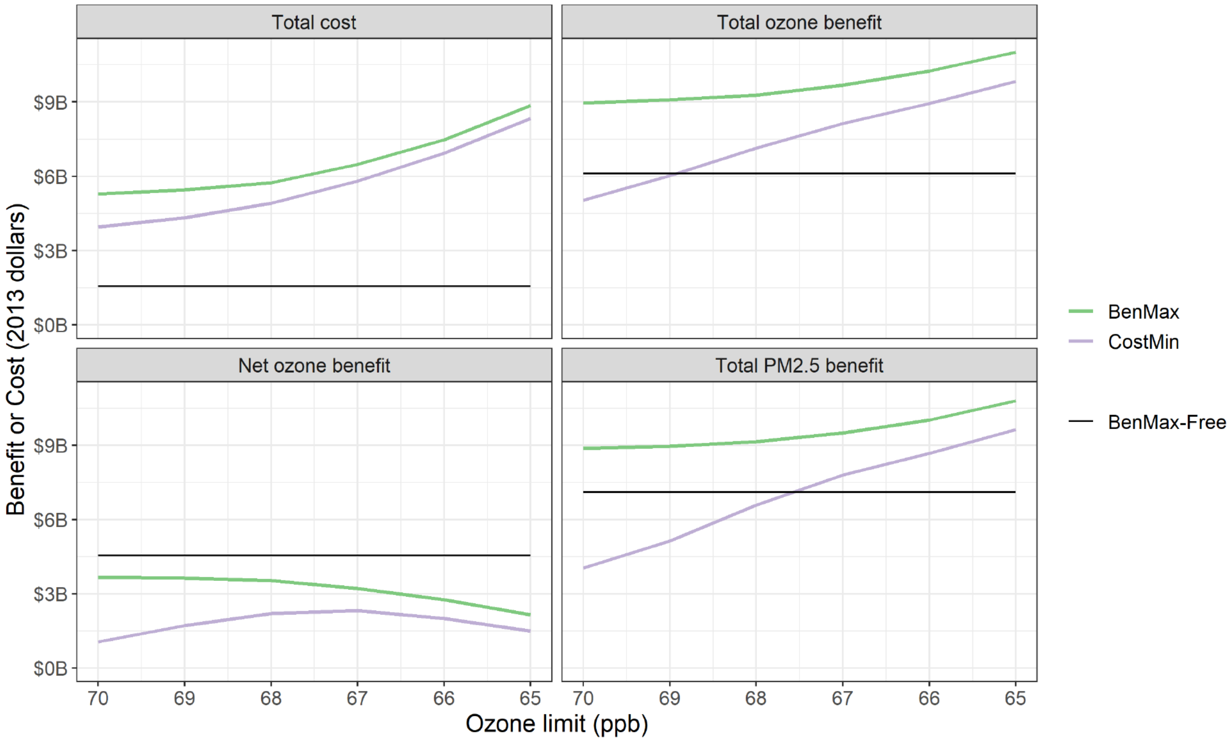

Figure 3. National cost and benefit metrics.

represent total contributions from each state to partial changes in emissions.

A final simplification is that we assume every ton of emissions reduced within each state will have an identical impact on ozone response regardless of where the emissions reductions come from within the state. Using finer resolution in the identification of source regions would increase accuracy in the source−receptor matrix. At the extremes, response factors based on tracking each emissions source individually would be the least uncertain but computationally infeasible, while factors based on nationally aggregated emissions provide coarse information that has nevertheless been used with success in regulatory applications in the past.[40] In past regulatory analyses focusing on identifying control strategies, EPA has determined that aggregating sources up to the state level when calculating air quality response factors for the purpose of analyzing pollution control strategies is appropriate.[29]

■ RESULTS AND DISCUSSION

In this section, we present results from the set of scenarios defined previously. We find that the unconstrained net benefits maximization scenario results in lower costs and greater net ozone benefits than the cost minimization scenarios, largely because the latter require expensive backstop controls to achieve constraints in California. The geographic distribution of emissions reductions is different as well; for example, emissions reductions are greater in many of the eastern states under the net benefits scenario. Also, compared to the cost minimization scenarios, the economic efficiency benefits of the unconstrained net benefits maximization scenario accrue at the expense of greater inequality as measured by the AI.

National Impacts. Aggregate cost and benefit values for the contiguous U.S. are depicted in Figure 3. Clockwise from top left, the panels represent total control costs, total ozone reduction benefits, net ozone benefits, and total $PM_{2.5}$ benefits. The horizontal axis represents varying ozone limits on a descending scale.

Total costs are considerably lower for the *BenMax-Free* scenario than for the other sets of scenarios, including the constrained *BenMax* scenarios. This suggests that, under the assumptions imposed for this analysis, the marginal costs exceed the marginal benefits of meeting a 70 ppb standard in some parts of the country. As expected, as the design value constraints are tightened, the gaps between the constrained scenarios and the *BenMax-Free* scenario grow. At the same time, the gap between the constrained *BenMax* and *CostMin* scenarios tends to shrink. This is because many of the same controls used to maximize net benefits in the constrained *BenMax* scenarios under low stringency are employed at high stringency in the *CostMin* scenarios.

Total ozone benefits exhibit similar patterns to total costs, with constrained scenarios increasing in benefits as the stringency of the standards increases. The shape of the benefit curve is convex for the constrained *BenMax* scenarios and more linear overall for the *CostMin* scenarios, while total ozone benefits for the *BenMax-Free* and *CostMin-69* scenarios are almost identical. Given the gulf in total costs between the two scenarios, this suggests significantly higher net benefits under the *BenMax-Free* scenario.

Net ozone benefits are depicted in the lower left panel of Figure 3. We note a few features that we expect to see based on optimization theory: first, the *BenMax-Free* scenario has greater net ozone benefits than any of the constrained *BenMax* scenarios; and second, the net ozone benefits of the constrained *BenMax* scenarios decrease as policy stringency increases. In addition, the decrease in net ozone benefits of the constrained *BenMax* scenarios accelerates as stringency is tightened, resulting in a substantial gap in net ozone benefits

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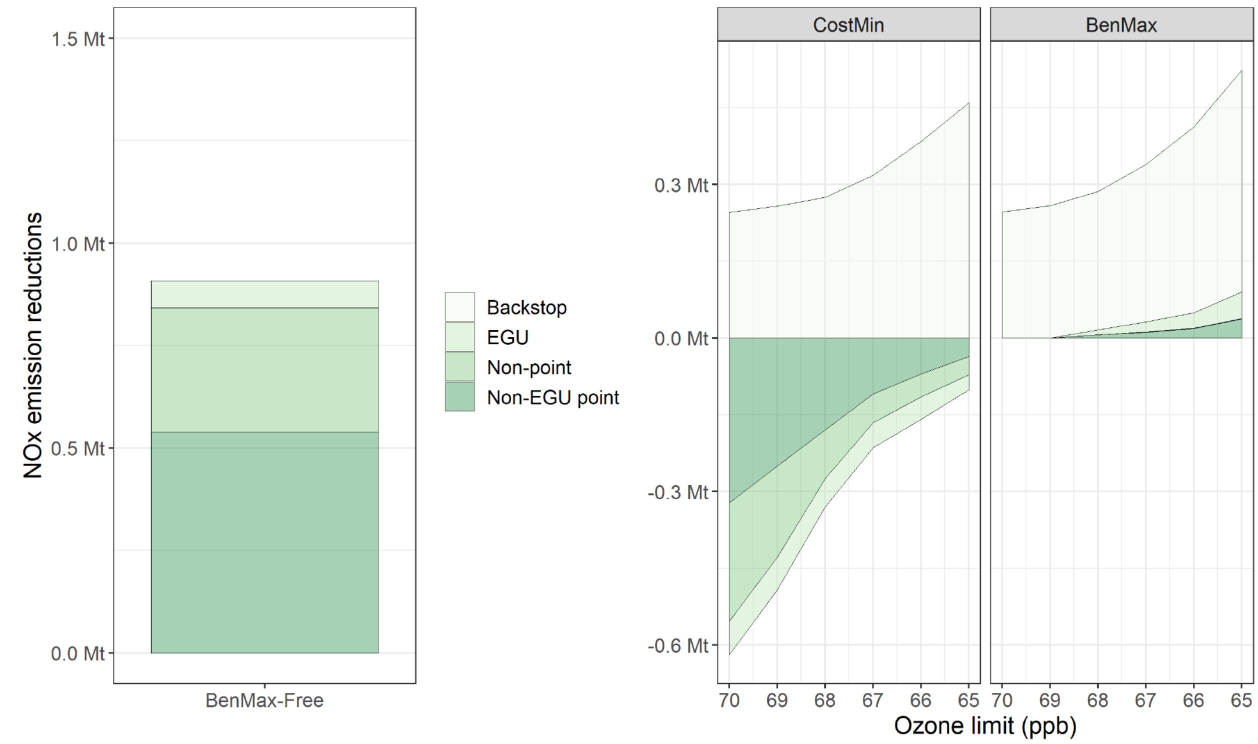

Figure 4. National NO_x emissions reductions by type for the *BenMax-Free* scenario (left) and difference in reductions from the *BenMax-Free* scenario by target stringency (right).

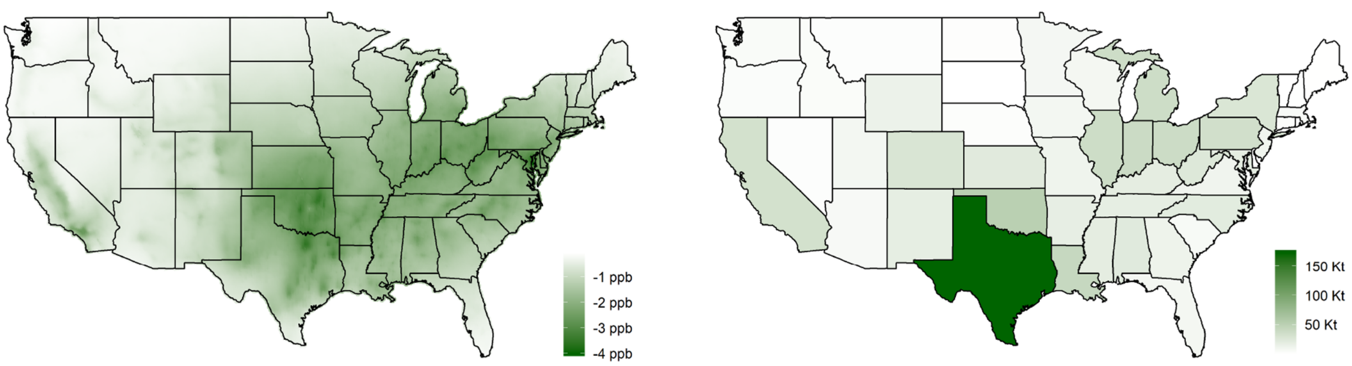

Figure 5. Changes in ozone concentrations (left) and state-level NO_x emissions reductions (right) for the *BenMax-Free* scenario.

between the *BenMax-Free* and *BenMax-65* scenarios. In contrast, the relationship of stringency and net ozone benefits for the *CostMin* scenarios is nonmonotonic, peaking at a 67 ppb standard. Still, net ozone benefits are positive for all *CostMin* scenarios.

The lower right panel depicts the (postprocessed) total $PM_{2.5}$ benefits associated with NO_x reductions. In terms of magnitude, the benefits are on par with the ozone benefits, particularly for the constrained *BenMax* scenarios. The patterns are also like the ozone benefit patterns, although the benefits associated with the *CostMin* scenarios are most similar to the *BenMax-Free* scenario benefits at 68 (rather than 69) ppb.

Underlying differences in costs and benefits across scenarios are the magnitudes of emissions reductions and the locations of the sources behind those reductions. Figure 4 depicts total national NO_x emissions reductions for the *BenMax-Free* scenario (left panel) and the differences in reductions for the *CostMin* and constrained *BenMax* scenarios from that scenario as a function of policy stringency (right panel). Reductions are broken out into the control categories described previously. We focus on NO_x emissions reductions rather than VOC reductions for two reasons: first, NO_x emissions reductions contribute far more to reductions in ozone concentrations; and second, VOC emissions reductions are stable across all scenarios.

In the *BenMax-Free* scenario, national NO_x emissions are reduced by 0.9 million tons (Mt) out of a total of 7.9 Mt present in the 2023 emissions database. Those reductions are composed of controls at non-EGU point sources (59.5%), nonpoint sources (33.3%), and EGUs (7.2%). No reductions are due to the high-cost backstop control, which provides context for the marginal health benefits to ozone reductions in high population areas.

In contrast to the *BenMax-Free* scenario, the constrained scenarios both rely significantly on backstop control to meet even the least stringent policy. In both cases, use of the backstop control accelerates as stringency increases. Reductions from nonbackstop sources in the *CostMin-70* scenario are

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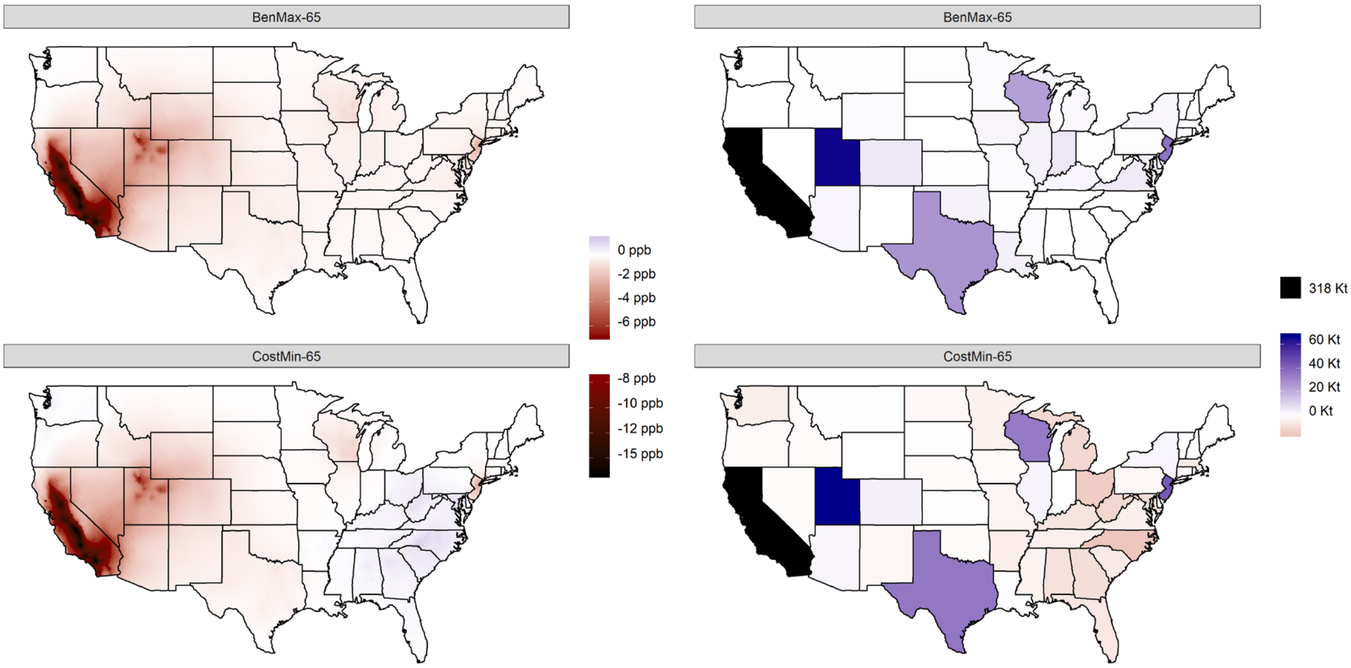

Figure 6. Changes in ozone concentrations (left) and state-level NO_x emissions reductions (right) for the *BenMax-65* (top) and *CostMin-65* (bottom) scenarios: difference from *BenMax-Free* scenario.

less than half of the level in the *BenMax-Free* scenario. As stringency increases, reductions from those sources increase significantly. For the constrained *BenMax* scenarios, at a 70 ppb target, there is no difference in the amount of nonbackstop emissions reductions, but the constrained scenario requires almost 0.3 Mt of backstop reductions. As stringency increases, the amount of additional non-EGU point and EGU reductions increases, but at a much slower rate than the increases in backstop reductions.

The assumed value of the backstop cost is a crucial parameter in our analysis; see the SI for a sensitivity analysis on this parameter. We view our default value of $15 000 per ton as a conservative estimate. By comparison, the average cost of nonbackstop reductions in the *CostMin-65* and *BenMax-Free* scenarios, for example, are $1800 and $1700, respectively.

Subnational Impacts. In this section, we present results for NO_x emissions reductions and ozone concentrations in two stages. First, we illustrate differences from the baseline resulting from unconstrained net benefits maximization (the *BenMax-Free* scenario). Then we illustrate differences between the *BenMax-Free* scenario and the design value-constrained scenarios.

Figure 5 illustrates how ozone concentrations change across the country from their 2023 baseline values under the *BenMax-Free* scenario (left panel), and from which states emissions reductions originate (right). Relative changes in state-level NO_x emissions range from a 22% reduction in Maryland to a less than 2% reduction in South Dakota. These modest changes lend credibility to the use of linear air quality response factors in NO_x-limited regimes since previous work has found that ozone response to NO_x changes is close to linear for emissions perturbations of less than about 30% in NO_x-limited regimes.[33]

By far, Texas is the state with the greatest amount of emissions reductions. Significant reductions also occur in neighboring states Oklahoma and Louisiana. This suggests that there are relatively low-cost abatement opportunities available in these states, since Oklahoma and Louisiana are not particularly populous states. The other cluster of states with high levels of emissions reductions is the industrial Midwest (Ohio, Michigan, Indiana, and Illinois) and Pennsylvania. Finally, some higher levels of emissions reductions are found in states with nonattainment areas, such as California, Colorado, and New York.

Not surprisingly, we observe a correlation (r = 0.31) between emissions reductions and decreases in ozone concentrations across states. The states noted above for having large emissions reductions also tend to have substantial decreases in ozone concentrations, at least in some areas of the state. In addition, some areas with relatively fewer emissions reductions, particularly in the mid-Atlantic and southeastern U.S., still benefit from substantial decreases in ozone concentrations.

To assess the impact of objective function choice and the design value constraint, we illustrate differences in ozone concentrations and emissions reductions resulting from the constrained scenarios relative to the *BenMax-Free* scenario in Figure 6. The top panels depict *BenMax-65* scenarios, and the bottom panels depict *CostMin-65* scenarios. The left panels depict ozone concentrations, while the right panels depict emissions reductions.

The top panels illustrate the impacts of imposing a 65 ppb design value constraint to a net benefits maximization framework. Additional controls are applied in several states, most notably California, Utah, Wisconsin, Texas, and New Jersey, compared to the unconstrained *BenMax* scenario. Impacts in California are particularly stark, as NO_x emissions from the state are reduced by an additional 0.32 Mt. Recalling Figure 4, we observe that these additional reductions are achieved entirely through backstop control. As a result of additional control in California and Utah, additional health benefits accrue to several other states in the western U.S. through reduced ozone concentrations.

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The bottom panels illustrate the impacts of not accounting for benefits in the objective function while imposing a 65 ppb design value constraint. Again, additional controls are applied in California, Utah, Wisconsin, Texas, and New Jersey beyond what those that are applied to maximize net benefits. In contrast, the heat maps for the *CostMin-65* scenario illustrate the parts of the country for which it is net beneficial to reduce emissions beyond the levels needed to meet the 65 ppb standard. This applies to most of the Ohio valley, southeastern, and mid-Atlantic states.

Inequality Metrics. In Table 1, we present AI coefficients for a subset of scenarios and inequality tolerance parameters.

Table 1. Atkinson Inequality Metrics for Selected Scenarios

scenario	ϵ = 0.75	ϵ = 3
baseline	0.0078	0.0318
BenMax-65	0.0055	0.0226
BenMax-70	0.0059	0.0244
BenMax-Free	0.0076	0.0302
CostMin-65	0.0055	0.0227
CostMin-70	0.0061	0.0255

The estimated AI is uniformly larger for the baseline and each policy scenario when assuming an inequality tolerance parameter of 3, reflecting a lower tolerance for risk inequality. Compared to the baseline, each of five policy scenarios yield a smaller AI; this suggests that in the course of reducing the risk of attaining a more stringent ozone standard, each approach promotes a more equitable distribution of ozone-related risk. The benefits maximizing and cost minimizing scenarios for the 65 ppb air quality standard yield nearly identical AI values, suggesting that both approaches reduce the level of risk inequality by an equal margin. Conversely, the benefits maximizing scenario achieves a lower AI than the cost minimizing scenario for the 70 ppb scenario, achieving greater estimated benefits and resulting in a more equitable distribution of risk. Finally, the benefits maximizing approach—designed to produce the largest health benefits without regard to cost and without targeting a specific design value target—yields the smallest overall change in the AI among the policy scenarios.

Implications and Extensions. To illustrate the capabilities of CABOT-O_3, we compared optimal emissions reductions from stationary sources and associated costs and benefits when minimizing costs subject to meeting ambient air quality standards versus maximizing net benefits, both with and without air quality constraints. Given our parametrization of the model, some regions of the country reduce emissions more when maximizing net benefits than when minimizing costs subject to air quality constraints, while others reduce less. In turn, this corresponds to differential impacts on ambient ozone concentrations. In the scenarios we considered, net benefits from reduced ozone concentrations are 49−77% lower when cost minimizing versus maximizing net benefits. However, the AI based on ozone concentrations is 16−28% lower (corresponding to more equitable ozone exposure) when cost minimizing versus maximizing net benefits. This illustrates a fundamental trade-off between equity and economic efficiency that can manifest when comparing air quality policy designs. Future work on the CABOT model will relax some of the assumptions made in this work, such as imposing linear air quality response coefficients, and develop new capabilities, such as explicitly modeling $PM_{2.5}$ and expanding the set of modeled emissions sources.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.0c01053.

Comprehensive mathematical formulation of CABOT-O_3 (ZIP)

Detailed information on how the 2023 baseline pollution concentrations and air quality transfer coefficients were derived (PDF)

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Notes

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