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Prioritizing Justice in New York State Climate Policy: Cleaner Air for Disadvantaged Communities?

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About RFF

Resources for the Future (RFF) is an independent, nonprofit research institution in Washington, DC. Its mission is to improve environmental, energy, and natural resource decisions through impartial economic research and policy engagement. RFF is committed to being the most widely trusted source of research insights and policy solutions leading to a healthy environment and a thriving economy.

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About NYC-EJA

The New York City Environmental Justice Alliance (NYC-EJA) is a non-profit, 501(c)3 citywide membership network linking grassroots organizations from lowincome neighborhoods and communities of color in their struggle for environmental justice. NYC-EJA empowers its member organizations to advocate for improved environmental conditions and against inequitable environmental burdens by the coordination of campaigns designed to inform City and State policies.

Sharing Our Work

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1. Introduction

As a result of historically unjust systems and policies, the neighborhoods where low-income communities and communities of color live, work, learn, and play are often sites for or affected by polluting infrastructure, vehicle congestion, and other environmental hazards. Racist systems and policies along with economic discrimination continue to diminish the health and quality of life of communities of color and low-income communities and make them more at risk to other hazards like climate change (Peña-Parr 2020; Donaghy et al. 2023). As fossil fuel consumption and pollution have increased exponentially over the past century, not only has the climate change outlook worsened, but vulnerable communities have also disproportionally suffered injury, disease, death, displacement, and loss of property because of these same trends (Resnik 2022).

To address the growing inequities, community leaders have advocated for clean air, water, and land and fought against trash incinerators, highways, and fossil fuel power plants being placed in their neighborhoods. National and state climate policy has rapidly evolved in the past decade—not only are efforts to reduce greenhouse gases (GHGs) increasing, but recent efforts have also put racial, social, and economic justice at the forefront of the policy conversation. With leadership from communities affected first and worst by pollution and other environmental and climate risks (often referred to as “frontline communities”), policies are now expected to achieve not only climate goals but also improvements in environmental and economic justice. Another key goal is to ensure a just transition, making sure that low-income communities and communities of color don’t face disproportionate burdens or exclusion from the benefits of the transition from a fossil fuel economy to a resilient, equitable, and regenerative society.

One of the most prominent examples of justice-oriented climate policy is New York State’s recent climate law, the Climate Leadership and Community Protection Act (CLCPA). As the state moves to implement this groundbreaking law, rigorous research and analysis are needed to shed light on policy design options that can achieve the dual goals of cutting GHG emissions and improving air quality and other public health outcomes for “disadvantaged communities,” as defined by the state. This requirement is the motivation for this study.

Bringing together leading environmental justice (EJ) advocates, economic researchers, public health scientists, and air quality modelers (see Appendix A), our study investigates EJ impacts in the context of the CLCPA. Specifically, we model the impact of policies on the electric power, on-road transportation, ports, and residential building sectors, and the resulting fine particulate ($PM_{2.5}$) air pollution experienced by disadvantaged communities and nondisadvantaged communities alike. We compare two policy scenarios: one inspired by the Climate Action Council’s (CAC) scoping plan for implementing the CLCPA, and one inspired by the policy priorities of environmental and climate justice stakeholders in New York. A key question driving our research is, to what extent do the policies contemplated in the CLCPA scoping plan indeed (as required by the CLCPA) “not result in a net increase in copollutant emissions or otherwise disproportionately burden disadvantaged communities” and/or “prioritize measures to maximize net reductions of … copollutants in disadvantaged communities”? And furthermore, how do the scoping plan policies compare—in this regard—with those policies advocated by New York’s EJ stakeholders?

Our analysis has revealed 10 major findings and insights:

1. **GHG reductions in 2030 are substantial under both cases relative to the business-as-usual (control) case but are greater under the stakeholder case (58 percent vs. 34 percent reduction).**
2. **The stakeholder case leads to greater statewide emissions reductions** for all $PM_{2.5}$ precursors (nitrogen oxides, NO_x; sulfur dioxide, SO_2; and volatile organic compounds, VOCs) than the CAC-inspired case.
3. **The stakeholder case leads to greater statewide $PM_{2.5}$ concentration reductions (air quality improvements) than the CAC-inspired case in 99 percent of census tracts.**
4. **In the CAC-inspired case, average air quality improvements in disadvantaged communities are comparable to the improvements made in nondisadvantaged communities. In the stakeholder case, improvements in disadvantaged communities are greater than those in nondisadvantaged communities.**
5. Although, on average across the state, both cases improve air quality (reduced $PM_{2.5}$ concentrations), **some census tracts do experience a worsening of air quality (increased $PM_{2.5}$ concentrations): in the CAC-inspired case, about 6 percent of the state's roughly 5,000 tracts experience worse air quality, a fourth of which are disadvantaged communities, whereas in the stakeholder case, only three census tracts experience worse air quality, none of which are disadvantaged communities.**
6. **The most vulnerable communities (the top 10 percent of tracts in the state's social vulnerability measure, and the 10 percent with historically worse air quality) experience particularly pronounced improvements under the stakeholder case but experience average air quality improvements in the CAC-inspired case.**
7. Both policy cases make air quality improvements in disadvantaged communities, **but the impacts are too evenly shared with nondisadvantaged communities to reverse the historical disparity in air pollution concentrations.**
8. In an illustrative calculation, **the stakeholder case offers the greatest public health benefits to elderly Black New Yorkers** relative to their Hispanic, Asian, and white counterparts. Although 22 percent of New York City's 65 and older population is Black, this group accounts for 42 percent of the avoided deaths from $PM_{2.5}$ reductions; white residents make up 41 percent of the city's 65 and older population but account for 37 percent of the avoided deaths.
9. **Both cases, as modeled, meet the CLCPA EJ goal to "not disproportionately burden disadvantaged communities," if we define burden to mean increasing $PM_{2.5}$ concentrations.**
10. **The greater benefits associated with the stakeholder case relative to the CAC-inspired case require greater investment**, since the stakeholder policies are more ambitious and offer more generous subsidies to encourage electrification of buildings and vehicles. The emissions reductions and air quality improvements for disadvantaged communities certainly favor the stakeholder case, driving valuable health and equity outcomes that may well outweigh the policy costs, but estimating benefits and costs was beyond the scope of this project.

2. The New York Climate Policy and Environmental Justice Landscape

2.1. The Climate Leadership and Community Protection Act (CLCPA)

The CLCPA, passed in 2019 after years of debate and advocacy, sets ambitious GHG emissions goals, including an 85 percent reduction in economywide GHG emissions by 2050, 70 percent renewable energy by 2030, and a 100 percent zero-emissions electricity sector by 2040. The law also mandates that the state achieve 9,000 MW of offshore wind by 2035; 3,000 MW of energy storage by 2030; 6,000 MW of solar by 2025; and 22 million tons of carbon reduction through energy efficiency and electrification.

In addition, the law explicitly sets goals for environmental and climate justice—addressing the disinvestment and disproportionate environmental burdens that communities of color and low-income communities have experienced. The preamble states that "actions undertaken by New York State to mitigate GHG emissions should prioritize the safety and health of disadvantaged communities, control potential regressive impacts of future climate change mitigation and adaptation policies on these communities, and prioritize the allocation of public investments in these areas."

Not only does the CLCPA require reductions in GHGs like methane and carbon dioxide (CO_2), it also targets local air pollutants—what the law refers to as copollutants—such as $PM_{2.5}$ and SO_2. The law specifically directs the New York State Department of Environmental Conservation (NYSDEC) to "ensure that activities undertaken to comply with the regulations do not result in a net increase in copollutant emissions or otherwise disproportionately burden disadvantaged communities" and to "prioritize measures to maximize net reductions of GHG emissions and co-pollutants in disadvantaged communities." Stated simply, the CLCPA requires state climate regulations to prioritize air quality in disadvantaged communities—including by requiring that environmental burdens are not shifted from wealthier communities to lower-income, minority communities. The CLCPA also establishes a Climate Justice Working Group (CJWG) tasked with establishing criteria for identifying disadvantaged communities and representing EJ priorities throughout the various stages of CLCPA implementation. The final criteria were adopted on March 27, 2023, after a public comment period and public hearings held across New York State. Additionally, the law stipulates that 35 to 40 percent of the benefits and investments go to disadvantaged communities.

2.2. Environmental Justice

The Climate Justice Alliance, a national network of frontline communities and organizations demanding a just transition, defines environmental justice as the right of all people, regardless of race or socioeconomic background, to live, work, and play in communities that are safe, healthy, and free of life-threatening and harmful conditions. The alliance works to realize a vision for a just transition, which is a "place-based set of principles that build economic and political power to shift from an extractive economy to a regenerative economy." The alliance states that the "Just Transition must advance ecological resilience, reduce resource consumption, restore biodiversity and traditional ways of life, and undermine extractive economies, including capitalism, that erode the ecological basis of our collective well-being. This requires a re-localization and democratization of primary production and consumption by building up local food systems, local clean energy, and small-scale production that are sustainable economically and ecologically. This also means producing to live well without living better at the expense of others."

The Climate Justice Alliance and the EJ movement more broadly are led by (and advocate for) frontline communities who experience climate and environmental hazards first and worst. EJ communities are frontline communities: low-income communities and communities of color who face disproportionate exposure to environmental hazards due to both intentional design and structural racism. The Climate Justice Alliance describes the **origins of the EJ movement** as growing "out of a response to the system of environmental racism where communities of color and low-income communities have been (and continue to be) disproportionately exposed to and negatively impacted by hazardous pollution and industrial practices. Its roots are in the civil rights movement and are in sharp contrast to the mainstream environmental movement, which has failed to understand or address this injustice. The EJ movement emphasizes bottom-up organizing, centering the voices of those most impacted, and shared community.

Historically, low-income communities and communities of color have been systematically disinvested from, with racist policies and practices such as redlining used to value certain neighborhoods and residents above others (Hoffman et al. 2020). These policies and systems have caused wealth and resource gaps that endure to this day, investing in quality-of-life improvements in wealthier areas while pushing polluting industries into lower-income communities (Hoffman et al. 2020; Nardone et al. 2020; Schell et al. 2020). We see these disparities reflected in the location of power plants, transportation depots, and city parks. The impacts of this unequal investment are clear in public health data, with environmentally driven poor health outcomes like asthma most prevalent in EJ communities (New York City Department of Health and Mental Hygiene 2020).

Policymakers have paid little attention to these historical racist practices and the resulting disparities in distributional effects that have maintained and widened resource gaps. Without intentional consideration and targeted policy implementation, an unjust distribution of costs and benefits of policies and programs will continue to cause EJ communities to experience greater burdens than their white and wealthier counterparts.

2.2.1. Community Leadership and Solutions

As policymakers seek solutions to climate change, EJ experts and community leaders have emphasized the importance of doing so in a way that centers racial and economic justice, addressing this history of abuse. EJ advocates have been calling for climate policies that not only reduce GHG emissions but also ensure that the costs of an energy transition do not fall unduly on disadvantaged communities, and make improvements in the environmental conditions, public health, and adaptive capacity of disadvantaged communities.

EJ and climate justice stakeholders in New York have played a central role in representing the needs of underserved communities, as reflected in numerous provisions in the CLCPA. In the creation and execution of this research project, EJ and climate justice stakeholders were centrally involved to ensure that community concerns and expertise were woven into the fabric of the research design and process. It was crucial that the EJ stakeholder policy case reflect what these EJ stakeholders are fighting for and most want to see enacted to protect their communities. Accepting and incorporating their knowledge and leadership are important steps in the process of dismantling historical inequities and ensuring that all parties involved have a seat at the negotiating table for environmental policies such as the CLCPA.

3. Our Research

As New York moves to meet the CLCPA decarbonization goals, the state will implement policies that phase out behaviors and technologies that generate GHG emissions. Our research seeks to inform this process by analyzing the GHG and air pollution impacts of three policy cases: a business-as-usual case, meant to represent what would happen to emissions and air quality without the actions contemplated in the two policy cases; the stakeholder policy case, meant to reflect EJ policy priorities; and the CAC-inspired policy case, meant to reflect a plausible set of policies coming out of the state's scoping plan process, which defines the policy goals and tools that ought to be used to meet the legal requirements of the CLCPA. Details on the policy cases can be found in Section IV. We focus on how the policy cases affect $PM_{2.5}$ concentrations in communities at the census tract level across the state.

To compare policy outcomes between disadvantaged communities and nondisadvantaged communities, we use an EJ screen (referred to in this report as a climate health and vulnerability index) and an EJ map. The EJ screen and map reflect the disadvantaged community criteria and methodology developed by the state through the CJWG. Using this EJ screen and map, we track the effects of changing $PM_{2.5}$ concentrations on disadvantaged and other communities.

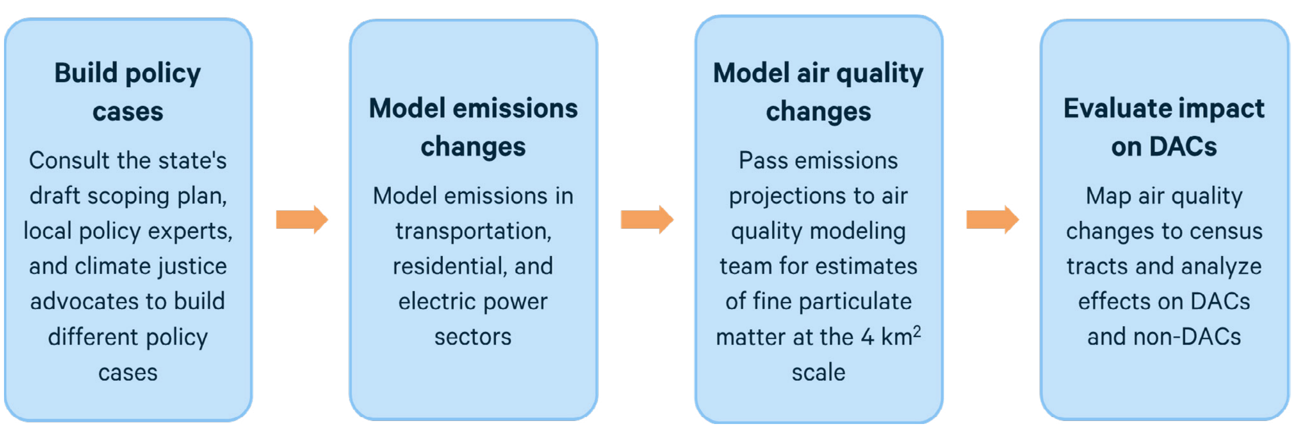
Several characteristics of our research set it apart from other research efforts. Our contribution to examining the outcomes of decarbonization policies on EJ communities at a state level is unique. Additionally, we use a combination of behavioral models and one of the most sophisticated air quality models to assess and trace the consequences of the two policy cases for disadvantaged communities (DACs) and non-DACs. Further, mapping these results visually at the $4km^2$ scale gives readers an unprecedented ability to assess and understand the geographic distribution of results.

3.1. Methodology

This project involves several models that work together to estimate the emissions and air quality impacts of different policies. The first step in our research is to build and compare the three cases—business-as-usual case, CAC-inspired policy case, and stakeholder policy case—in consultation with New York policy experts (see Appendix A and Section IV). Next, we use four economic models that estimate the future emissions impacts of different policies in each of the three cases (see Appendix B). Models of the electric power sector, the light-duty vehicle market and fleet, the medium- and heavy-duty vehicle market and fleet, as well as nonmarine port activities and the residential building sector are included in our analysis.

The emissions estimates produced by the economic models are used as inputs in an air quality model that projects changes in $PM_{2.5}$ resulting from meteorological conditions, chemical reactions, and other factors (see Appendix C). We then incorporate the CJWG's criteria for identifying DACs in our EJ screening and mapping tool to analyze outcomes for the three cases in 2030 (see Appendix D). By comparing emissions levels and air quality changes in DACs with non-DACs, we can ascertain the impacts of different implementations of the CLCPA for vulnerable communities. Figure 1 depicts the flow of research for this project.

Figure 1. Research Process



The research and findings from this project contribute to the current body of work investigating the impacts of the state's climate policies. The most expansive work in this space was conducted by New York State Energy Research and Development Authority (NYSERDA) and NYSDEC in partnership with **E3** in 2021 to inform the scoping plan process. Their work focused on establishing estimated pathways of decarbonization across all sectors affected by the CLCPA. Our work is more focused on a few critical sectors for which we have robust behavioral models. For a full list of differences with the state-sponsored analysis, see Appendix F.

We also acknowledge that important boundaries to our research may influence the interpretation of the results. For example, our air quality modeling is at a $4km^2$ grid resolution, which in some cases is larger than a DAC boundary. We use one of the most advanced air quality models for our estimates, which incorporates detailed representations of atmospheric science and chemical processes. We have selected a spatial resolution that preserves the accuracy of that model. To aid in the interpretation of our work, we describe the limitations and caveat for our analysis in Appendix G, including a small error in the transportation emissions used as an input in the air quality model.

4. The Cases

We focus on 2030 as the year for modeling economic activity and related air pollutant concentrations throughout New York State. Our modeling begins with a business-as-usual case, which includes policies in place prior to the passage of the CLCPA and continues through 2030. We also model two policy cases: the CAC-inspired policy case, which assumes policies are implemented to meet the goals of the CLCPA as stated in the CAC scoping plan, and the stakeholder policy case, which assumes policies are implemented in line with the priorities and preferences of prominent EJ advocates in New York. The details of all three scenarios are described below.

4.1. Business-as-Usual (BAU) Case

The models incorporate a variety of forward-looking economic and demographic projections to anticipate future conditions. For example, future oil and natural gas prices, population projections, and income and wage growth are all considered. The energy models in this project, like many others, use Energy Information Agency (EIA) projections for these high-level drivers of change. The projections are found in EIA's Annual Energy Outlook (AEO), which is based on runs of the National Energy Modeling System.

The latest AEO available at the start of our project was the AEO2021 and embodies the agency's most recent economic activity projections. EIA limits its modeling to sets of policies (mostly federal, and in some cases, state) that are already in place, not policies that might be implemented in the future. Its projections do not assume that a carbon tax or any other federal CO_2 reduction plan is implemented.

Our modeling work took place over the course of 2022. We were required to lock in assumptions about what federal and state policies to model in the BAU case in January 2022. As a result, the effects of neither the Infrastructure Investment and Jobs Act nor the Inflation Reduction Act are included in our baseline. We made the following adjustments from the AEO2021 reference case to adapt it to our research:

- We used the AEO2020 projections for key transportation parameters, since these assume the Obama-era fuel economy standards are in place, rather than the Trump administration rollbacks represented in AEO2021.
- We used the reference cases for both AEO2020 and AEO2021 for oil and gas supply based on alignment with other modeling exercises and to avoid potentially biasing results by selecting an AEO case with high or low growth.[1]
- We used E3's New York–specific assumptions about the transportation sector, including the increase in vehicle miles traveled in the state.

4.2. CAC-Inspired Policy Case (CPC)

The CPC was developed based on the Climate Action Council's (CAC) draft scoping plan and conversations with New York State policy experts. We identified policies in the relevant sectors and adjusted where needed to fit the needs of our models. Table 1 provides a list of the CPC policies we model with brief descriptions.

Not all these policies are explicitly mentioned in the scoping plan. Our modeling work is based on behavioral responses to economic policies, so we had to add detail and specificity to policies where none existed. The CPC represents one reasonable interpretation of how the priorities in the scoping plan may be executed. The details were established using a mix of New York policy proposals, examples from other state and federal climate policy proposals, and feedback from New York policy experts.

4.3. Stakeholder Policy Case (SPC)

The SPC was developed with various EJ organizations operating throughout New York. These groups identified local and statewide priorities and gave feedback on the draft scoping plan's proposed policies in the sectors we analyzed through several workshops and written comments. Table 1 lists the SPC policies that we included in our modeling and reasons why they diverge from the CPC.

There are many policies considered essential by climate and environmental justice advocates that we were unable to integrate into our research. We excluded policies for three primary reasons: (1) the policy applies to sectors that we are not modeling (e.g., agriculture policies), (2) we were unable to estimate accurate emissions changes from

1 The difference in 2030 CO_2 emissions is about 5.6 percent between the reference and high growth cases and about 10 to 11 percent between the high and low cases. Thus, we favor an unbiased choice—the reference case.

the policy because of model limitations (e.g., public vehicle fleets are excluded in our transportation model), and/or (3) the objective of the policy affects an outcome other than emissions reductions or air quality improvements (e.g., job training programs). The exclusion of these policies is in no way a reflection on their importance, feasibility, or impact but rather a result of the reality of our modeling limitations. See Appendix A for a list of policies that the stakeholder groups identified as critical to their communities that we were unable to include in our models.

Furthermore, some if not all of the policies we model will affect conditions and outcomes that we do not estimate. For example, regional employment, water pollution levels, and health outcomes are all important metrics of a thriving community that are shaped by climate policies but not included in our modeling. Consequently, although we can make inferences about some of these outcomes, they are excluded from our policy analysis. The decision not to model these outcomes is not a judgment on their significance; they are simply outside our research scope.

Table 1. Details of Policy Cases

Policy	CPC	SPC	Motivation for stakeholders
Economy-wide			
Carbon regulation[2]	An economy-wide carbon fee is established to achieve emissions reductions across sectors we are analyzing. Fee is $25/ton in 2030.[3] Fee was determined iteratively with our models to meet state's target after other policies were in place, similarly to how carbon cap would be modeled.	Carbon fee introduced in 2023 at $55/ton, increases 5% annually to $77/ton in 2030. Copollutant prices ($2017): NO_x: $9,025/short ton SO_2: $36,382/short ton $PM_{2.5}$: $231,965/short ton	SPC carbon-pricing scheme reflects ambition of CCIA polluter fee. It prices copollutants based on social marginal cost in addition to CO_2. This could also be achieved with an economy-wide cap on pollutants.

2 Economy-wide carbon regulation (cap or fee) in both policy cases is accompanied by a border carbon adjustment for imported and exported electricity. That border carbon adjustment is a fee on electricity imports to New York State and an equal subsidy on electricity exports from New York State. The level of the fee and subsidy is the price on New York in-state CO_2 emissions times the average GHG emissions rate of electricity generation in adjacent regions. In this GHG emissions rate calculation, each pound of methane is counted the same as 30 pounds of CO_2.

3 This price was set to meet emissions reductions targets only in the sectors we model. A carbon price may play a larger role in eliciting emissions reductions in other sectors. The relative cost of emissions reductions in those sectors may require a higher price to achieve the desired result. Observing further emissions reductions with a low price in our policy case implies that there are relatively low-cost reductions that were not incentivized by the other modeled policies. Several policies included in the policy case force relatively high-cost emissions reductions (like the ZEV mandate in the transportation sector) that would not be achieved with the modeled carbon price alone.

Electricity sector			
Clean energy standard	70% of electricity must come from clean energy sources, as defined in CLCPA.	Same as CPC.	—
Distributed solar target	Mandates 10 GW solar installed by 2025.	Same as CPC.	—
Battery storage target	Mandates 3 GW battery storage installed by 2030.	Same as CPC.	—
Offshore wind target	Mandates 9 GW offshore wind installed by 2035.	Same as CPC.	—
Transmission investment	Two new DC lines will be built in New York: Clean Path and Champlain Hudson Power Express.	Same as CPC.	—
Nuclear subsidies[4]	Extend ZECs for nuclear until after 2030; extend nuclear licenses to 80 years.	End ZECs for nuclear in 2029 when they are set to expire; do not extend nuclear licenses; no new generating units to be developed in NYS.	SPC reflects lack of consensus on how supporting nuclear affects electricity costs and trade-offs with supporting other technologies.
Demand response policy, flexible demand, distributed energy resource subsidy[5]	Shift 6% of peak electricity to off-peak times based on New York integration analysis flexible load assumptions in 2030 (developed by E3 Consulting).	Same as CPC.	—
Peaker plant policy[6]	Shut down fossil fuel peaker plants in line with stated policy, enforcing NYC NO_x rule and Pollution Justice Act of 2022 (Brisport's S4378B).	All NYS fossil fuel peaker plants close by 2030.	Peaker plants disproportionately contribute to air pollution in disadvantaged communities.
New combustion fuels, CCUS	Allow biofuels, natural gas, hydrogen, and CCUS if economical after other abatement policies are in place.	Ban use of new natural gas and CCUS in power sector by 2025.	SPC reflects more ambitious transition away from polluting generators, does not support investment in technologies that may prolong fossil fuel use (deemed as "false solutions").

4 Our modeling took place before the passage of the Infrastructure Investment and Jobs Act or the Inflation Reduction Act, so the Civil Nuclear Credit program and the nuclear tax credit are not included in our modeling. These would likely reduce the costs of sustaining nuclear in the CPC and prevent retirement of nuclear in the SPC.

5 Our power sector model has limited ability to model demand response and incentives for distributed energy resources directly, so we model these as an assumed shift in peak demand. We use the assumptions from the state analysis for this purpose.

6 Peaker plants generally run only when demand for electricity is very high, or "peaking." They are generally less efficient than other fossil fuel generators because they are designed to ramp up energy production quickly when needed.

Residential buildings			
Heat pump subsidy[7]	Starting in 2023, provide $4,750 subsidy for households with 80% or less of state median income and multifamily households; provide $3,000 subsidy for all other single-family homes.	Starting in 2023, provide full heat pump cost subsidy to households with 60% percent or less of state median income; $4,750 subsidy to households with 80% percent or less of median income; $3,000 subsidy for all other single-family homes.	SPC reflects more ambitious support for electrification of low-income households.
Shell efficiency upgrades[8]	By 2030, shell efficiency upgrades targeted to 25% of homes based on building vintage.	By 2030, shell efficiency upgrades targeted to homes in top 25% of energy burden.	SPC prioritizes upgrades for highest-burdened homes, rather than most inefficient homes.
Fossil fuel phaseout	Before 2030, no bans on fossil fuel appliances.	Starting in 2023,[9] households cannot replace fossil fuel appliances at end of their useful life with more fossil fuel appliances.	SPC reflects more ambitious timeline for replacing fossil fuel technology in residential buildings.
Building standards	Starting in 2027, NYSERDA Stretch Code is enforced for new residential construction standard.	Same as CPC.	—

7 Heat pumps are assumed to be air-source heat pumps, and subsidies are assumed to fully cover the costs associated with building upgrades needed to install heat pumps.

8 Shell efficiency upgrades are defined as an upgrade of the building standard when the home was built, to the latest NYSERDA stretch building code. The model considers the efficiency associated with each of these standards.

9 At the time of constructing this policy case, the state was considering a fossil fuel hook-up ban for residential buildings. It was not included in the 2023 budget but it was after we modeled the SPC.

Light-duty vehicles			
California's Advanced Clean Cars 2 Rule	By 2030, 50% of new-vehicle sales are PEV (expected to require 100% ZEV sales by 2035).	Same as CPC.	—
Feebate for ZEVs	Means test for rebates and vouchers: Subsidy begins at $5,000 for lowest income group and declines to $1,000 for highest income group, in increments of $1,000. Tiered fee system for new-vehicle purchases based on vehicle miles per gallon. Reduced fee based on means test or household income (exemptions: 100% for low income, 50% for middle income, 0% for high income).	Same as CPC.	—
Scrappage incentive	No scrappage incentive.	Subsidy per vehicle (means tested): $3,000 for households above 200% of federal poverty line, $5,000 for households below 200%.	
Eligible vehicles: any ICE vehicle at least 15 and not more than 25 years old	Scrappage incentives can accelerate retirement of high-emissions vehicles and may provide greater subsidies to low-income households with older vehicles.		
Electricity rates for EVs*	Assume 25% reduction in electricity rates for EV charging for all households.	Free electricity for EV charging for all low- to middle-income households.	SPC reflects more targeted aid to low-income households.
Infrastructure investments*	Grants up to $2,000 for Level 2 home charger installation.	Same as CPC.	—
Bus service expansion	By 2040, double service availability and accessibility of municipally sponsored upstate and downstate suburban public transportation services.	Same as CPC.	—
Clean fuel standard	Standard follows Senator Kevin Parker's proposed S4003A (2019-20 legislative session), likely with less aggressive decarbonization pathway.	No low-carbon or clean fuel standard implemented.	SPC reflects EJ concern that low-carbon fuel incentives will delay full electrification.

Medium- and heavy-duty vehicles			
California's Advanced Clean Trucks Rule	New-ZEV sales goals: By 2030, Classes 2b and 3, 35%; Classes 4-6, 50%; Classes 7–8 (long haul), 35%. By 2035, 80% for all classes.	New-ZEV sales goals for all classes: By 2030, 50%. By 2035, 80%.	SPC reflects more ambitious ZEV goals for 2030 in the MHDV sector.
California's Advanced Clean Fleets Rule	By 2045, for vehicle fleet owners, 100% of new MHDV purchases must be ZEV.	Same as CPC.	
Feebate for ZEVs	Non-ZEV vehicles incur 5% purchase fee (assumed as increased purchase cost). Purchase incentive levels vary by vehicle class and year.	Same policy design, with higher incentives (as with CPC, purchase incentive levels vary by vehicle class and year).	SPC incentives reflect more ambitious ZEV targets.
Investment in ZEV infrastructure	Grants up to ~$25k for each new MHDV for charging.	Same as CPC.	—
Electricity rates for EVs*	Reduced electricity rates for MHDV charging.	Same as CPC.	—
Public financing for EV procurement*	Assume zero cost of capital for ZEVs (EV, H2).	Same as CPC.	—
Clean fuel standard	Standard follows Senator Kevin Parker's proposed S4003A (2019-20 legislative session), likely with less aggressive decarbonization pathway.	No low-carbon or clean fuel standard implemented.	SPC reflects EJ concern that low-carbon fuel incentives will delay full electrification.
Port electrification	By 2030, assume 100% electrification of equipment[10] purchased new or used.	Same as CPC.	—

Notes: CCIA = Climate Community and Investment Act; CCUS = carbon capture, utilization, and storage; EV = electric vehicle; H2 = hydrogen vehicle; ICE = internal combustion engine; LDV = light-duty vehicle; MHDV = medium- or heavy-duty vehicle; PEV = plug-in electric vehicle; ZEC = zero-emissions credit; ZEV = zero-emissions vehicle.

10 This only includes equipment and terminal vehicles (any type F vehicle that operates within terminals). Drayage is included in the overall truck flows, and so is subject to all of the policies (most prominently, the Advanced Clean Trucks rule and feebate) listed above that apply to MHDVs.

5. Results

This results section has four subsections: **Economic Modeling Results**, which describes estimated changes in energy demand and technology adoption across our modeled sectors; **Greenhouse Gas, $PM_{2.5}$, and Precursor Emissions Results**, which describes estimated emissions changes in our modeled sectors; **Location of Emissions Changes**, which describes the location of estimated changes in $PM_{2.5}$ emissions; and finally **Air Quality Results**, which describes estimated changes in $PM_{2.5}$ concentrations across community types and provides context for understanding the public health benefits of changes in air quality.

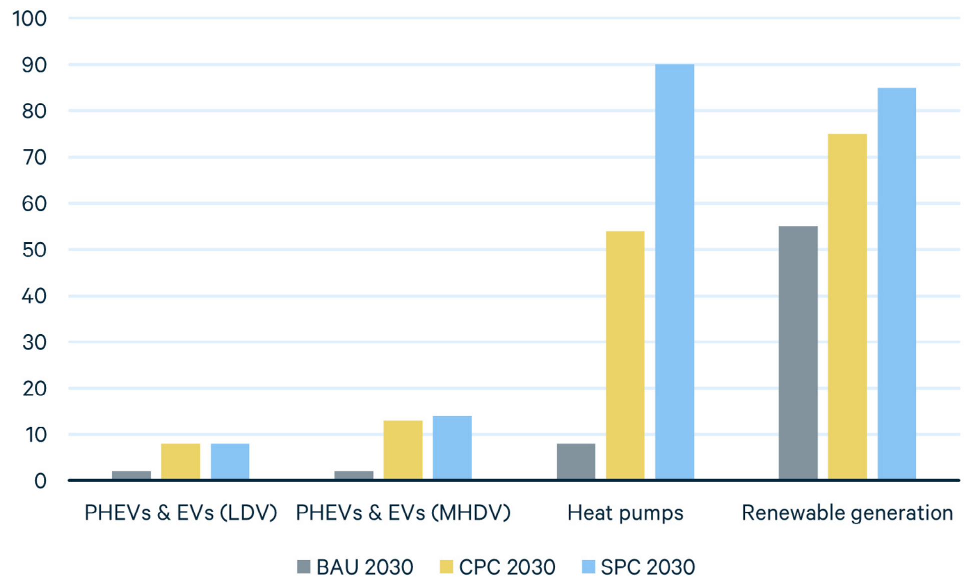
Our results focus on the differences between our two main policy cases (CPC and SPC), with reference to the BAU case. Significant changes in technology adoption and emissions are estimated to already occur under the BAU case, relative to the historical baseline. For example, even under the BAU, our modeling projects that New York State's electricity sector CO_2 emissions will fall to 17 million short tons in 2030, down from 31 million in 2020 (US EIA 2023), primarily as a result of the addition of solar and wind generation capacity. State policy to close peaker plants in areas with high population density also contributes to the steep decline in SO_2 and NO_X by 2030 under the BAU. Additionally, federal vehicle emissions standards and the continual retirement of older, more polluting vehicles leads to significantly lower emissions from cars and trucks. In the residential sector, the transition to natural gas furnaces in lieu of traditional oil furnaces significantly reduces $PM_{2.5}$ and SO_2 by 2030, even without additional policy.

5.1. Economic Modeling Results

The policies we modeled have a wide range of ambition and vary in their timelines for implementation. These results illustrate how far each policy case goes in pushing economic behavior that will lead to decarbonization and air quality improvements. The full sectoral analysis of economic results can be found in Appendix H. Figure 2 shows a summary of the key technologies and their adoption rates across each policy case.

Both policy cases prompt a dramatic increase in clean energy generation relative to the BAU. Compared with the CPC, **SPC policies boost renewable generation and storage capacity**. Relative to the CPC, the SPC delivers a 30 percent boost for solar, a 40 percent boost for wind, and nearly a 200 percent increase in storage capacity. The SPC also cuts nuclear, natural gas, and waste and biomass generation relative to the CPC (roughly 35 percent less for nuclear and 30 percent less for natural gas and waste).

Figure 2. Clean Technology Adoption Rates, by Policy Case (Percentage)



Heat pump adoption is also higher in both policy cases relative to the BAU. The SPC has the highest heat pump subsidies for low- and middle-income households; the CPC subsidy level is more modest. The SPC also includes a ban on new gas furnace purchases, rapidly phasing out fossil fuel heating. **This leads to an approximately 90 percent heat pump adoption rate in the SPC, compared with a 54 percent adoption rate in the CPC**. In addition to the statewide adoption rates, we find a range of adoption across counties in each case. For instance, the adoption rate varies across counties from 77 to 96 percent in the SPC, from 27 to 78 percent in the CPC, and from 2 to 15 percent in the BAU case. The higher adoption rates tend to be in the southeastern part of the state, such as Staten Island and Long Island.

Both policy cases also encourage adoption of light-duty zero-emissions vehicles (ZEVs). In the BAU, New York has about 241,000 EVs—about 2 percent of all on-road vehicles. **The CPC and SPC yield roughly four times more EV sales than the BAU**, driven by their more ambitious ZEV standards. Compared with the BAU, the policy cases also increase the average fuel economy of on-road vehicles by about 15 percent. The largest difference between the policy cases is in fuel consumption, which is driven by the different prices on carbon emissions. Fuel consumption is about 6 percent lower in the CPC and 12 percent lower in the SPC compared with the BAU. The SPC reduces fuel consumption more than the CPC because of its higher carbon price.

Similar to the light-duty vehicle findings, the mandate for zero-emissions medium- and heavy-duty vehicles (MHDVs) is a primary driver of the shift to a cleaner fleet. Because of the MHDV ZEV rule (see Table 1), by 2030, **it is expected that about 14 percent and 13 percent of the fleet will be ZEV (mostly battery electric) in the SPC and CPC, respectively**. Key drivers of the difference between cases (although small) are the more ambitious ZEV sales mandate and carbon price, as well as the copollutant fees, of the SPC; and the low-carbon fuel standard program (LCFS), which is specific to the CPC. Our findings suggest that significant financial incentives will be required to achieve the desired ZEV adoption. The models estimate that the various fees considered (on carbon, copollutants, and internal combustion engine vehicles) and the existing BAU vehicle incentives programs (e.g., New York City Clean Truck, New York Truck Voucher Incentive Program) will not be enough to fulfill the mandate.

Both policy cases increase total New York electricity demand because of the high rates of electrification in the residential and transportation sectors. Under the CPC, electricity demand increases by 17 percent, and under the SPC, by 29 percent, compared with the BAU. This leads to greater generation needs and contributes to higher electricity prices.

Our research did not include a comprehensive cost-benefit analysis, but we can observe that **the more ambitious investments in the SPC are associated with higher costs**. Both policy cases lead to modest increases in wholesale electricity prices, compared with the BAU (a 10 percent increase for the CPC and an 18 percent increase for the SPC). The subsidy levels for heat pumps for low- and middle-income households are much higher in the SPC than in the CPC, leading to higher government spending. The higher carbon price in the SPC also contributes to higher fuel costs, which reduces vehicle miles traveled in the transportation sector.

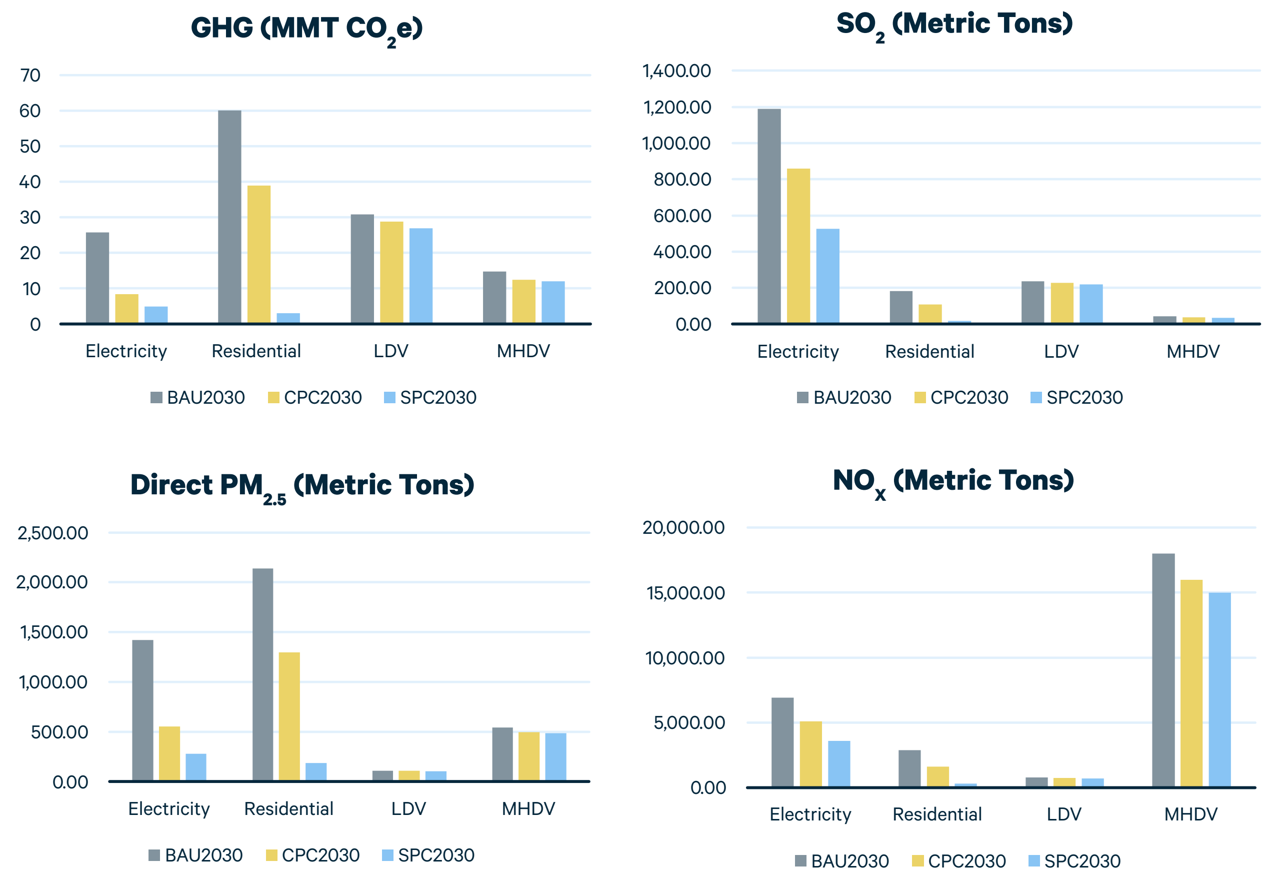
5.2. Greenhouse Gas, $PM_{2.5}$, and Precursor Emissions Results

Emissions of multiple types are expected to decline as a result of the CLCPA. That said, the different policy cases lead to significantly different emissions outcomes. For example, in 2030, **CPC carbon emissions reductions are about 30 percent below the BAU, and SPC carbon reductions are estimated to be about 54 percent below the BAU**. The 2030 percentage reduction below the BAU for methane is even more dramatic in the SPC (91 percent reduction) than in the CPC (31 percent reduction).

$PM_{2.5}$ and precursors are also significantly affected by the different policy cases. The CPC creates estimated statewide reductions below the BAU of 25, 18, and 42 percent for SO_2, NO_x, and direct $PM_{2.5}$, respectively. The SPC creates estimated reductions of 52, 32, and 75 percent for the same pollutants, relative to the BAU. Figure 3 shows statewide 2030 emissions for the three sectors we model under each case.

Reduced natural gas generation in both policy cases, relative to the BAU, leads to significant electricity sector emissions reductions in 2030. CPC policies reduce New York power plant NO_x and SO_2 emissions by smaller proportions than the other emissions types because waste-fueled generation accounts for large portions of the state's power plant NO_x and SO_2 emissions, and the CPC policies do not appreciably change waste-fueled generation. Even in the BAU, waste-fueled generation accounts for more than half of New York power plant NO_x and SO_2 emissions, despite producing less than 10 percent as much generation as natural gas does. **The reduction of waste-fueled generation in the SPC is a significant contributor to the emissions reductions in that scenario.**

Figure 3. Emissions across Policy Cases, by Sector, 2030



Similarly, in the residential building sector, both GHGs and local air pollutants decline under both scenarios because of reductions in fossil fuel (natural gas and diesel) use for heating. Although emissions decline under both scenarios, **SPC reductions in both GHGs and local air pollutants associated with the residential sector are more than double those of the CPC**, with 90 to 100 percent reductions from the BAU across the various emissions types. These emissions changes are the result of the adoption of electric heat pumps (Figure 2).

For light-duty vehicles, the emissions changes are more modest than for the other sectors because of minimal vehicle stock change by 2030. The CPC reduces CO_2 emissions by 6 percent and the SPC by 12 percent below the BAU—the same as the fuel consumption reductions reported above.[11] Compared with the BAU, the CPC and SPC reduce direct $PM_{2.5}$ emissions of NO_x and SO_2 by small amounts (3 to 8 percent across the two cases). The SPC does reduce emissions by about double the CPC, although the reduction is still modest (e.g., 4 percent in the CPC versus 8 percent in the SPC for SO_2; see Table I-1 in Appendix I). The main policy driving this difference is the ZEV standards, since EVs do not emit these pollutants directly when running on electricity.

11 Methane (from incomplete combustion and upstream fugitive emissions associated with gasoline production and distribution) accounts for a trivial share of light-duty vehicles' GHG emissions.

The medium- and heavy-duty vehicle sector is also estimated to have reduced emissions by 2030, but the differences between the two policy case implementations are small. The CPC reduces CO_2 emissions by 16 percent and the SPC by 18 percent below the BAU (reductions in methane are similar; see Appendix H), primarily resulting from the penetration of ZEVs, with the SPC having a slightly larger share of ZEVs by 2030. From the BAU, the CPC achieves a further reduction of 15 percent for SO_2, 11 percent for NO_x, and 8 percent for direct $PM_{2.5}$; the SPC reduces these emissions by 18, 17, and 10 percent below the BAU, respectively (see Table I1 in Appendix I).

5.3. Location of Emissions Changes

As stated above, the focus of this study is to estimate how New York climate policy affects $PM_{2.5}$ pollution exposure in disadvantaged communities. This requires analyzing emissions—and ultimately air quality—by location, going beyond the statewide emissions estimates described above. This is because pollution is not spread uniformly across the state: where you live matters in terms of the air you breathe, which is a key aspect of environmental justice. To get at this geography of pollution (and related disparities in pollution exposure), we begin by studying where emissions occur—emissions from burning fossil fuels (and some waste and biomass) to generate electricity, heat homes, and power heavy trucks and passenger vehicles on New York roads. Identifying the location of emissions is a prerequisite for determining where pollution ultimately settles (after being mixed and morphed in the atmosphere), which is how we determine the geography of air quality and associated public health implications, discussed below. It is important for the reader to make a clear distinction between emissions and air quality—a distinction we will continue to discuss.

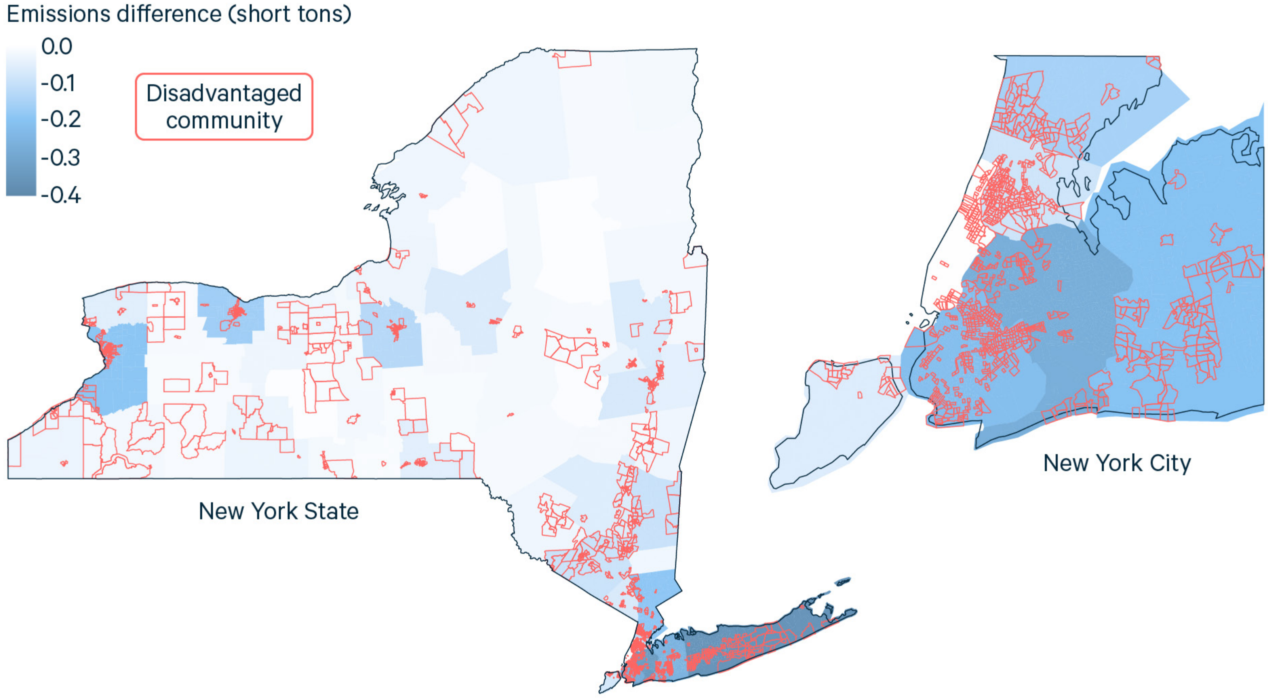
This section covers details about where emissions changes take place, to the greatest level of spatial detail possible. For simplicity of presentation, we restrict our discussion to direct emissions of $PM_{2.5}$, even though the models predict changes in NO_x, SO_2, and VOCs (and other pollutants). We focus on direct $PM_{2.5}$ because it has the greatest impact on local air quality. The extent to which other pollutants combine to form secondary $PM_{2.5}$ is covered in the following section, Air Quality Results.

A number of our models indicate the largest emissions reductions (by mass) tend to occur in densely populated areas. This stands to reason, since the more people who live in an area, the more fuel combustion tends to take place. This is especially the case for sectors like transportation and residential buildings, where fuels are burned (resulting in emissions) in the location where the population is concentrated.

This trend is reflected in Figure 4, which shows the estimated direct $PM_{2.5}$ emissions reductions (in 2030) from LDVs under the CPC. As we can see, the deeper emissions reductions (darker plots) are located around New York State's metropolitan areas—especially New York City, Buffalo, Rochester, and Syracuse. It is worth noting that in the CPC, subsidies are not targeting these metro geographies—in fact, the model shows relatively uniform *percentage* reductions in fuel use and emissions across the state. Simply the fact that there are more people in metro areas means that these uniform percentage reductions lead to larger quantity reductions. These trends continue under the SPC (see Appendix J).

It is also evident from Figure 4 that many DACs are located in these metro areas, which means this trend is estimated to provide above-average benefits to DACs. That said, there are numerous DACs located outside metro areas, and these DACs are estimated to experience smaller emissions improvements associated with changes to the passenger vehicle fleet (however, this is also because nonmetro DACs experience less LDV pollution in the first place). It is also important to observe that although nonmetro DACs may see less emissions reductions from LDVs, none experience an increase in LDV emissions.

Figure 4. Light-Duty Vehicle Direct $PM_{2.5}$ Emissions, BAU vs. CPC, 2030



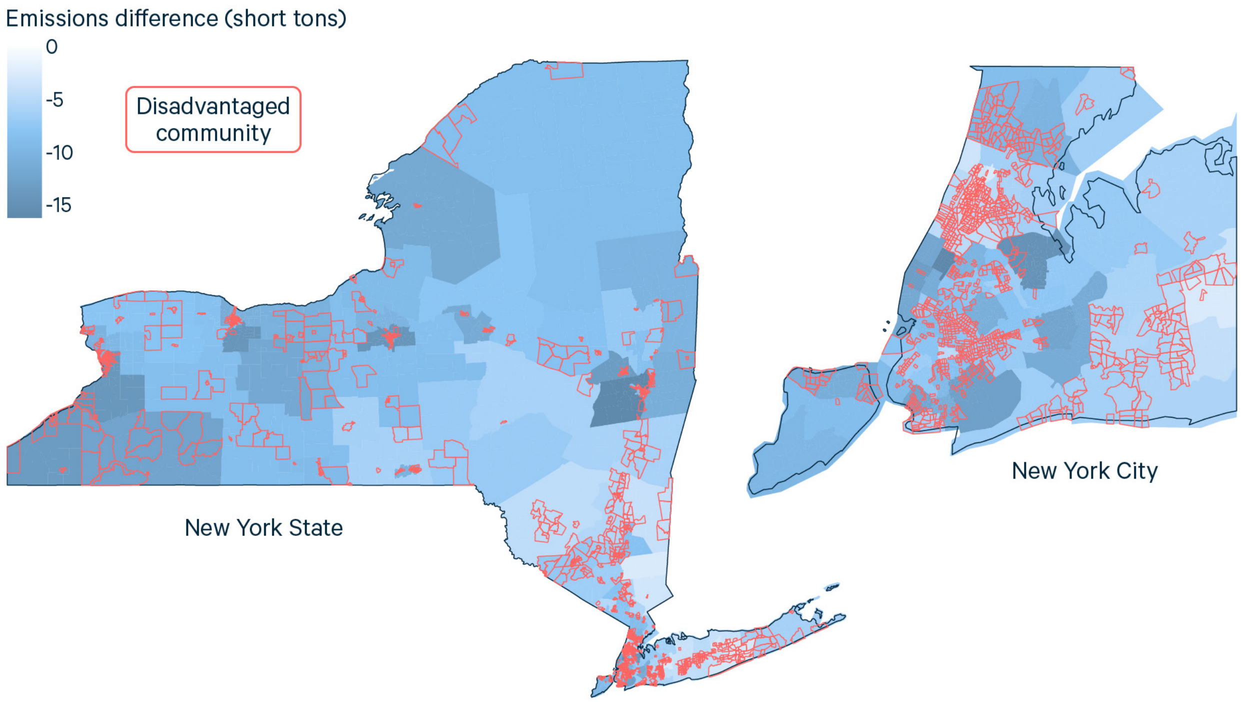
Key Findings for Figure 4

- Relative to the BAU, the CPC leads to direct $PM_{2.5}$ emissions reductions from LDVs across the state.
- No regions experience increases in direct $PM_{2.5}$ emissions from LDVs.
- Direct $PM_{2.5}$ emissions reductions from LDVs are most pronounced in New York City and other high-density areas.

We see some of this same population density-driven trend in emissions changes (around metro areas) from the residential sector under the CPC. However, as shown in Figure 5, other factors influence the distribution of emissions. For example, in addition to population density, the means testing of heat pump subsidies (favoring low-income households) leads to greater emissions reductions in low-income communities. The heterogeneity in building conditions, climate, and other household attributes also influences the adoption of heat pumps and resulting emissions reductions.

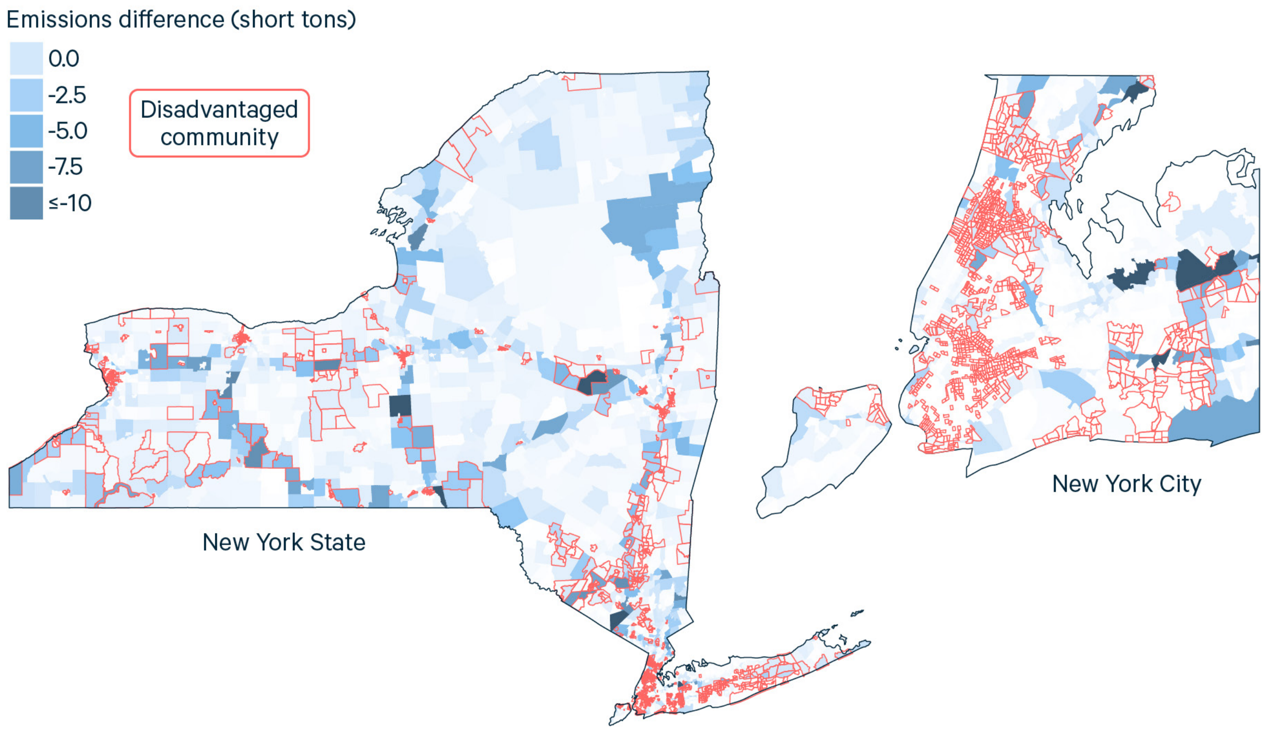
As with LDV emissions, we see that a large number of DACs experience sizable benefits associated with residential emissions reductions. And again, although some DACs experience more modest benefits, we do not observe any DACs that experience an increase in residential emissions.

Figure 5. Residential Home Heating Direct $PM_{2.5}$ Emissions, BAU vs. CPC, 2030



> **Key Findings for Figure 5**
>
> - Relative to the BAU, the CPC leads to direct $PM_{2.5}$ emissions reductions from residential heating across the state.
> - No regions experience increases in direct $PM_{2.5}$ emissions from residential heating.
> - Direct $PM_{2.5}$ emissions reductions from residential heating are most pronounced in high density areas like New York City.

Figure 6. Medium- and Heavy-Duty Vehicle Direct $PM_{2.5}$ Emissions, BAU vs. CPC, 2030



Note: There are some outlying tracts with particularly pronounced emissions reductions in the MHDV sector. They are marked with a dark blue outside of the legend scale.

Key Findings for Figure 6

- Relative to the BAU, the CPC leads to direct $PM_{2.5}$ emissions reductions from MDHVs across the state.
- No regions experience increases in direct $PM_{2.5}$ emissions from MDHVs.
- Direct $PM_{2.5}$ emissions reductions from MDHVs are most pronounced along major highways.

One of the limitations of the LDV and residential models is that they estimate emissions at a somewhat coarse geographic scale (at the county level for the LDV model, and at the level of the public use microdata area, or PUMA, for the residential model). This limits the ability to identify more localized differences in pollution exposure. This limitation can really matter for something like transportation emissions, where pollution exposure is often a function of how close one is to a specific highway or port depot—a level of geographic granularity that goes below the county or PUMA level.

The MHDV model provides this finer geographic granularity. For the MHDV fleet, emissions were estimated for each major road segment ("network link") along the primary and secondary highway system in New York (see Appendix E). In this analysis of the location of emissions changes, $PM_{2.5}$ is displayed by census tract.[12]

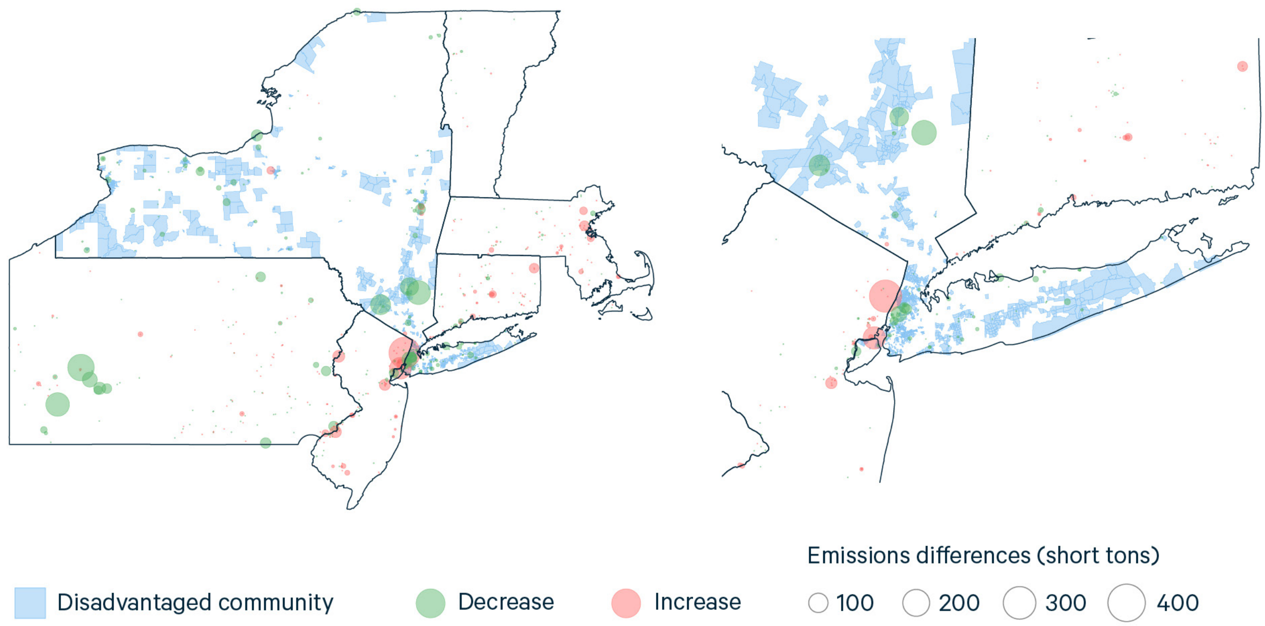
As shown in Figure 6, there is some clustering of emissions reductions around metro areas; however, the predominant trend is emissions reductions along highways—the major intercity corridors. This is mainly because the majority of long-haul heavy-duty truck traffic occurs on these highway network links, and so any vehicle improvements (and associated emissions reductions) made to the MHDV fleet will be concentrated on those highways.

A large percentage of DACs clustered in the urban core of cities (e.g., in Brooklyn and parts of Manhattan) are not located near these major intercity corridors, and so they are estimated to experience less benefit from MHDV emissions reductions. However, a number of nonmetro DACs that experience relatively modest emissions reductions from policies affecting residential buildings and LDVs (above) are estimated to see some of the largest benefits from policies affecting the MHDV fleet. Indeed, there is a close correlation between the location of many nonmetro DACs and New York's intercity highway system (and therefore the deepest MHDV emissions reductions). This could partly be due to the fact that one of the criteria for designating DACs (as determined by the New York CJWG) is high exposure to traffic. No census tracts experience an increase in $PM_{2.5}$ emissions, and reductions are greater under the SPC than in the CPC, following largely the same geographic distribution.

Our estimates of electricity emissions are even more geographically granular than the MHDV model, with the specific location of each power plant represented in the E4ST electricity sector model (see Appendix E). Figure 7 shows the location of 2030 emissions reductions from implementing the CPC, with green dots representing a decrease in power plant emissions at a given location and red dots indicating an increase in emissions (this is the first sector where we observe emissions increases).

12 Link emissions are attributed to census tracts based on what percent of the link is in each tract.

Figure 7. Change in Direct $PM_{2.5}$ Emissions, by Electric Power Generator, BAU vs. CPC, 2030



Key Findings for Figure 7

- Most of the power-generating units in New York decrease their direct $PM_{2.5}$ emissions in the CPC relative to the BAU (green dots).
- The largest decreases are at generating units close to or in New York City.
- Emissions change at many generating units outside the state; some of the largest increases occur at generating units close to and upwind of New York City (e.g., in New Jersey); the largest out-of-state decreases occur at coal-fired generating units in Pennsylvania.

For the electricity sector, we show estimates for adjacent states as well because New York policy has a greater effect on out-of-state emissions in the electricity sector than in other sectors, and because electricity emissions get dispersed over a broader geographic area than emissions from the other sectors we model because of the tall smokestacks at power plants. Given this, New York electricity policy changes would affect emissions both in New York and in other states and Canadian provinces.

Just comparing the number of green and red dots, we can see that although most power-generating units in New York State decrease emissions in both policy cases relative to the BAU (green dots), the CPC results in a fair number of power-generating units that *increase* emissions (red dots); however, they tend to be small increases, and many are located out of state.

Examining the size of the dots, we see that the largest decreases in emissions are at power plants close to or in New York City—again reflecting a trend of emissions reductions near population centers. As with other metro-centered reductions, the concentration of emissions reductions near the New York City region is beneficial for public health, since that is the most densely populated part of the state. However, while the metro region is estimated to experience reductions at in-state plants, just over the border in New Jersey, emissions increases are expected.

Looking at the dots outside New York State, we find that emissions both increase and decrease at many power-generating units. This holds for both policy cases. The largest increases are at those New Jersey generating units that are close to and upwind of New York City, and the largest decreases occur at Pennsylvania coal-generating units that are also upwind of the state but farther away.[13]

In terms of how these emissions changes may affect New York communities, as stated above, reductions or increases in the New York City metro area will tend to have significant public health effects because of its population density. New York City is also where many DACs are located, and so emissions changes will have a significant impact on DACs: if emissions decline in that area, many DACs will benefit, and if emissions increase, many DACs will be harmed. However, because of the stack heights of power plants and the tendency of their emissions to be carried long distances by prevailing winds, the pollution exposure in a given community may not be directly linked to emissions changes at local power plants. To produce a more accurate estimate of pollution exposure at the community level, we must go from estimating emissions by location to estimating *air quality* by location, which is the next step in our analysis.

5.4. Air Quality Results

Our research goes beyond economic and emissions impacts to identify local air quality effects of the policy cases we studied. The key difference between emissions changes and air quality is that the latter reflects how and where emissions actually accumulate, after being transported and transformed by weather patterns and by mixing with other pollutants. Air quality is more relevant for human health because it looks at the composition of the air people breathe, instead of emissions flows from a source of pollution.

Our air quality analysis combines the geographic emissions information discussed above with scientific information about how meteorological patterns and chemical processes contribute to the distribution of pollutants. The air quality modeling approach we use (one of the most technically advanced in the field; see Appendix C) estimates average hourly $PM_{2.5}$ concentrations at the $4km^2$ grid level. In many ways, this is a large area for thinking about community-level air quality impacts,

13 Out-of-state emissions in the region may be impacted by changes in program ambition of the Regional Green House Gas Initiative, which caps carbon emissions from the power sector, or IRA subsidies, which provide incentives for clean energy.

but we determined that it was the most geographically granular estimate feasible.[14] Our results cover the overall air quality changes in New York State and specific community comparisons that highlight outcomes for different types of disadvantaged communities. For the full methodology for the air quality modeling process, see Appendix C.

5.4.1. Air Quality Changes in Each Policy Case

Figures 7 and 8 show changes in 2030 average hourly concentrations of $PM_{2.5}$ at the census tract level across the state, with a more detailed view of New York City.[15] Darker colors in these figures indicate greater reductions in $PM_{2.5}$ concentrations and hence greater improvements in air quality. For both policy cases, improvements are highly concentrated in high-density areas, particularly New York City. This reflects emissions changes discussed in **Section 5.3. Location of Emissions Changes** (above), which explains how increased heat pump and electric vehicle adoption tends to disproportionately benefit areas with high housing density and traffic congestion. Additionally, there tend to be more power-generating units built to service high-density areas. Though there can be more distance between generators and the demand they serve—and emissions from power plants can be spread over large distances—we do observe significant emissions reductions at power plants close to the New York City area. Although the darkest colors on the map occur mainly there, other urban areas also see more pronounced improvements relative to their rural neighbors.

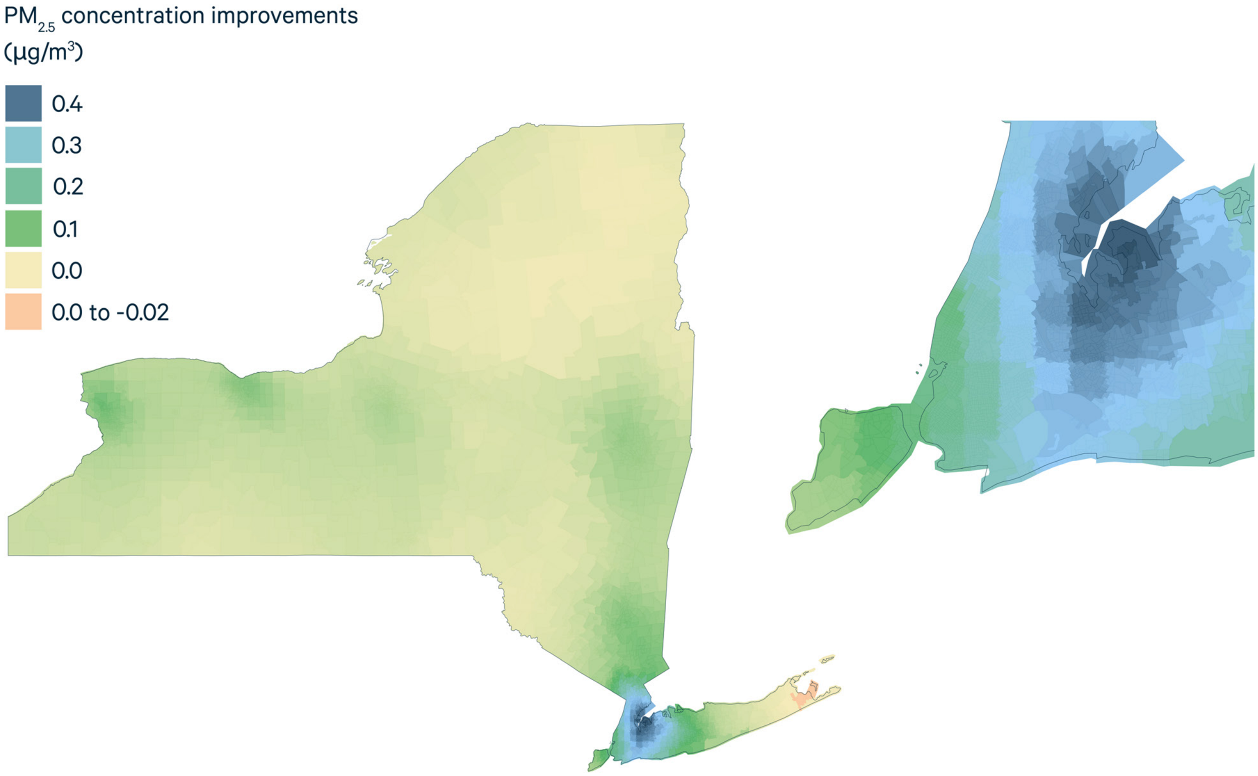
One significant difference between the two policy cases is that **the SPC achieves overall greater air quality improvements than the CPC**. The population-weighted average $PM_{2.5}$ concentration change from the BAU to the CPC is 0.03 $\mu g/m^3$, with a range of 0.05 $\mu g/m^3$ increase to 0.10 $\mu g/m^3$ decrease. In comparison, the SPC achieves a population-weighted average reduction below BAU of 0.18 $\mu g/m^3$, with a range of 0.04 $\mu g/m^3$ increase to 0.40 $\mu g/m^3$ decrease. The averages and ranges of $PM_{2.5}$ concentrations are quite striking, and there is much greater variation in the SPC, which has a standard deviation of 0.12 $\mu g/m^3$. More information on variation in air quality improvements can be found in Appendix L. **Very high air quality improvements in the New York City area are largely responsible for the difference in average air quality improvement in the two cases**.

14 It is possible to model changes at 1km^2, but our modeling team felt it presented the risk of "false precision," where results would indicate a greater amount of accuracy than scientifically justified. Our estimates at 4km^2 were determined to maximize geographic granularity without imposing false precision.

15 Our air quality model (see Appendix C) estimates the $PM_{2.5}$ concentration in every hour of 2030 for each 4km^2 grid cell in the state of New York. We then estimate the 2030 average hourly concentration for each 4km^2 cell, which is mapped onto each census tract. Therefore, Figures 8, 9, and 10 reflect differences in 2030 average hourly $PM_{2.5}$ concentration levels for each tract.

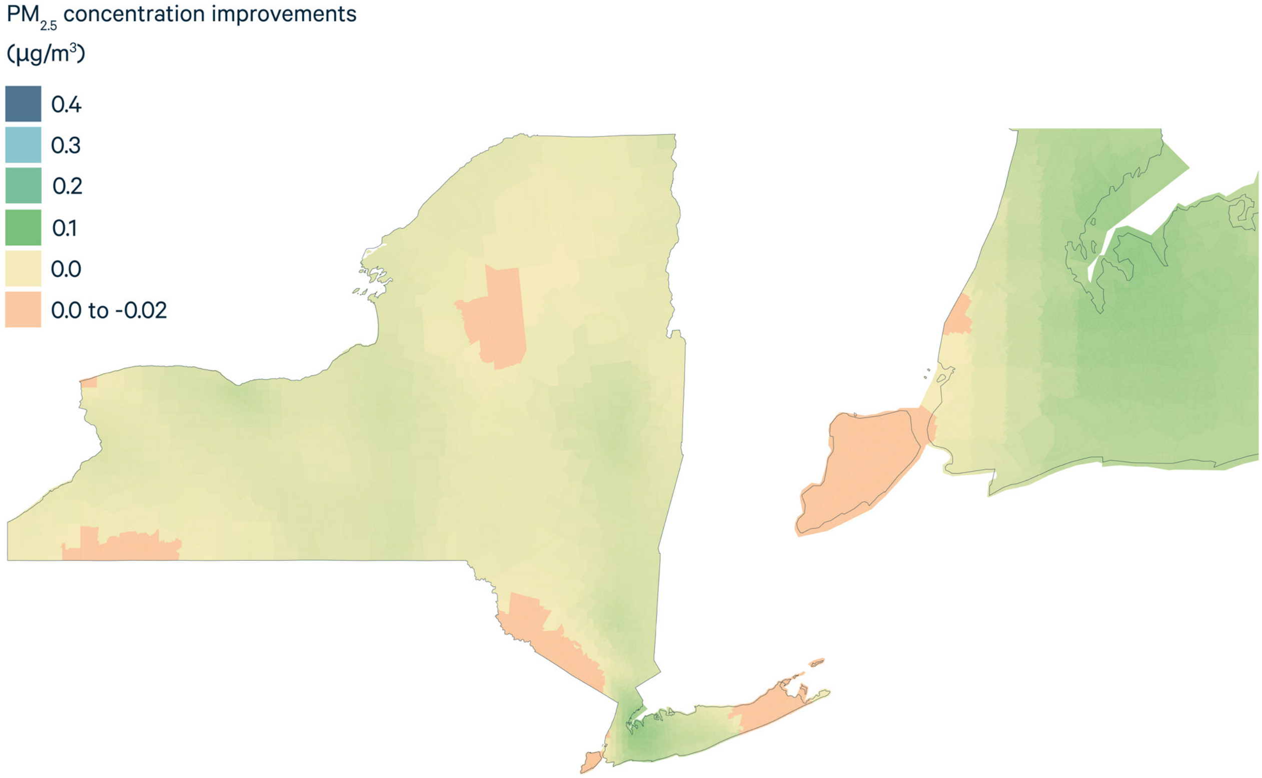
An additional important finding is that—as the ranges stated in the previous paragraph show—both cases cause air quality to worsen (increased $PM_{2.5}$ concentrations) in some census tracts, and **although the CPC causes a worsening of air quality in some DACs, the SPC does not erode air quality in any DACs**. In the CPC, 296 tracts (of nearly 5,000) are predicted to have worse air quality than in the BAU, 72 of which are DACs. In the SPC, only three census tracts experience worse air quality, none of which are DACs.

Figure 8. New York $PM_{2.5}$ Concentration Improvements, BAU to SPC, 2030



Note: These maps represent air quality improvements across New York State and in New York City specifically, relative to the BAU. The blue color represents greater improvements in air quality (higher $PM^{2.5}$ concentration reductions in µg/m^3) while the yellow color represents smaller improvements in air quality. Tracts are shaded in orange if they experience worse air quality relative to the BAU.

Figure 9. New York $PM_{2.5}$ Concentration Improvements, BAU to CPC, 2030



Note: These maps represent air quality improvements across New York State and in New York City specifically, relative to the BAU. The blue color represents greater improvements in air quality (higher $PM_{2.5}$ concentration reductions in $\mu g/m^3$) while the yellow color represents smaller improvements in air quality. Tracts are shaded in orange if they experience worse air quality relative to the BAU.

Key Findings for Figures 8 and 9

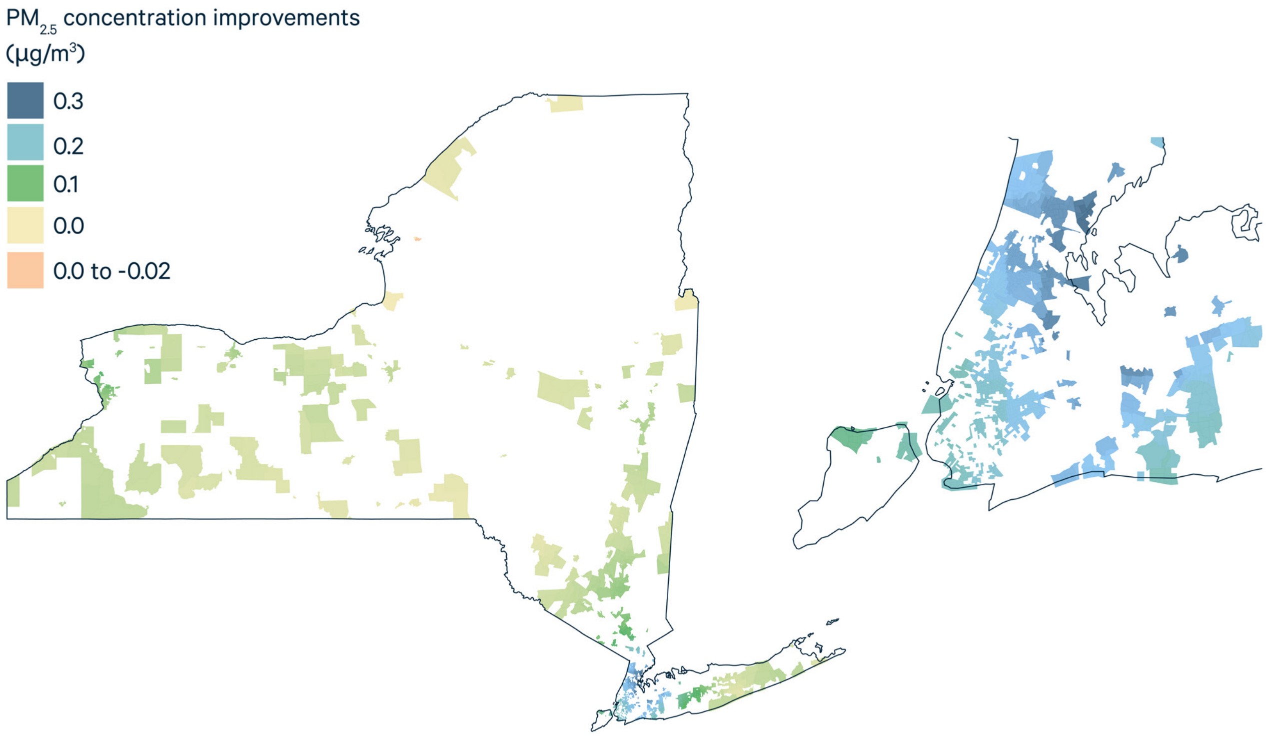
- Air quality improvements under the SPC are greater than air quality improvements under the CPC.
- Air quality worsens in more tracts under the CPC compared with the SPC; 72 of these tracts are DACs. The SPC does not erode air quality in any DACs.
- Air quality improvements are most concentrated in urban areas, with high population densities.
- Air quality improvements are more heterogeneous in the SPC, which has an even more dramatic spread between New York City and the rest of the state than the CPC.

5.4.2. Outcomes for Disadvantaged Communities

Although statewide results are critical to understanding overall impacts of potential CLCPA implementations, we also consider impacts across different types of communities—specifically, disadvantaged communities, as defined by the draft CJWG criteria, and non-DACs. Policies implemented as a part of the CLCPA may not harm or burden DACs, and emissions and pollution reductions in those communities must be prioritized.

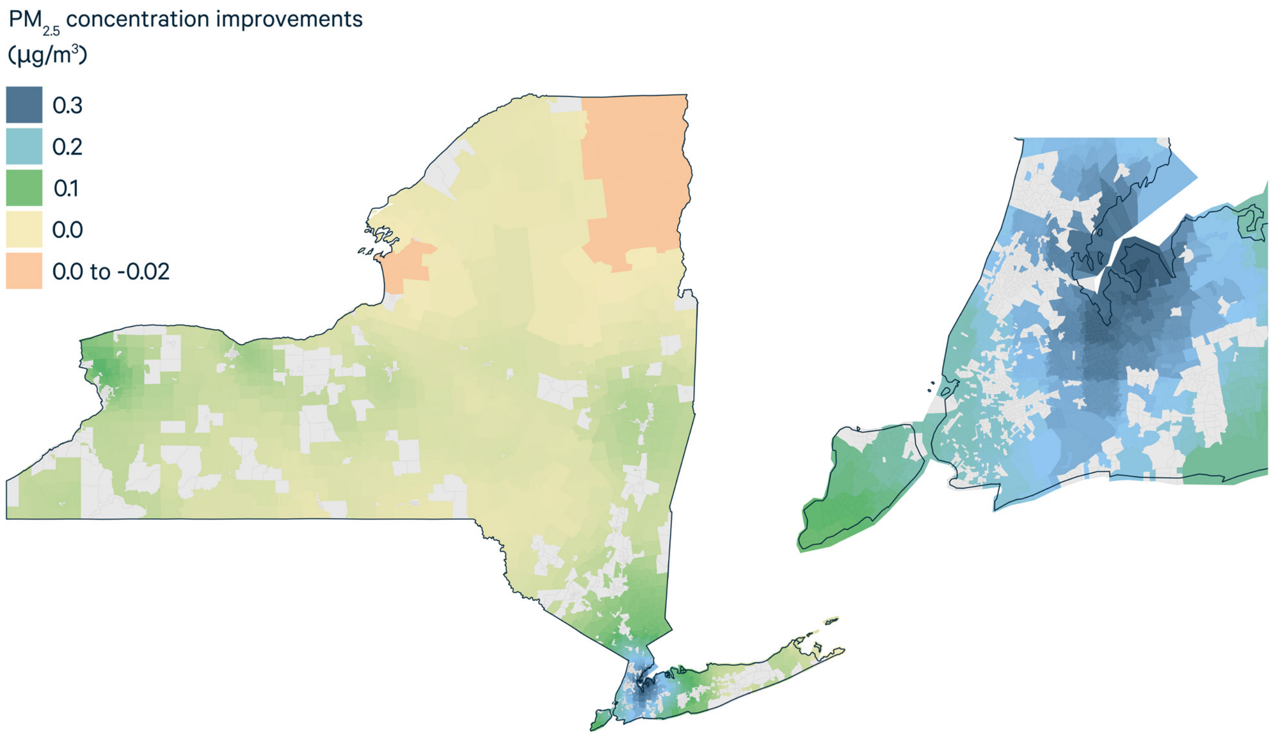
Figure 10. Air Quality Improvements for CJWG Community Types, CPC to SPC

10A. Disadvantaged Communities, Statewide and NYC



Note: These maps represent air quality improvements across New York State and in New York City in the SPC, relative to the CPC. The blue color represents greater improvements in air quality (higher PM2.5 concentration reductions in µg/m3) while the yellow color represents smaller improvements in air quality. Tracts are shaded in orange if they experience worse air quality in the SPC relative to the CPC.

10B. Nondisadvantaged Communities, Statewide and NYC



Note: These maps represent air quality improvements across New York State and in New York City in the SPC, relative to the CPC. The blue color represents greater improvements in air quality (higher PM2.5 concentration reductions in µg/m3) while the yellow color represents smaller improvements in air quality. Tracts are shaded in orange if they experience worse air quality in the SPC relative to the CPC.

Key Findings for Figure 10

- Air quality improvements for DACs and non-DACs are more pronounced in the SPC.
- Greatest differences are observed in New York City, which has a high number of DACs.
- Differences in air quality improvements between communities are most strongly associated with their location in the state. The greatest improvements occur in the locations that have the highest baseline emissions and the poorest baseline air quality.

Figure 10 presents two maps of New York State, highlighting DACs (page 28) compared to all other communities (page 29). This helps illustrate how air quality differences are distributed across community types when comparing the CPC and SPC.

The average difference in $PM_{2.5}$ concentrations between the CPC and SPC for DACs is 0.15 µg/m^3, favoring the SPC. This is compared with an average difference of 0.14 µg/m^3 for non-DACs, still favoring the SPC. These findings indicate **that the additional air quality benefits associated with the SPC are relatively evenly distributed across DACs and non-DACs, as defined by the CJWG**. More information on variation in air quality improvements for DACs and non-DACs can be found in Appendix L.

Table 2 shows more specific population-weighted improvements by subcategories of communities. These findings indicate that although the SPC improves air quality relatively equally among DACs and non-DACs, certain subcategories of disadvantaged communities see particularly pronounced improvements. **We find that implementing the SPC (compared with the CPC) would provide higher-than-average benefits to communities with high socioeconomic vulnerability and communities with historically high $PM_{2.5}$ exposure.** (Population characteristics and vulnerability index are defined in Appendix D.)

These findings indicate that a broad definition of disadvantaged communities that combines a long list of vulnerabilities and exposures could obscure dramatic changes in communities that are particularly vulnerable in only a few dimensions.

Table 2. Population-Weighted Air Quality Improvements, by Community Type ($PM_{2.5}$ µg/m^3)

Community type	Improvement from BAU to SPC	Improvement from BAU to SPC	Improvement from CPC to SPC
All tracts	0.18	0.03	0.15
Non-DAC tracts (65% of tracts)	0.17	0.03	0.14
DAC tracts (35% of tracts)	0.19	0.03	0.16
High exposure (top 10%)	0.16	0.03	0.13
High vulnerability (top 10%)	0.24	0.03	0.21
High elderly population (top 10%)	0.09	0.03	0.06
High historical $PM_{2.5}$ (top 10%)	0.31	0.05	0.26

A final important finding is that even under the SPC, where air quality improvements are greater for DACs than for non-DACs, the improvements are not large enough to eliminate disparities in pollution exposure. Under the BAU, 2030 average hourly pollution exposure in DACs is 0.20 μg/m^3 higher than in non-DACs, and this difference declines by only one one-hundredth (to 0.19 μg/m^3) under the SPC. This same trend is evident when comparing non-DACs with high-exposure and high-vulnerability tracts; however, the relative improvements are greater for these groups. Note that this difference is smaller compared with our 2012 baseline, where $PM_{2.5}$ concentrations in DACs were approximately 0.50 μg/m^3 higher than in non-DACs.

5.4.3. Contextualizing Air Quality Changes

Despite very significant reductions in direct $PM_{2.5}$ and its precursor *emissions* under the policy cases compared with the BAU, the changes in average hourly $PM_{2.5}$ *concentrations* can be characterized as "small"—around 0.18 μg/m^3 in the SPC against a baseline $PM_{2.5}$ concentration around 7 μg/m_3. Appendix K offers a variety of explanations for why this number may be more modest than expected. In this section, we provide context for the health implications of these changes, suggesting they still have significant benefits, particularly for Black New Yorkers.

Exposure to $PM_{2.5}$ is a well-known killer leading to premature mortality in the over-30 population (Di et al. 2017; Krewski et al. 2009; Lepuele et al. 2012). Studies show that for a 10 μg/m^3 reduction in $PM_{2.5}$ concentrations, mortality risks to those 30 and older fall 6 to 14 percent from baseline mortality rates. Of course, 10 μg/m^3 is a huge change in $PM_{2.5}$: the National Ambient Air Quality Standard for $PM_{2.5}$ is 12 μg/m^3.

To contextualize our findings, we wanted to roughly estimate how the expected air quality changes could improve health outcomes. To do this, we consider the difference in the population-weighted change of $PM_{2.5}$ concentrations we see across the state in the SPC compared with the BAU—around 0.18 μg/m^3. Holding constant the state's current over-30 population of 15 million people and using the national death rate of 800/100,000 people, **the total deaths avoided by implementing the SPC would range from 13 to 302 every year in which this change in air quality persists (relative to the BAU)**.

We can provide additional context if we focus on the data we have on New York City's elderly (65 and over) population by race and ethnicity. We focus on the city because this area would see the largest reductions in $PM_{2.5}$ concentrations—around 0.4 μg/m^3. In addition, there are profound racial and age differences in both the mortality rates and the relationship we noted above between $PM_{2.5}$ and the percentage change in mortality rates (termed a concentration-response factor, or CRF; see Di et al. 2017).[16]

16 To make these new calculations, we use population by age and race, CRFs by age and race, and baseline mortality by age and race, as well as the New York City $PM_{2.5}$ change in the SPC of 0.4 μg/m^3 compared with the BAU. We have age and race population data for the city's five counties, we have national-level CRFs from a major $PM_{2.5}$–mortality study (Di et al. 2017) for people 65 and over and for five racial categories: white (non-Hispanic), Black (non-Hispanic), Hispanic, Asian, and Native American. The CRFs for the national population are shown in Table 3 and are far larger for Blacks than for other groups, with whites having the lowest CRF.

Table 3. Concentration-Response Factors and Mortality Rates, by Race and Ethnicity

Race, ethnicity[17]	CRF[18]	Mortality rate range (deaths/1,000 people)
White	6.3	.01 to .11
Black	20.8	.02 to .10
Asian	9.6	.006 to .08
Hispanic	11.6	.01 to .08
Native American	10.0	.005 to .03

We also obtained mortality rates by age and race or ethnicity from the **NYC death micro SAS datasets**. Here again, we see that Blacks have another disadvantage compared with whites, Hispanics, and Asians, since their baseline mortality rates are higher than for these other groups for all three age categories. With $PM_{2.5}$ being reduced, Blacks gain more health benefits than other groups. We apply these national data for the 65-and-over group to New York City's elderly population,[19] which is 1.3 million people.

The bottom line: by implementing the SPC rather than the BAU, 160 deaths among New York City's elderly are avoided in 2030, and the disparity by race or ethnicity disproportionately benefits Black New Yorkers. With Black New Yorkers making up approximately 22 percent of the city's over-65 population, the deaths avoided for this group are 42 percent of the 160 total. In contrast, white New Yorkers make up 41 percent of the city's over-65 population, with deaths avoided only 37 percent of all deaths avoided (Table 4).

17 We include racial and ethnic groups for which we have data.

18 In terms of statistical significance of the CRFs by race, Di et al. (2017) show in their Figure 2 that the CRF for Blacks is significantly larger than for all other groups and that the CRF for whites is significantly smaller than those for all other groups. CRFs for Native Americans, Asians, and Hispanics appear to be not statistically different from one another.

19 The baseline mortality rates are available by race or by age for NYC counties, but not both. Because of the complication that "white" and "Black" include Hispanics, we rely on Spiller et al. (2021), who estimated national mortality rates by race and ethnicity for whites, Blacks, and Hispanics age 65 and older. We use the available New York City data for Asians and Native Americans and scale the national data for Blacks, whites, and Hispanics to be applicable to New York City by adjusting these rates for the proportional difference between the Asian death rate nationally and Asian death rate in the city.

Table 4. Avoided Deaths in New York City, by Race and Ethnicity, SPC Relative to BAU

Race, ethnicity	Percentage of population 65+	Percentage of avoided deaths attributable to $PM_{2.5}$
Asian	14%	6%
Black	22%	42%
Hispanic	22%	15%
White	41%	37%

In addition to estimating mortality effects of policy implementation, we investigate how a number of other health outcomes ("morbidity indicators") would be affected by the SPC. To do this, we simply show the relationship between mortality avoided and various other health effects avoided, including asthma attacks, lost workdays, and restricted activity days. This relationship is taken from a table of results (Table 5-5) in the $PM_{2.5}$ NAAQS Regulatory Impact Analysis for 2012 (EPA 2013). Using the ratio of the number of deaths avoided to the number of other health impacts avoided and multiplying by the approximately 206 deaths avoided in New York State from the SPC, we get the results shown in Table 5. The reduced number of asthma attacks, cases of chronic respiratory diseases, and restricted activity days is 100 times to almost 1,000 times greater than deaths avoided (Table 5).

Table 5. Annual $PM_{2.5}$ and GHG Impacts, SPC relative to BAU

Benefits associated with reduced $PM_{2.5}$		
Adult mortality	~206 avoided deaths	~$2 billion
Asthma exacerbation	~ 7,000 avoided	~$0.7 million
Reduced workdays	~ 11,800 avoided	~$3 million
Reduced activity days	~ 70,000 avoided	~$8 million
Benefits associated with reduced GHGs		
Social cost of carbon[20]	Avoided damages	~$10 billion

Source: EPA (2013). Values in the table represnt impacts of PM2.5 and GHG reductions for one year, 2030.

20 This is based on the NY social cost of carbon with a 2 percent discount rate ($137 in 2030).

We also quantify the health impacts as monetary savings, as the US Environmental Protection Agency did in its 2013 report. The mortality impacts are quantified using the value of statistical life, which is about $10 million (EPA 2023). The other health effects are quantified through cost savings, such as reduced hospital visits and recovered workdays. We estimate annual monetary savings associated with the SPC public health benefits we calculate (there are others) in the rightmost column of Table 5. Finally, the monetary benefits of the reductions in CO_2 and methane emissions (81 MMT, see appendix I) are shown in the last row of the table, using New York State's estimate of the social cost of carbon ($137/ton CO_2 in 2030). **Therefore, comparing the SPC with the BAU, the social benefits of GHG reductions would exceed $10 billion, and the health benefits of $PM_{2.5}$ concentration reductions would exceed $2 billion.**

6. Conclusion

This research project is one of the first to combine behavioral economic modeling with geospatially granular air quality modeling and stakeholder-driven demographic mapping to examine the air quality impacts of New York's Climate Leadership and Community Protection Act for disadvantaged communities. One of the key goals for the research project is to assess which set of policies would maximize air quality benefits to DACs. Two implementations of the CLCPA are considered: a set of policies based on the New York Climate Action Council scoping plan, and a set of policies favored by the environmental justice stakeholder community, convened by our partners at NYC Environmental Justice Alliance. Our research reveals several insights about how implementation of the CLCPA may affect technology adoption, emissions, and subsequent air quality across the state between DACs and non-DACs. Generally, our research showed greater improvements for DACs in the stakeholder policy case compared with the CAC-inspired case.

Both cases result in substantial reductions in GHG emissions relative to a business-as-usual scenario modeled for the year 2030. But the stakeholder policy case results in greater reductions, not only in GHGs but also in emissions of NO_x, SO_2, VOCs, and direct $PM_{2.5}$, which translates into greater reductions in $PM_{2.5}$ concentrations across the state.

These results occur because the stakeholder case features more stringent policies than the CAC-inspired case, and because in most cases policies that reduce GHGs also reduce copollutants (including those traditionally referred to under the Clean Air Act as criteria air pollutants). Key policy drivers of the greater improvements in the stakeholder case are a higher price on carbon and copollutants, more generous subsidies for heat pumps targeted at low-income households, and stricter phaseouts of fossil fuels in the electricity and residential sectors.

In the strict letter of the law, both cases meet the CLCPA regulatory mandate to "not result in a net increase in co-pollutant emissions or otherwise disproportionately burden disadvantaged communities," defining *burden* in terms of air pollution concentrations. However, although there is no statewide net increase in copollutant emissions, under both cases some communities (at the census tract level) do experience a worsening of air quality. And although this occurs in about 4 percent of DACs under the CAC-inspired case, no DACs are affected in the stakeholder case.

In general, DACs do better than non-DACs under the stakeholder case compared with the CAC-inspired case. This differential effect occurs in part because New York City and other cities experience disproportional $PM_{2.5}$ concentration reductions compared with other parts of the state, and cities have a higher concentration of DACs.

Furthermore, if we focus on the communities that are the most vulnerable (according to a range of metrics), say in the 10th percentile of the state's measure of social vulnerability, the stakeholder policies deliver even more favorable air quality improvements compared with the CAC-inspired policy set.

However, even though both policy cases make air quality improvements in DACs, neither reverses the historical disparity in air pollution: overall air quality in DACs continues to be worse compared with non-DACs, and this difference is even more pronounced in high-vulnerability communities (where air quality tends to be the worst).

Our focus is on air quality impacts, and it can be difficult to understand the importance of even small air quality differences. Therefore, as an aid in contextualizing our results, we approximate some public health implications of our estimated $PM_{2.5}$ concentration changes, including, most prominently, annual deaths avoided. We also look closely at the elderly Black population in New York City relative to the elderly of other races and ethnicities, to account for this group's increased vulnerability to poor air quality. We find that the greater air quality improvements in New York City, combined with its higher Black population and their greater vulnerability, lead to even greater health improvements than the statewide average would indicate.

Given all the benefits of the stakeholder case over the CAC-inspired case, it should not be surprising to see that this stakeholder case requires greater investment than the CAC-inspired case: its policies are more rigorous and offer more generous subsidies. For example, for residential heating, to achieve the much higher penetration of heat pumps observed in the stakeholder case, government subsidies need to be far higher than in the CAC-inspired case. In the power sector, a higher carbon price and a ban on new fossil fuel generation leads to slightly higher electricity prices. Although a full cost-benefit analysis was outside the scope of this work, previous regulatory analyses that evaluate stringency of GHG and air pollution policies often find that the environmental and health benefits of added stringency outweigh the costs.[21]

We see through this analysis that more ambitious policies are effective at decreasing emissions and improving air quality on a greater scale than more moderate policies. We also see that some disadvantaged communities benefit from the more aggressive

21 See recent regulatory impact analyses from the US Environmental Protection Agency, including Table ES-4 in the agency's assessment of national air pollution standards for coal plants completed in 2023: **https://www.epa.gov/system/files/documents/2023-04/MATS%20RTR%20Proposal%20RIA%20Formatted.pdf**

policy case and begin to make up their deficit in environmental protection relative to non-DAC communities, although nearly all communities see benefits. By considering the impact on environmental justice communities, policymakers can ensure that historically underserved neighborhoods are protected and are able to experience the intended benefits of environmental policies.

Our findings show that more ambitious and more targeted climate policies yield the greatest benefits in climate change mitigation. The higher New York sets its policy sights, the greater the capacity for decreasing emissions and poor air quality. Because of these greater improvements in air quality and emissions, NYC Environmental Justice Alliance encourages the use of more ambitious and targeted approaches, like the policies modeled in the stakeholder policy case. These options provide a larger capacity for emissions reductions, which is critical to addressing the climate change crisis expeditiously.

Disadvantaged communities have so much to lose if these targets are not met or if mitigation efforts are not directed toward those who are at greatest risk. These at-risk communities also have so much to gain if their policy requests are implemented and their safety is prioritized as policymakers and community leaders work to undo the historical damage that they have been forced to accept as their legacy. By prioritizing environmental justice communities' leadership in this space, communities can fully benefit from the positive impacts their visions of the future can yield when put into practice.

This work has revealed new insights on community-level improvements associated with New York's landmark climate act. The boundaries of this work have also revealed ripe areas for future research. Interested readers should consult Appendix G on the limitations of our work, but three areas offer the greatest opportunity for future research.

First, being able to predict economic behavior requires sophisticated models for all parts of the economy. Our models cover electric utilities, home heating, and heavy-duty and light-duty vehicles. Agriculture, manufacturing, and commercial heating are missing from our analysis but contribute significantly to emissions and air pollution. Because some of the policies being discussed in New York will be economy-wide, we miss the reactions of those sectors and probably underestimate how much the CLCPA will affect air quality and emissions. It would be valuable for future work to build and apply these models.

A second limitation is that we model conditions only in 2030 (with and without the CAC-inspired and stakeholder policies). Many policies, such as incentives to encourage EV adoption, take time to have a significant effect. Had we run the models for a longer period (say, to 2040 or 2050), CO_2 and copollutant emissions would have declined more. However, the further in the future forecasts are made, the more uncertain they become. We opted to minimize such uncertainty. Future analyses could run the models further into the century.

Finally, the expense associated with operating a full-complexity air quality model (compared with reduced-complexity models) limited the number of cases we could complete in this phase of work. As a result, we could not test the air quality impact of individual policies housed in each policy case, or attribute pollution concentration changes to specific emissions sources (source attribution). In our next phase of work, we hope to conduct more focused policy analysis highlighting the air quality impacts of one specific policy: economy-wide carbon pricing through a carbon cap.

This work offers unique insights into the distributional air quality impacts of CLCPA implementation. It provides a framework for evaluating future policies that affect the magnitude and location of emissions changes through addressing economic behavior and methods that can be useful in evaluating how environmental justice communities in particular will be affected. Though in its early stages, work in this field presents many opportunities for future research still to explore.

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Appendix A. Building the Policy Cases

The original plan for this research was to directly model the policies laid out in the draft scoping plan, and adjustments desired by the environmental justice policy community in New York. However, the draft scoping plan lacks the specificity (e.g., level of stringency of individual policies, their timing) required to model policies, and the integration analysis conducted by the state models outcomes rather than policies (e.g., "90 percent of vehicle sales are electric by 2030"). Therefore, to proceed, the research team had to design policies to deliver the state's desired outcomes and fill in policy details where they were missing.

The following general principles guided the development of both policy cases:

- We include only policies in sectors for which we have economic modeling capabilities (on-road transportation, ports, residential buildings, and electrical power).
- We include only policies that are "modelable" by our group—that is, they predictably affect inputs in our models that have a known or estimated relationship to outputs. For example, a tax on gasoline has a known impact on fuel prices, which is an input to our transportation model, so it can be easily incorporated into our modeling. On the other hand, a subsidy for bicycle purchases has an unknown impact on miles traveled in a car, so it cannot be incorporated in our modeling.
- We set stringency or ambition of policies by considering what behavioral responses are credible for our models to address. For example, our transportation model, which is parameterized by analysis of historical data, cannot credibly estimate the impact of an EV subsidy of $100,000 per light-duty vehicle because there is no historical record for a subsidy of this size.
- We determine type of policy, level of policy ambition, and timing of policy implementation based on the following:
    - precedents from other prominent and comparable jurisdictions, such as California, which has implemented many of the policies included in the New York scoping plan and is referred to frequently in the scoping plan;
    - precedents from New York policy proposals, especially proposals that have been introduced in the state legislature; and
    - other approaches, as needed.

Because of modeling limitations, we did not include several policies of interest to stakeholders:

- microgrid construction;
- detailed retail rate design (power sector–wide);
- renewable energy zones;
- state vehicle fleet electrification (including buses);
- technology investments (through research and development);
- congestion pricing;

- ZEV credit trading;
- dealer incentives;
- residential demand response to peak–off peak prices;
- retrofit rebate options (modeled as fixed assumption);
- renter protections;
- interconnection investment;
- Clean Dispatch Credit Program;
- publicly subsidized financing for LDV ZEVs; and
- state MHDV ZEV procurement.

Appendix B. Background on Economic Models

B.1. Economic Models

B.1.1. Power Sector

The Engineering, Economic, and Environmental Electricity Simulation Tool (E4ST) is power sector modeling software built to project the effects of policies, regulations, power infrastructure additions, demand changes, and more (E4ST 2022). E4ST simulates in detail how the power sector will respond to such changes. It models successive multiyear periods, predicting hourly generator and system operation, generator construction, generator retirement, and various other outcomes in each period. The E4ST model of the United States and Canada contains the 19,000 existing generators with their detailed individual characteristics, tens of thousands of buildable generators, including location- and hour-specific wind and solar data, and all of the high-voltage (>200 kV) transmission lines as well as chronically congested lower-voltage transmission lines. E4ST's advantages over other models include its high spatial detail, its realistic representation of power flows and system operation, its integration of an air pollution and health effects model, its comprehensive benefit-cost analysis capabilities, its high-quality generator data, its inclusion of Canada, and its adaptability, transparency, and shareable nature. E4ST has been used to analyze various policies and investments. It has also been used for multiple peer-reviewed papers in leading journals. E4ST was developed by researchers at Resources for the Future, Cornell University, and Arizona State University, with funding, input, and review by the US Department of Energy, the National Science Foundation, the New York Independent System Operator, the Power Systems Engineering Research Center, the Sloan Foundation, Breakthrough Energy, and others.

B.1.2. Light-Duty Vehicles

This description of the light-duty model is adapted from Funke et al. (2022). The model for light-duty vehicles contains two components: new-vehicle sales and on-road fuel consumption. The first component characterizes vehicle sales by year (2018 through 2030) and region (California, other ZEV states, and all other states, to enable an explicit representation of the ZEV program). On the demand side of the market, consumers choose vehicles that maximize their subjective well-being, which depends on the vehicle's price, fuel costs, horsepower, size, and other features, such as all-wheel drive. Preferences for those vehicle attributes vary across 60 demographic groups, defined by income, age, urbanization, and geographic region.

Consumer preferences are estimated based on survey responses from 1.5 million new-car buyers between 2010 and 2018. The survey data include information about household demographics, such as income, as well as detailed information about the vehicle purchased. Vehicles are defined at a highly disaggregated level, with about 1,200 unique vehicle models offered each year. Consumer preferences for fuel costs, fuel type, and other vehicle attributes are estimated from their vehicle choices.

Each manufacturer chooses vehicle prices and fuel economy (and decides whether to introduce electric vehicles) to maximize profits while meeting regional ZEV standards and federal fuel economy and GHG standards. Vehicle prices depend on marginal costs, consumer demand, ZEV standards, and federal fuel economy and GHG standards. Manufacturers select a larger markup of prices over marginal costs when consumer demand is less sensitive to price. Because high-income consumers are typically less price responsive than low-income consumers, markups tend to be higher for vehicles purchased by high-income buyers than for vehicles purchased by low-income consumers. The ZEV, fuel economy, and GHG standards cause manufacturers to reduce prices of electric vehicles and increase prices of gasoline vehicles. These price changes help manufacturers achieve the standards.

Each year, manufacturers also decide whether to introduce new electric vehicles to the market. Vehicle production and entry costs, as well as shadow prices of the standards, are estimated from observed choices of vehicle prices, fuel economy, and entry between 2010 and 2018, under the assumption that each manufacturer makes these choices to maximize its own profits.

We simulate the equilibrium in a market (model year and region) given assumptions about the total number of consumers in the market, fuel prices, battery costs, electric vehicle subsidies, and standards. For each simulated market, the output includes entry of new electric vehicles and prices, fuel economy, and sales of each vehicle. The number of consumers in the market and fuel prices are taken from the EIA AEO 2021. Battery costs are from 2021 projections by Bloomberg NEF. Marginal costs of electric vehicles decrease over time in accordance with the vehicle's battery capacity and the projected battery cost reduction. Declining battery costs cause manufacturers to reduce electric vehicle prices over time, all else equal.

The output of the new-vehicle component feeds into the on-road fuel consumption component of the model. For each county and year, this component of the model characterizes total gasoline and electricity consumption and tailpipe and upstream emissions from vehicles owned by households. Vehicles are defined by fuel type (gasoline, diesel fuel, electric, and plug-in hybrid), class (cars and light trucks), age, and county.

Simulations of the model begin with the stock of on-road vehicles in 2017 that is estimated from the National Household Travel Survey (NHTS). We compute fuel consumption rates for gasoline and plug-in hybrid vehicles by vehicle age, class, and state from the NHTS. The state-level vehicle stocks and fuel consumption rates are disaggregated to the county level using the Bureau of Transportation Statistics LATCH Survey.

At the beginning of the year, a fraction of vehicles are scrapped, where scrappage rates depend on vehicle age, class, and vehicle price and are estimated from historical registrations data from RL Polk. Scrappage rates are adjusted by registration taxes according to estimates from Jacobsen and van Benthem (2015).

The on-road vehicle stock is augmented by the new vehicles sold in the vehicle market component of the model. From that component, we compute new-vehicle sales by fuel type, class, and region. We compute the average fuel consumption rate (gallons per mile traveled) for gasoline and plug-in hybrids by region. The regional estimates are disaggregated to the county level using the LATCH data.

Total national vehicle miles traveled (VMT) data are obtained from the AEO 2021. National VMT is allocated across counties and vehicles according to the per mile fuel costs and consumer driving preferences that are estimated from the 2017 NHTS and vary by vehicle class and age. Compared with the baseline, a scenario with higher fuel costs causes total VMT to decrease according to the assumed elasticity of VMT to fuel costs of –0.1. Fuel costs also affect the distribution of VMT across vehicles.

The model is then iterated forward one year, and the entire process is repeated. The output of the model includes VMT, tailpipe and upstream emissions, gasoline consumption, and electricity consumption by fuel type, county, and year for 2017–2030.

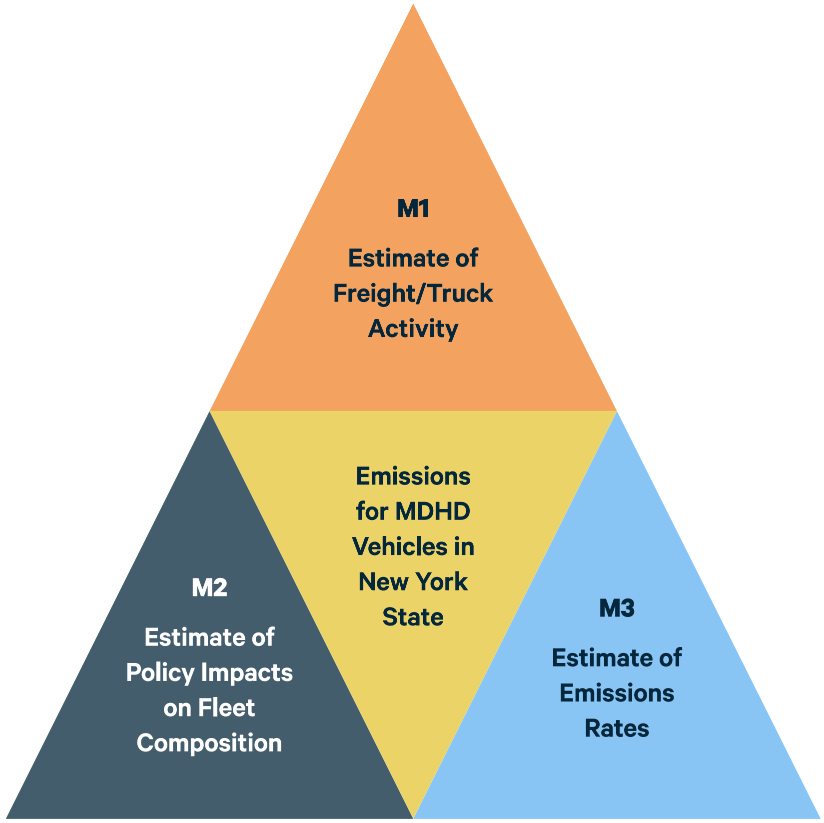
B.1.3. Medium- and Heavy-Duty Vehicles

Prior to this work, there was no model that could predict MHDV flows for New York at the resolution required to do air pollution modeling, or to estimate the local impacts from the freight flows to local communities. The latter information is critical considering the goal of estimating community impacts, especially to disadvantaged communities. To overcome this limitation, this project developed a new modeling framework that integrates outputs and information from a set of publicly available sources of socioeconomic data (e.g., Census, ZIP code business patterns), and other truck and economic models. The modeling framework has three main modules (Figure B1).

The first module (M1) is used to estimate vehicle activity at a network link level. This is a static representation of truck travel along the primary and secondary highways for different vehicle types for the 2012 baseline and 2030 scenarios. To develop M1, the team integrated outputs and data from the following sources:

- **Freight Analysis Framework (FAF) version 4.** FAF was developed by the Bureau of Transportation Statistics and the Federal Highway Administration to model aggregate freight flows throughout the nation. M1 uses FAF model outputs to gather the aggregated multimodal freight flows in and out of the major regions in the state.
- **New York Best Practice Model (NYBPM).** NYBPM is a travel demand model for the New York Metropolitan Transportation Council region with high resolution in the following counties: Manhattan, Queens, Bronx, Brooklyn, Staten Island, Nassau, Suffolk, Westchester, Rockland, Putnam, Orange, and Duchess. Additionally, the model estimates some flows in the network corresponding to some other regions.
- **Freight and freight trip generation models for New York State.**
- **Public Commodity Flow Survey microdata.** This information provides shipment-level data on commodities, shipment distances, and modes.

Figure B1. Key Components of MDHV Modeling Framework



Overall, those various data sources allow estimating aggregated truck flows in the New York network. Integrating the data sets involved several subprocesses. For example, FAF and New York Metropolitan Transportation Council had different projection years and vehicle definitions, as well as their geographic resolution. The team used the various data sets to estimate vehicle type ratios to translate freight flows into truck traffic and estimate short- versus long-haul trip demand, and used indicators of industry-generated flows to infer the vehicle type characteristics and behaviors. For the projections, the process uses linear interpolation to estimate freight flows in the FAF and NYBPM model results for 2030 because FAF projections were available for only 2012 and 2045, and for the New York Metropolitan Transportation Council, only 2025 and 2035 data were available. Additionally, leveraging the increased resolution of the NYBPM, the team estimated adjustment factors for the FAF model in urban areas throughout the state. It was also necessary to create a crosswalk between the vehicle definitions in FAF (two types), the NYBPM (four types), and the five truck definitions in MOVES. The resulting five vehicle types include light commercial trucks (primarily nonpersonal use) (32), single-unit short-haul trucks (52), single-unit long-haul trucks (53), combination short-haul trucks (61), and combination long-haul trucks (62). The final outputs of M1 are VMT per day or year on every network link (modeled) for the baseline and future scenarios for the five vehicle types.

Module 2 (M2) integrates a truck vehicle choice model, a transportation transition (truck turnover) model, and the design of policy scenarios. This was necessary to evaluate the impact of policies to foster the introduction of ZEVs following the California Air Resources Board's Advanced Clean Truck (ACT) rule and the (still under development) Advanced Clean Fleet program, among others discussed in the draft scoping plan for New York State. Specifically, M2 uses the Transportation Transitions Model (TTM), developed at the Institute of Transportation Studies Davis (ITS Davis), which estimates fleet turnover based on sales target requirements (e.g., ACT) considering assumptions about vehicle characteristics and travel activity. Because of lack of New York data, the research team used assumptions drawn from their expertise and the experience in California, extrapolating to assume that New York would follow a similar trajectory as California. The main outputs of the TTM are stock turnover by model year and major vehicle categories (e.g., diesel, ZEV).

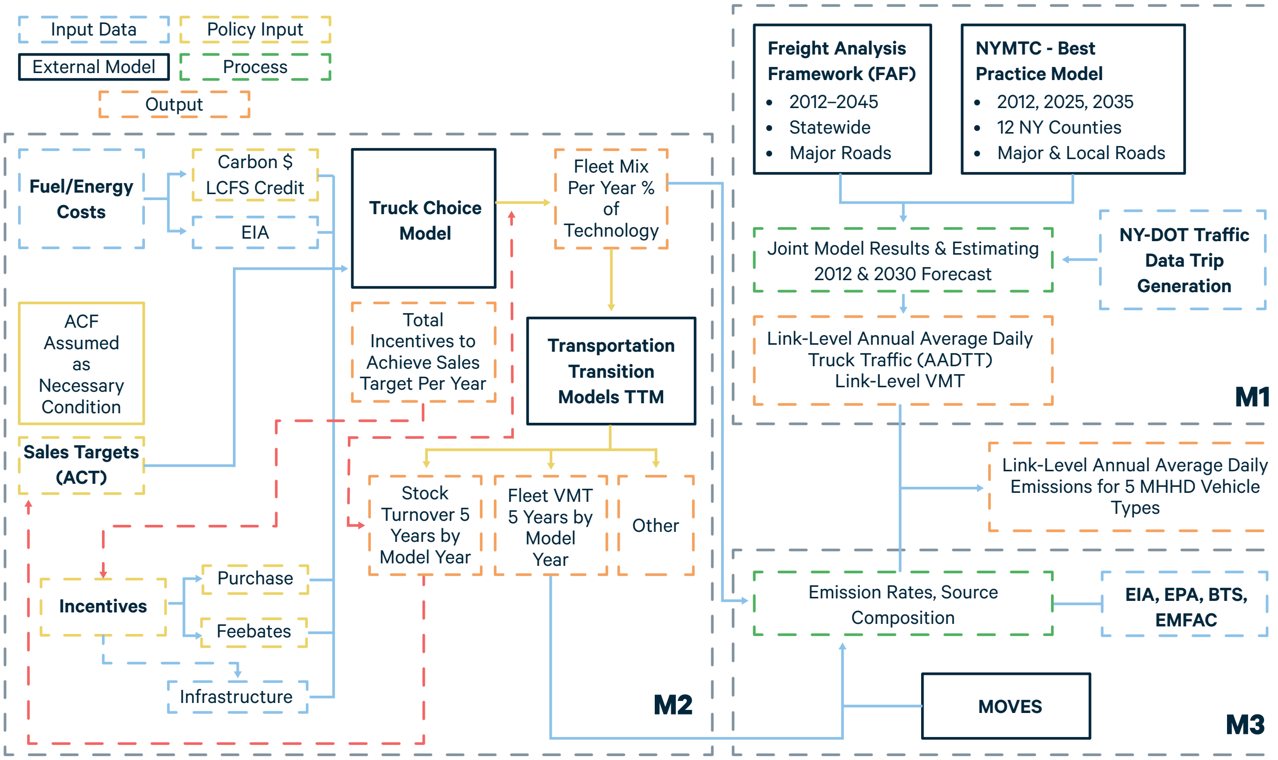
M2 also uses the ITS Davis Truck Choice Model (TCM) to estimate the share of ZEV technologies (e.g., battery electric, hydrogen fuel cell) that satisfy the transition estimates from the TTM, and the level of incentives required to achieve such sales targets. The TCM considers variables and factors such as vehicle specifications, price, fuel or energy efficiency, incentives (e.g., purchase vouchers, infrastructure, feebates, low-carbon fuel standard credits), operational and maintenance costs, and carbon and co-pollutant costs, among others. The output of the TCM is the fleet mix per year by share of technology.

The team then implemented the SPC and CPC through the TTM and TCP. The final outputs of M2 are then the share of vehicle technologies for various vehicle categories in the policy scenarios. It is important to note that the TTM and TCP estimates are at the state level and are assumed to be uniform statewide. Additionally, the models used in M2 consider the following vehicle categories: heavy-duty long-haul, heavy-duty short-haul, medium-duty delivery, heavy-duty vocational, medium-duty vocational, and heavy-duty pickup trucks. Considering the definitions of the vehicle types from M1 (and MOVES), the team related M2 and M1 outputs to be consistent with the five vehicle types from M1.

Finally, module 3 (M3) uses the Environmental Protection Agency's Motor Vehicle Emissions Simulator (MOVES 3) to generate an emissions profile for a vehicle fleet in New York State. As the output of M3, the team estimated an average tailpipe emission rates in grams per mile for various pollutants for the five vehicle types based on MOVES estimates for the 2012 baseline, and a 2030 business-as-usual scenario. Figure B2 shows a schematic of the key inputs, processes, and outputs of the various modeling framework components.

Altogether, the modeling framework then generates a composite emissions rate for the SPC and CPC, modifying the base rates from M3 and the outputs from M2. The scenario-based composite rates are then used to estimate total tailpipe emissions at the link level throughout the state. These emissions are aggregated with the emissions from the light-duty sector and the port emissions to estimate emissions change factors at a 36km^2 grid.

Figure B2. Modeling Framework Diagram



B.1.4. Residential Buildings

A residential energy demand model was developed to predict the adoption and use of space-conditioning equipment in households in New York State in 2030. The novelty of the model is that, rather than using a representative household for all of New York, the model predicts the probability of heating appliance ownership for a broad range of households identified by a range of socioeconomic characteristics, as well as building and climate conditions. The model outputs used in this project include state-level electricity demand for heating and cooling and oil and gas demand for space and water heating and cooking, by PUMA.

This model implements policies such as heat pump subsidies and building shell efficiency standards for new construction and retrofits. We implement the fossil-fuel phaseout in the SPC as a floor on heat pump adoption. Below, the model design and methods for implementing these policies are described. More details about the methodology can be found in Poblete-Cazenave and Rao (2023).

B.1.4.1. Model Design

The space-conditioning model used here is an extension and adaptation of the space-conditioning module of the energy demand model first presented in Poblete-Cazenave and Pachauri (2021), an indirect utility maximization model, where households choose among different appliances and fuels to satisfy their energy needs. The model is estimated using simulation-based structural econometrics. The advantage of using simulation-based modeling for our purposes lies in the ability to use different data sets to create simulated households with characteristics obtained from multiple surveys, and to simulate future populations with additional assumptions on population drivers.

We start with the 73,149 household observations in New York in the American Community Survey as a base for the simulated households, which includes standard socioeconomic attributes. Additional attributes about the building condition, such as vintage and insulation, are imputed to these simulated households from the Residential Energy Consumption Survey (RECS 2015) using a common set of attributes between the two surveys. We project the stock of residences to 2030 using housing unit and income projections, assuming the new stock reflects the current distribution of household characteristics.

We separately use a multinomial discrete choice model to estimate the probability of adoption of different heating technologies based on the Northeast US sample of the American Housing Survey for 2015, which contains detailed information on heating equipment, buildings, and socioeconomic attributes. The predictors include socioeconomic household characteristics, including income, race, and age. Physical conditions include floorspace, building shell conditions (e.g., insulation), and building material type. We also included average building insulation R-values based on vintage, which were modeled as heating appliance efficiency penalty factors. Climate conditions (heating degree days) were differentiated by climate zones.

We combine the estimated coefficients from this discrete choice model with the parameter values of the simulated New York households in 2030 to obtain their probability of owning different heating appliances.

Since the surveys are representative at the PUMA spatial scale, we present results as appliance penetration rates and fuel consumption at the PUMA scale.

B.1.4.2. Energy Consumption

The model estimates fuel consumption for all heating appliances, as well as air-conditioning consumption for cooling and gas consumption for water heating and cooking, since these are required to determine air pollution estimates. Using simulation-based estimation methods on Residential Energy Consumption Survey data, the model obtains a distribution of energy consumption estimates for different appliances, which, joined with estimated sociodemographic effects, are used to calculate the utility-maximizing total energy consumption for each simulated household (Poblete-Cazenave and Pachauri 2021). We scale up the heat pump electricity consumption estimates for the Northeast, given that the underlying survey data reflect ownership largely in warmer areas (South and Mid-Atlantic). We use an engineering-based adjustment that takes into consideration building shell characteristics, climate-adjusted heat pump efficiency, and heating degree days to reflect theoretically expected consumption values. Finally, total county-level electricity consumption numbers are calibrated to match utilities' monthly consumption data in the base year for the state from NYSERDA, whereas gas consumption estimates are kept as obtained from the model, given their proximity to utilities' values.

B.1.4.3. Data

We use industry-standard rules of thumb for heating demand per square foot of floorspace for different climate zones. Hence, heat pump costs vary with climate and size of dwelling. For future technology cost and performance, we use US EIA's Updated Buildings Sector Appliance and Equipment Costs and Efficiencies (2018). For heat pump cost and performance, we use the National Renewable Energy Laboratory's Electrification Futures Study (2017). The approximate average heat pump cost for the sample is $11,300.

For fuel prices, we use the high oil and gas supply case of EIA's Annual Energy Outlook 2021.

For residential income growth, we use AEO 2021. For growth in residential units and climate zone designations, we use the New York State Climate Action Council Draft Scoping Plan, Integration Analysis Technical Supplement, Section I, Annex 1: Inputs and Assumptions.

For determining fossil fuel phaseout retirement schedules, we use NYSERDA's Residential Statewide Baseline Study 2015, Volume 1, based on the Single Family and Tenant Survey, which has a breakdown of the share of households by age (Table 20).

For building shell R-values for future construction, we use the NYSERDA Stretch Codes. For existing building shell R-values by vintage, we use data from the National Renewable Energy Laboratory's ResStock model.

B.1.4.4. Ports

To estimate port emissions for the 2012 baseline and 2030 future scenarios, the team relied on a number of sources, notably past port emissions inventories for New York and New Jersey, to develop a model to extrapolate emissions as a function of cargo-handling equipment and intraterminal heavy-duty vehicle activity. For cargo handling, the team considered equipment such as terminal tractors, straddle carriers, forklifts, and other primary and ancillary equipment. The estimation process relies on two processes: first, service hours for each type of equipment are based on container movements and hourly use per year from inventory data, and then emissions factors per hour are used to estimate total yearly emissions for various pollutants. Similarly, for the heavy-duty vehicle component, inventory estimates of VMT at auto terminals, container terminals, and between terminal warehouses are then multiplied by corresponding heavy-duty port and yard trucks' emissions factors to estimate total emissions for the baseline. For 2030, the team estimated container movement growth and used this average growth factor to expand the count of cargo-handling equipment and heavy-duty vehicles' intraport activity and the associated emissions. Changes in emissions between 2012 and 2030 are estimated based on the literature and scaled as a function of the relationship between 2030 and 2012. For the SPC and CPC, based on experiences in California, the estimates assume a very high share of electrification for equipment and yard trucks. The drayage movements outside terminals are included in the truck flows modeled directly on the network. For drayage, the analyses follow the same assumptions of the general fleet.

The port's model considered the following facilities: Brooklyn Port Authority marine terminal, Port Jersey Port Authority marine terminal, Elizabeth Port Authority marine terminal, and the Howland Hook marine terminal. The analyses assume the same emissions factors and policies across these facilities, although some are in New Jersey.

Appendix C. Background on Air Quality Modeling

Our air quality modeling produces $PM_{2.5}$ concentrations at a grid resolution of $4km^2$ across New York State for 2012 and 2030 under the BAU and two policy scenarios. Two air quality models were used: a 3-D air quality model containing comprehensive representations of atmospheric transport, physics, and chemistry to simulate $PM_{2.5}$ concentrations at a grid resolution of $36km^2$ (Weather Research and Forecasting model with chemistry extension, WRF-Chem), and a computationally efficient statistical model utilizing the $36km^2$ simulation results from the 3-D air quality model to predict $PM_{2.5}$ concentrations at a grid resolution of $4km^2$. The 3-D air quality model can be applied at both grid resolutions, but it is prohibitively expensive to run the year-long simulation at the $4km^2$ resolution.

WRF-Chem is a state-of-science online-coupled weather-chemistry model. The newest version, WRF-Chem v4.3, is used. The results are compared with those from an older version of WRF-Chem v3.7 and the Community Multiscale Air Quality (CMAQ) model v5.0.2, generated previously under a separate project.

Figure C1 shows the US modeling domain at a horizontal grid resolution of $36km^2$ (D01) with an insert showing the $4km^2$ modeling domain, centered on New York State.

Figure C1. Domain of Air Quality Modeling

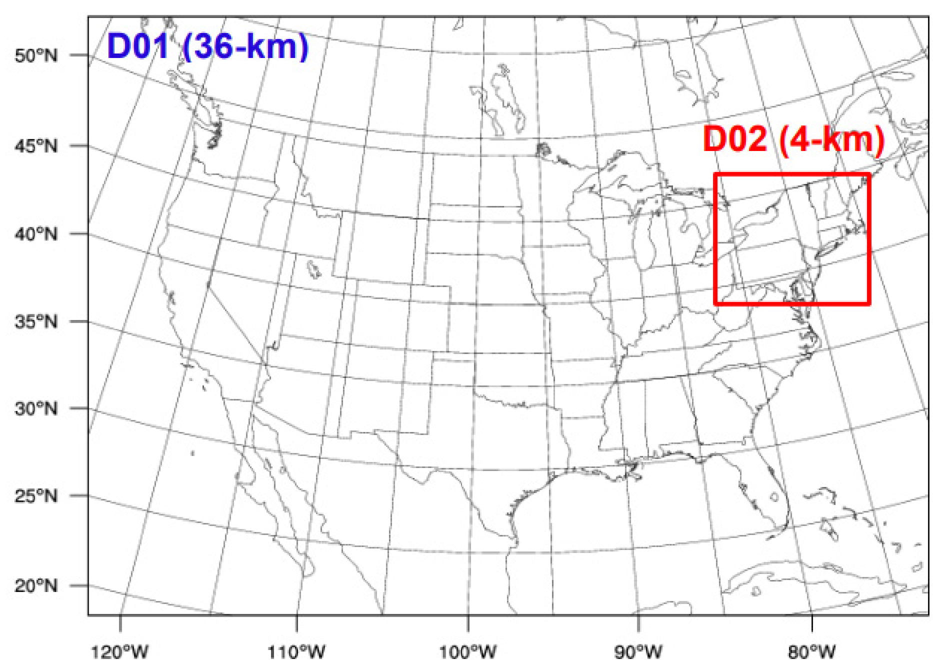


Figure C2. Spatial Distributions of Annual Means Predicted by WRF-Chem v4.3 at a Grid Resolution of 36km (2012)

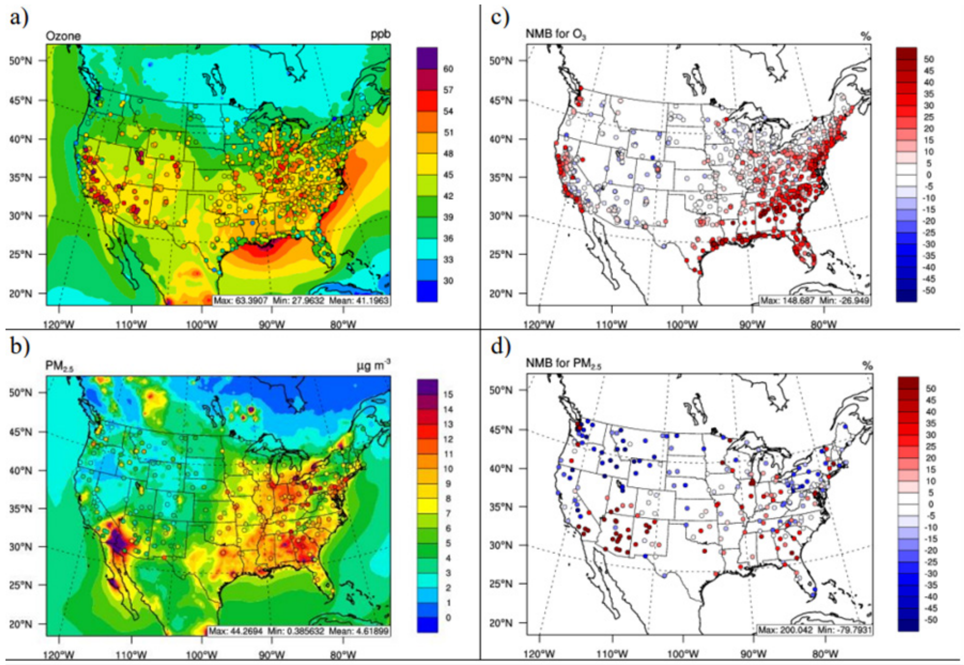


Figure C2 shows the 36km^2 grid resolution spatial distributions of simulated (a) max 8-h O3 overlaid with surface observations from AQS and CASTNET (b) daily $PM_{2.5}$ overlaid with surface observations from CSN and IMPROVE, and normalized mean bases (NMBs) of annual mean (c) max 8-h O_3 and (d) daily $PM_{2.5}$ predicted by WRF-Chem v4.

Table C1 shows the domain-mean performance statistics for max 8-h O_3 and daily $PM_{2.5}$ against data from several surface networks. The NMBs are within ±11 percent and the NMEs are <14 percent for O_3, and the NMBs are within ±9 percent and the NMEs are <50 percent for $PM_{2.5}$, which are well within the thresholds for good performance.

Table C1 also compares the performance statistics for the 3-D simulations of 2012 at 36km^2 over CONUS using three models including WRF-Chem v4.3, WRF-Chem v3.7, and CMAQ v5.0.2. The model used for this project, WRF-Chem v4.3, shows the best performance for $PM_{2.5}$ against CSN with NMBs of -2.3 percent vs. 21.3 percent by CMAQ v5.0.2 and 8.8 percent by WRF-Chem v3.7. For daily $PM_{2.5}$ against IMPROVE, WRF-Chem v4.3 gives an NMB of 8.4 percent, which is better than 9.6 percent by WRF-Chem v3.7. For daily $PM_{2.5}$ against AQS, WRFChem v4.3 gives an NMB of –5.0 percent, which is better than –7.8 percent by CMAQ v5.0.2. Overall, WRFChem v4.3 performs better for $PM_{2.5}$ predictions against surface observations when compared with WRF-Chem v3.7 and CMAQ v5.0.2.

To translate the predictions to a 4km^2 grid resolution, we interpolate the 36km^2 model predictions of $PM_{2.5}$ concentrations to a modeling domain centering on New York State at the 4km^2 grid resolution, and validate the interpolated $PM_{2.5}$ predictions with available surface observations from the US EPA AQS data network. The interpolated $PM_{2.5}$ predictions for 2012 show excellent performance, with an NMB of 4 percent and NME of 40 percent, which is consistent with the performance of WRF-Chem $PM_{2.5}$ predictions at $36km^2$.

Table C1. Performance Statistics for 3-D Simulation of 2012 at 36km over CONUS

Species/ network/ units	Mean obs	WRF-Chem v4.3					WRF-Chem v3.7					CMAQ v5.0.2				
		Mean sim	R	MB	NMB (%)	NME (%)	Mean sim	R	MB	NMB (%)	NME (%)	Mean sim	R	MB	NMB (%)	NME (%)
Max 8-hr O_3 AQS (ppb)	44.4	49.2	0.4	4.8	10.8	14.6	43.2	0.5	-1.2	-2.8	10.1	52.3	0.6	7.9	17.7	18.0
Max 8-hr O_3 CASTNET (ppb)	41.7	39.3	0.3	-2.4	-5.8	12.4	35.1	0.5	-6.6	-15.9	17.6	44.7	0.6	3.0	7.1	10.5
$PM_{2.5}$ CSN ($\mu g\ m^{-3}$)	10.2	10.0	0.5	-0.24	-2.3	21.0	11.1	0.5	0.9	8.8	22.9	12.4	0.5	2.2	21.3	28.9
$PM_{2.5}$ IMPROVE ($\mu g\ m^{-3}$)	4.6	5.0	0.6	0.4	8.4	32.1	5.1	0.7	0.5	9.6	28.8	4.7	0.7	0.1	1.4	37.0
$PM_{2.5}$ AQS ($\mu g\ m^{-3}$)	8.9	8.5	0.3	-0.4	-5.0	50.0	9.1	0.3	0.1	1.5	50.5	8.2	0.4	-0.7	-7.8	48.8

Appendix D. Identifying Disadvantaged Communities

When our work started, we did not have the final Climate Justice Working Group definition of disadvantaged communities, but we did have the preliminary list of indicators being used to calculate the index. The team at the Yale School of Public Health worked with this list of indicators, sourced their own data, and experimented with different index designs prior to the release of the CJWG index methodology. Their work on index design is the subject of an upcoming working paper. For this report, we leveraged the same methodology as CJWG, to create alignment. When "disadvantaged communities" are referenced in the report, we are referring to the list defined by the Climate Justice Working Group.[1]

The index leverages 44 statewide indicators at the census tract level representing environmental burdens, climate change risks, population characteristics and health vulnerabilities. The index is based on two main groups of statewide indicators at the census tract level:

- Environmental burdens and climate change risks (19 indicators)
    - potential pollution exposures
    - land use associated with historical discrimination or disinvestment
    - potential climate change risks
- Population characteristics and health vulnerabilities (25 indicators)
    - income
    - education and employment
    - race, ethnicity, and language
    - health impact and burdens
    - housing, energy, and communications

For each indicator, we calculated the percentile rank (0–100) for a given census tract across all census tracts in the state. The use of percentiles weakens the impact of extreme values for a given indicator and can represent a relative score for a census tract for that indicator. For certain types of land use (e.g., remediation sites, power generation facilities), since a significant number of census tracts have zero values, we directly allocated a zero percentile to these census tracts and recalculated the percentile ranks for the remaining census tracts with nonzero values.

Next, we calculated the weighted average of indicator percentile ranks within each group (0–100) for a given census tract. Certain metrics within groups were given double the weight: for example, in the population characteristics and health vulnerabilities group, income less than 80 percent of the area median income, income less than 100 percent of federal poverty line, Latino/a or Hispanic, and Black or African American (Figure D1).

1 A map and description of the criteria can be found here: **https://climate.ny.gov/Resources/Disadvantaged-Communities-Criteria**

Figure D1. Indicators and Their Respective Weights Used to Construct the CHVI

Environmental burdens and climate change risks

Potential pollution exposures (1X)

- (1X) Vehicle traffic density
- (1X) Diesel truck and bus traffic
- (1X) Particulate Matter ($PM_{2.5}$)
- (1X) Benzene concentration
- (1X) Wastewater discharge

Land use associated with historical discrimination or disinvestment (1X)

- (1X) Remediation sites
- (1X) Regulated Management Plan (chemical) sites
- (1X) Major oil storage facilities
- (1X) Power generation facilities
- (1X) Active landfills
- (1X) Municipal waste combustors
- (1X) Scrap metal processors
- (1X) Industrial/manufacturing/mining land use
- (1X) Housing vacancy rate

Potential climate change risks (2X)

- (1X) Extreme heat projections (>90°F days in 2040–2069)
- (1X) Projected flooding risk
- (1X) Low vegetative cover
- (1X) Agricultural land
- (1X) Driving time to hospitals

Population characteristics and health vulnerabilities

Income, education, & employment (1X)

- (2X) <80% area median income
- (2X) <100% of federal poverty line
- (1X) Without bachelor’s degree
- (1X) Unemployment rate
- (1X) Single-parent households

Race, ethnicity, & language (1X)

- (2X) Latino/a or Hispanic
- (2X) Black or African American
- (1X) Asian
- (1X) Native American or Indigenous
- (1X) Limited English proficiency
- (1X) Historical redlining score

Health impacts & burdens (1X)

- (1X) Asthma ED visits
- (1X) COPD ED visits
- (1X) Heart attack hospitalizations
- (1X) Premature deaths
- (1X) Low birthweight
- (1X) Without health insurance
- (1X) With disabilities
- (1X) Adults age 65+

Housing, energy, & communications (1X)

- (1X) Renter-occupied homes
- (1X) Housing cost burden (rental costs)
- (1X) Energy poverty/cost burden
- (1X) Manufactured homes
- (1X) Homes built before 1960
- (1X) Without health insurance

The score for a given census tract was calculated as the product of its percentile rank in each of the two main groups (Figure D2). Then the Climate Health Vulnerability Index (0–100) was calculated as the percentile rank of the final score for a given census tract among all census tracts in New York State. This final score represents each census tract's relative ranking in the state.

Figure D2. Formula for Calculating the CHVI

Environmental burdens and climate change risks × **Population characteristics and health vulnerability** = **Climate health vulnerability index**

Below, census tract 41 at the Bronx (census tract ID 36005004100) is used to illustrate the construction of the Climate Health Vulnerability Index.

Figure D3. Percentile Rank of Each Indicator in Both Criterea Groups for Census Tract 41 (The Bronx)

Environmental Burdens and Climate Change Risks

Potential pollution exposures		
Indicator	**Raw value**	**Percentile**
Vehicle traffic density	700.74	51.1
Diesel truck and bus traffic	372.52	42.3
$PM_{2.5}$	7.76	50.3
Benzene	0.71	99.5
Wastewater discharge	0.00086	48.4
Overall factor score		58.32

Land use associated with historical discrimination or disinvestment		
Indicator	**Raw value**	**Percentile**
Remediation sites	1.03	52.4
Regulated Management Plan (chemical) sites	1.00	85.5
Major oil storage facilities (incl. airports)	1.18	73.1
Power generation facilities	1.73	81.3
Active landfills	0	0.0
Municipal waste combustors	0	0.0
Scrap metal processors	0.10	46.2
Industrial/manufacturing/mining land use	2.36	67.9
Housing vacancy rate	4.60	22.8
Overall factor score		47.68

Potential climate change risks		
Indicator	**Raw value**	**Percentile**
Extreme heat projections	40.60	78.06
Coastal and inland flood projections	2.92	94.32
Low vegetative cover	96.17	69.68
Agricultural land	0	0.00
Driving time to hospitals	4.68	11.79
Overall factor score		50.77

Population Characteristics and Health Vulnerabilities

Income, education, and employment		
Indicator	**Raw value**	**Percentile**
<80% area median income	93.73	99.5
<100% of federal poverty line	46.89	99.0
Without bachelor's degree	88.86	92.2
Unemployment rate	21.5	99.1
Single parent households	26.14	98.8
Overall factor score		98.17

Race, ethnicity, and language		
Indicator	**Raw value**	**Percentile**
Latino/a or hispanic	70.5	96.9
Black or African American	38.5	82.2
Asian	0.2	9.2
Native American	3.7	91.8
Limited English proficiency	30.26	93.1
Historical redlining score	4	100.0
Overall factor score		81.54

Health impacts and burdens		
Indicator	**Raw value**	**Percentile**
Asthma emergency department visits	480.2	100.0
Chronic obstructive pulmonary disease emergency department Visits	135	86.4
Heart attack (myocardial infarction) hospitalization	12.8	99.3
Premature deaths	41.83	94.7
Low birthweight births	7.84	80.5
Without health insurance	10	86.3
With disabilities	16.9	84.7
Adults aged 65 and above	6.3	4.6
Overall factor score		79.55

Housing, energy, and communications		
Indicator	**Raw value**	**Percentile**
Renter-occupied homes	87.48	90.0
Housing cost burden (rental costs)	707	8.6
Energy poverty/cost burden	4	82.4
Manufactured homes	0	0.0
Homes built before 1960	48.45	35.9
Without internet (home or cellular)	26.1	84.4
Overall factor score		50.20

The figure below shows how the final figure for the tract is calculated.

Figure D4. Calculation of the Final Climate Health Vulnerability Index Score for Census Tract 41 (The Bronx)

	Environmental burdens and climate change risks			**Population characteristics and health vulnerabilities**			
	Potential pollution exposures	Land use associated with historical discrimination or disinvestment	Potential climate change risks	Income, education, and employment	Race, ethnicity, and language	Health impacts and burdens	Housing, energy, and communications
Factor scores	58.3	47.7	50.8	98.2	81.5	79.5	50.2
Weighted average of factor scores	[1 (58.32) + 1 (47.68) + 2 (50.77)]/(1+1+2) **= 51.88**			[98.17 + 1 (81.54) + 1 (79.50) + 1 (50.20)]/(1+1+1+1) **= 77.36**			
Climate health vulnerabilitiy index score	51.88 x 77.36 = 4013.44						
Climate health vulnerabilitiy index percentile	**97.8**						

Appendix E. Supplementary Methodologies

E.1. Model Integration and Coordination

Our energy models operate independently of one another, but outputs of one may inform the inputs of another. For example, retail electricity prices may affect incentives to install an electric heat pump, or how much that heat pump is used. But how many heat pumps are operating also may affect electricity prices. Our model is not designed to find a general equilibrium solution, so we do our best to match electricity price and demand across model runs without that functionality. Our transportation models leveraged AEO electricity prices in the BAU case and increase prices proportional to the increases projected by the power sector for the policy cases. The residential model considers prices directly from the power sector model, iterating until it finds the appropriate combination of electricity price and residential demand. Electricity demands from residential and transportation sectors are passed to the power sector model for final emissions projections.

E.2. Ancillary Pollutant Valuation

To address the state carbon tax proposal, emissions taxes on conventional pollutants contributing to $PM_{2.5}$ (NO_X, SO_2, and direct particulates) are needed by sector. We assumed that the taxes would equal the dollar benefits to the US per ton of emissions reduced in New York State. The literature offers such estimates for regions and cities, as well as by source because sources (e.g., power plants) have a different pattern of dispersal and chemical transformation than ground-level sources (e.g., transportation, home heating by natural gas). But the literature doesn't provide these estimates for New York. To get those, we ran the COBRA model (formally, the CO-Benefits Risk Assessment Health Impacts Screening and Mapping Tool; **https://cobra.epa.gov/**), which assumes that the benefits of NO_X and SO_2 emissions reductions (to reduce $PM_{2.5}$ concentrations) are additive and separable. The model includes the benefits of reducing $PM_{2.5}$ concentrations on human health and values these benefits using standard unit values from the environmental economics literature.

The benefits from reducing pollution (2017$/short ton) from COBRA are as follows:

Table E1. Benefits from Reducing Polution (2017$/short ton) from COBRA

	Electricity	Vehicles	Residential fuel
$PM_{2.5}$	231,965	465,556	682,730
SO_2	36,382	59,664	55,507
NO_X	9,025	14,355	19,456

E.3. Methane

Decarbonization goals are defined in terms of carbon dioxide equivalent (CO_2e) rather than only CO_2. Of the many other greenhouse gases, the most important one, and the only one we track in this project, is methane. Since we are not modeling agriculture or waste dumps, our focus is solely on upstream methane emissions from oil and gas wells and how these emissions affect the accounting for meeting the decarbonization goals. We basically need two sets of information: the leak rate per final product consumed (gasoline, diesel, electric power) and the global warming potential of methane to CO_2 to transform the methane emissions into CO_2e. For the transportation sector, we used rates of 1.87 kg/gallon of diesel fuel and 1.79 kg/gallon of gasoline. We assume methane leakage of 0.000434 short tons per million Btu of natural gas use and 0.000174 short tons per million Btu of coal use, taken from Lenox et al. (2013), a source that includes coal and whose natural gas leakage estimates have stood up well in light of more recent research about methane leakage associated with natural gas extraction, transportation, and processing. This methane leakage rate for natural gas implies that approximately 2.4 percent of natural gas leaks. In line with the CLCPA-related documentation, we use the 20-year global warming potential, which is 85 (IPCC 2014), except where otherwise noted.

Appendix F. Comparison with New York State's Analysis

NYSERDA, DEC, and other state agencies worked together to perform their own analyses of various policy options the state might take to meet its 2050 goals. Our effort is independent of the state's effort but was developed in close consultation and interaction with the state agencies and full disclosure of our approach and assumptions. Still, we did not want to merely duplicate the state's approach because we wanted to maximize our contribution to the debate about the policy pathways going forward. Here we detail the main points of differences.

1. When we model certain policies, we use "behavioral" models that confront electric utilities, vehicle buyers, building residents, trucking companies, and port operators with specific policies and incentives for action and then, based on past behavior, record how they respond to those incentives. This is very different from the state's approach (conducted by the consulting firm E3), which is a "pathway" model that assumes how the economy will respond and then tracks the effect of that response on CO_2 emissions and (to a certain extent) air quality levels.

   As an example, consider the effect of raising the gasoline tax (not a policy modeled). Our model would raise that tax a given amount and, through previously estimated equations tracking how people behave in buying gasoline and electric vehicles of all types and how their driving changes, estimate CO_2 and vehicle NO_X and SO_2 emissions from the results. The E3 analysis, in contrast, assumes that x fewer gasoline vehicles and y more electric vehicles will be purchased without using a behavioral model.
2. Because of the necessity of having access to behavioral models, we are modeling only some sectors in New York responsible for emissions: residential buildings, on-road transportation, ports, and electricity generation. These sectors make up a significant portion of statewide carbon emissions, but we are not including commercial buildings, industry, waste, or agriculture emissions in our projections. E3's analysis is comprehensive across sectors, but we prioritized modeling sectors where we had some spatial distribution of emissions in our results, which is critical to understanding impacts on local air quality.
3. Our air quality modeling is more sophisticated and spatially granular than the state's (see Appendix C). We have opted to pursue the most spatially granular modeling level that balances modeling capabilities, computational resources, and our desire to identify air quality changes at a fine spatial scale. To model the entire state, this is the finest scale possible within the timeline and resources available to us. In contrast, the state's modeling effort uses COBRA, which estimates air quality outcomes at the county level.
4. Because of budget limitations, our emissions and air quality projections are only for 2030. Many decarbonization policies will begin to take effect in the next several years and significant emissions reductions will need to take place by 2030 for New York to meet the goals set out in the CLCPA. However, for many policies, the bulk of the impacts will happen after 2030, over the next several decades.

> Some policies we investigate may make little headway on emissions by 2030, but we include them for completeness. In future work, we would be interested in projecting these policy cases to 2050 and beyond to better capture their long-term emissions and air quality impacts.

The state's analysis includes 2030 results, so there is a point of comparison with ours, keeping the above caveat in mind. However, the state models emissions changes in 2050 as well.

Appendix G. Research Limitations and Caveat

Several limitations to this study result from study design choices, modeling limitations, data limitations, and the like, indicating areas for further research.

When modeling community exposure to air pollution, it is ideal to have the most geographically granular analysis possible, given that actual pollution exposure may vary at a level as granular as a city block.[2] As mentioned above, our analysis is at the $4km^2$ level. Although this is substantially more granular than the county-level analysis offered by the COBRA model (used in the state's analysis), it limits our ability to determine hyperlocal differences in air pollution exposure. The large scale and complex air quality models, such as WRF-Chem and CMAQ, can be downscaled to a grid resolution of $1km^2$ or less, but they have limited ability to confidently predict air quality at this scale because of limitations in model inputs (e.g., hyperlocal emissions) and representations of some atmospheric processes (e.g., turbulence, mixing, and chemistry at street intersections and above urban street canyons). Although hyperlocal air quality modeling methods do exist (Kim et al. 2022), it was determined that using them for this statewide and cross-sector project would likely lead to false precision, primarily because of the lack of statewide hyperlocal air quality data[3] required to validate the modeling. Further, applications of those models would require detailed information at hyperlocal scales (e.g., traffic fleets and emissions, urban street geometry, building dimensions and energy consumption) that would require considerable time and resources to develop.

To partly address this limitation in our air quality projections, we provide more localized details (for some sectors) on the emissions projections that drive air quality changes. For example, our medium- and heavy-duty transportation model estimates emissions at the road link level, and our power sector model estimates emissions at specific power plants. We explore these outputs in the Location of Emissions Changes section in the main text and below (Appendix J).

Another limitation is that we model policy cases as a bundle, rather than as individual policies. Ideally, we would be able to test sensitivity of different policy ambitions (e.g., a $100 subsidy versus a $500 subsidy) and test different combinations of policies to better understand the potential air quality impacts of individual policymaking decisions. However, the modeling process is computationally expensive and time intensive, limiting our ability to add more dimensions to this analysis. Our approach

2 **https://engineering.berkeley.edu/news/2021/09/google-street-view-study-shows-air-pollution-by-block/**

3 The New York Department of Environmental Conservation has begun an initiative to gather hyperlocal air quality data, covering communities with a cumulative population of about 5 million people at the time of publication. Efforts like this will provide the foundation of data to support hyperlocal air quality modeling in the future. For more information, see **https://www.dec.ny.gov/chemical/125320.html**.

restricts our final analysis to comparing cases as a bundle of policies, rather than individual policy changes. We believe attributing air quality changes directly to individual policies is a rich area for continued research. Detailed explanations of how policies affect economic decisions and emissions are in the Economic Modeling Results section in the main text and below (Appendix H).

Similarly, because of cost and time constraints in our modeling project, we model only a single policy year, 2030. This decision limits our ability to show the full effects of the CLCPA, which runs through 2050. This decision is especially limiting for policies that take time to affect aggregate emissions, such as policies to decarbonize the transportation fleet through mandates and subsidies for the sale of new vehicles (which represent a small percentage of the on-road fleet). Furthermore, we do not model all sources of New York emissions. Most notably, our current modeling does not incorporate commercial buildings or industrial facilities other than electric power generation. These two features of our analysis limit our ability to estimate the full effect of CLCPA implementation on New York's air quality.

Despite those limitations, our research is an ambitious undertaking to understand the variable $PM_{2.5}$ pollution impact of decarbonization polices in New York communities. This is just the first step in investigating this relationship, and many research opportunities remain, including studying the effects of additional pollutants. Again, limitations in budget made this impossible, but $PM_{2.5}$ is the pollutant of most concern and of higher impact than ozone, NO_X, SO_2, CO, and lead—the other pollutants covered by National Ambient Air Quality Standards under the Clean Air Act (EPA.gov).[4]

The caveat concerns an error discovered very late in our project involving direct $PM_{2.5}$ emissions and NO_x emissions from the transportation sector passed on to the air quality model. Tests on the effect of this error on our air quality simulations reveal minor to trivial differences between the SPC and CPC, which are the focus of this project. The emissions results reported in the Greenhouse Gas, $PM_{2.5}$, and Precursor Emissions Results section are unaffected, as are our main findings and conclusions.

To pass on the modeled emissions associated with our BAU and policy cases to the air quality model, we aggregated the emissions from the two separate transportation models—one for LDVs and the other for HDVs. We discovered that this aggregation process, which is complex because of differing spatial resolution across the two models, led to an underestimate of direct $PM_{2.5}$ reductions and an overestimate of NO_x reductions. The error was substantial in calculating emissions changes between 2012 and 2030, but the error occurred in a relatively uniform manner across policy cases (2030 BAU, CPC, SPC). The differences in emissions between the policy cases (measured as a percentage of the 2012 baseline) were much smaller.

4 Evidence suggests NO_x on its own can have significant impacts on respiratory disease (César et al. 2015), and it may have even more dramatic disparities between communities (Liu et al. 2021)

Specifically, a 36km^2 grid of the transportation emissions change factors (measured as the percentage change from the 2012 baseline) reveals that the maximum difference in direct $PM_{2.5}$ emissions in any grid cell between the CPC and SPC is about 3.5 percent of the 2012 baseline with the incorrect emissions. The maximum difference in the corrected emissions is also 3.5 percent of the 2012 baseline. However, in the corrected emissions there is more variation in emissions changes across grid cells.

Table G1 shows results from an example grid cell where the error is particularly pronounced. The first two columns show the reductions in each policy case relative to the 2012 baseline. There are large differences between the incorrect and correct results. The third column shows the difference between the policy cases. This is what we are most interested in. The impacts are clearly much smaller (on the order of a few percentage points). All values are percentage reductions from the 2012 baseline.

Appendix H. Economic Modeling Results

Here we describe how each policy case (CPC and SPC) affects technology adoption and behavioral choices that can influence emissions levels. The policies we modeled have a wide range of ambition and vary in their timelines for implementation. The results illustrate how far each policy case goes in pushing behavior that will lead to decarbonization and air quality improvements.

H.1. Electricity Sector

H.1.1. Electricity Demand and Price

Both policy cases increase total New York electricity consumption (inclusive of transmission and distribution losses) because of the high rates of electrification in the residential and transportation sectors. Under the CPC, electricity demand increases by 17 percent, and under the SPC, by 29 percent, compared with the BAU. Table H1 shows overall electricity demand, the electricity price, and the share of demand met by in-state generation under the two policy cases and BAU.

Table H1. New York State Electricity Consumption and Wholesale Prices

	BAU 2030	CPC 2030	SPC 2030
Electricity demand	155 million MWh	182 million MWh	200 million MWh
Electricity price	$98/MWh	$107/MWh	$116/MWh
Share of demand met in-state	89%	96%	96%

Both policy cases also lead to modest increases in wholesale electricity prices compared with the BAU (as driven especially by increased electricity demand and the economywide carbon-pricing policy)—a 10 percent increase for CPC and an 18 percent increase for SPC. Both policy cases also increase the proportion of electricity consumption met from within the state. Several policies contribute to this trend:

- the border electricity price adjustment mechanism;[5]
- the 70 percent renewable portfolio standard (which we assume must effectively be satisfied by generation within the state);
- the large required (per CLCPA) amounts of distributed solar, offshore wind, and electricity storage capacity within the state; and
- greatly increased electric vehicle requirements in the other ZEV states, three of which are adjacent to New York. They increase electricity demand in those states, partially offsetting the effect of New York's increased electric vehicle requirements by reducing the availability of generation from those states to sell electricity into New York and increasing those states' demand for generation from New York.

In-state generation in the CPC is also bolstered by the continued operation of the Ginna and Nine-Mile-Point nuclear generators (in the BAU and SPC, these large, nonemitting generators are retired by 2030). Together, these policy elements more than offset the downward effects that increased electricity demand and the power plant emissions fees in the CPC and SPC would otherwise exert on the in-state generation share.

H.1.2. Generation Mix

Both policy cases prompt a dramatic increase in clean energy generation, relative to the BAU. Table H2 shows the level of each generation type in each policy case, along with the percentage of total generation from each generation type.

5 The border mechanism sets a fee on electricity imports and an equal rebate on electricity exports to partially offset the competitive disadvantage that New York's CO_2e fee creates for New York generators, as described in the scenario descriptions section above. The fee and rebate are $11 in the CPC and $27 in the SPC.

Table H2. New York State Generation Mix (MWh and Percentage)

Generation Source	BAU 2030	Percentage	CPC 2030	Percentage	SPC 2030	Percentage
Total generation	138,471,392	100%	174,251,411	100%	191,065,047	100%
Nuclear	17,302,119	12%	27,069,379	16%	17,302,118	9%
Coal	—	0%	—	0%	—	0%
Natural gas	40,975,962	30%	14,589,190	8%	10,571,238	6%
With CCUS	—	0%	10	0.00%	—	0%
Solar	33,708,907	24%	73,055,753	42%	94,337,759	49%
Distributed solar	3,600,547	3%	19,808,517	11%	19,593,577	10%
Wind	15,578,218	11%	29,129,736	17%	40,257,449	21%
Hydro	27,870,324	20%	27,863,663	16%	27,849,494	15%
Geothermal	—	0%	—	0%	—	0%
Storage	−68,199	−0.05%	−518,083	−0.30%	−1,511,674	−1%
Hydrogen	—	0%	1	0.00%	—	0%
Waste & biomass	3,076,401	2%	3,044,666	2%	2,258,635	1%
Other	27,660	0%	17,107	0%	28	0%

SPC policies boost renewable generation and storage capacity above the CPC (30 percent boost for solar, 40 percent boost for wind, and a nearly 200 percent increase in storage capacity) and cut nuclear, natural gas, and waste-fueled generation (roughly 35 percent less for nuclear and 30 percent less for natural gas and waste-fueled generation).

The natural gas generation reductions are especially large for the higher-emitting natural gas generator types, which use steam cycles alone or combustion turbines alone. The policy differences that account for this further reduction in fossil-fueled generation are the fees or caps on NO_X, $PM_{2.5}$, and SO_2 emissions, the higher fee on CO_2 and methane emissions, the higher border electricity price adjustment ($27 instead of $11), the prohibition on new natural gas–fueled generation capacity, and the requirement that all of the state's fossil-fueled peakers retire, not just those subject to the current New York City peaker retirement requirement.

SPC policies increase solar, wind, and storage generation relative to CPC policies. These increases are not directly mandated but instead result from the expected price changes caused by the policy differences in the two cases. In particular, those policy differences raise electricity prices while creating stronger disincentives for energy generation methods that cause emissions, which allows more solar, wind, and battery storage capacity to be profitable.

CPC policies have very little effect on waste-fueled generation, reducing it by just 0.03 TWh. SPC policies, specifically the SO_2 and NO_X emissions fees, do reduce waste-fueled generation. We have not allowed either case to change waste-fueled capacity (building or closing facilities). In reality, this could occur, in which case the effects of the policies on waste-fueled generation would be larger.

The SPC explicitly bans new hydrogen and CCUS plants, but even in the CPC, where they are permitted, there is essentially no hydrogen or CCUS buildout by 2030.

H.2. Residential Building Sector

In the residential sector modeling, electricity demand (for heating and cooling) and natural gas and diesel ("heating oil") consumption are driven by future estimates of how readily heat pump technologies are adopted instead of alternatives, such as diesel boilers. In Table H3, we summarize heat pump adoption results for the BAU, CPC, and SPC (the percentage of total households in the state that have adopted heat pumps). In addition to the statewide adoption rates listed, we find a range of adoption rates across counties in each case. For instance, the adoption rate varies by county from 77 to 96 percent in the SPC, from 27 to 78 percent in the CPC, and from 2 to 15 percent in the BAU case. The higher adoption rates tend to be in the southeastern part of the state, such as Staten Island and Long Island.

Table H3. New York Homes with Heat Pumps

	BAU 2030	CPC 2030	SPC 2030
Heat pump adoption	8%	54%	90%

These adoption rates are largely determined in the model by the relative cost (including incentives to encourage adoption) of heat pumps compared with fossil fuel alternatives like boilers. Adoption rates are also influenced by the regional climate across the state, which determines how much a given heating or cooling technology is used and therefore how much cost savings a household receives from the more efficient heat pump.

As shown in Table 1 in the main text, the SPC has the highest heat pump subsidies for low- and middle-income (LMI) households; the CPC subsidy level is more modest. Other factors, such as age of household head, floorspace, race, and level of insulation, have an influence on the extent of uptake to a lesser degree, which results in different behavior across households. Since these are statistical results, the causal mechanisms are not determined.

H.2.1. Electricity Demand

Table H4 shows that the higher penetration of heat pumps shifts heating and cooling energy demand from gas and oil to electricity and enables more use of air conditioning, increasing electricity consumption in residential buildings. This includes shell efficiency upgrades, which do not vary across cases.

Table H4. New York Residential Electricity Demand (TWh)

	BAU 2030	CPC 2030	SPC 2030
Heating and cooling electricity	16,080	27,273	44,448

H.3. Transportation Sector

H.3.1. Light-Duty Vehicles

Passenger vehicle emissions depend on the emissions rates of on-road vehicles and vehicle miles traveled. Variation in the adoption rate of plug-in electric vehicles,[6] the fuel economy of gasoline vehicles, and VMT explain the differences in 2030 emissions across the two policy cases and the BAU. Table H5 shows how PEV adoption, fuel economy, and VMT vary across the cases.

Table H5. New York Light-Duty Vehicle Usage, By Case

	BAU 2030	CPC 2030	SPC 2030
On-road EVs	240,648	861,920	984,507
Electricity consumption from EV battery charging (million MWh)	0.92	3.84	4.41
Average fuel economy (miles per gallon)	34	38	40
Vehicle miles traveled (billions)	134.46	130.99	126.42
Gasoline consumption (billion gallons)	3.83	3.58	3.36

The first row shows the number of on-road EVs, which include plug-in hybrid vehicles such as the Chevrolet Volt as well as all-electric vehicles like the Tesla Model 3. In the BAU, New York has about 241,000 EVs—about 2 percent of all on-road vehicles. Note that the share of EVs in new-vehicle sales is substantially higher (about 8 percent) in the BAU in 2030, but the on-road share is less than the new share because new vehicles replace older vehicles gradually over time.

The policy cases (CPC and SPC) yield roughly four times more EV sales than the BAU. The main cause of this difference is that the policy cases include more ambitious zero-emissions vehicle (ZEV) standards than the BAU. The ZEV standards incentivize

6 In our use of the term "electric vehicle" we include plug-in hybrid vehicles such as the Chevrolet Volt, as well as all-electric vehicles such as the Tesla Model 3.

vehicle manufacturers to sell EVs. Other policies included in the modeling, such as EV purchase subsidies, effectively make it easier for manufacturers to attain the ZEV standards. In principle, subsidies could be sufficiently large to render ZEV standards irrelevant if they cause manufacturers to exceed the ZEV standards. However, for the cases we consider, the subsidies are smaller than that trigger, and the ZEV standards essentially determine the level of EV sales and hence the on-road vehicle counts reported in the table.

Table H5 also shows the amount of electricity consumed from charging EVs. These amounts are roughly proportional to the vehicle counts in the first row, and this consumption is an input to the electricity sector modeling discussed above.

Compared with the BAU, the policy cases increase the average fuel economy of on-road vehicles by about 15 percent. The ZEV standards, again, are the main explanation for the higher average fuel economy in the policy cases (fuel economy is computed assuming zero fuel consumption for all-electric vehicles). In the modeling, vehicle manufacturers achieve federal standards for corporate average fuel economy (CAFE) and GHGs. For a particular manufacturer, the average fuel economy and GHG emissions rate in a state can differ from the national average; that is, the manufacturer can undercomply in one state and overcomply in another state as long as it achieves the national standard. Because of this flexibility, when New York adopts the ZEV standard, the higher plug-in sales cause manufacturers to overcomply with the standards in New York (and other ZEV states). Consequently, adopting tighter ZEV standards in the policy cases causes average fuel economy of new vehicles to be higher than in the BAU, which in turn causes average fuel economy in non-ZEV states to be lower.[7]

The carbon prices in the policy cases raise the cost of purchasing both liquid fuels and electricity, which creates a disincentive to consume those products (and to drive) and therefore reduces VMT. The effect is somewhat larger in the SPC than the CPC because of the higher carbon price in the former.

The bottom row of the table shows the total fuel consumption, which is the product of the inverse of the average fuel economy (which yields the average on-road fuel consumption rate in gallons per mile) and VMT. Fuel consumption is about 6 percent lower in the CPC and 12 percent lower in the SPC, compared with the BAU. The SPC reduces fuel consumption more than the CPC because of its bigger effect on VMT.

H.3.2. Medium- and Heavy-Duty Vehicles

The factors that affect energy use and emissions for medium- and heavy-duty vehicles include VMT, vehicle type (e.g., semitrailer, urban delivery truck), vehicle efficiency and powertrain (e.g., internal combustion diesel engine, electric), duty cycles, and network conditions. As described in more detail in Appendix B, the MHDV modeling framework

7 The copollutant emissions taxes also contribute to the higher average fuel economy in the SPC. The taxes cause households to retire older vehicles sooner than they would have otherwise, which increases average fuel economy because those retired vehicles tend to be relatively old and have low fuel economy.

developed for this project comprises a number of models, which in summary combine truck flow VMT data with estimates of how vehicle and fuel costs influence vehicle purchase decisions. Vehicle purchase decisions then influence the mix of vehicles in the fleet in any given year, which when combined with VMT yields energy use and emissions estimates.[8] For example, electricity costs and carbon pricing affect vehicle operation costs, and purchase incentives affect vehicle purchase prices. Additionally, MHDV manufacturers face a new-sales ZEV mandate (modeled after California's Advanced Clean Truck rule), similar to the ZEV mandate for LDVs.

Similar to findings from the LDV modeling, the MHDV ZEV mandate is a primary driver of the shift to a cleaner MHDV fleet. Because of the MHDV ZEV rule (see Table 1 for details), by 2030, it is expected that about 14 percent and 13 percent of the fleet will be ZEV (mostly battery electric) in the SPC and CPC, respectively (See H6 for a projection of ZEV sales through 2045). Key drivers of the difference between cases (although small) are the SPC's more ambitious ZEV sales mandate and carbon price and its copollutant fees; the low-carbon fuel standard program is only in the CPC. Although the SPC and CPC assume different sales targets, with the SPC requiring a larger share of Class 7–8 EVs during the transition period, the consideration of the LCFS will provide additional credit incentive that can help fleets reduce the cost gap between ZEVs and the incumbent vehicle technologies. Alone, the LCFS is not expected to be the main driver of ZEV adoption.

Electricity consumption from direct battery charging for these vehicles is estimated to be 2.13 and 1.93 million MWh in 2030 for the SPC and CPC, respectively. Although these numbers are only about half of the electricity demand estimated for LDVs in 2030, without the two policy packages, penetration of ZEV MHDVs (and associated electricity demand) by 2030 is negligible in the BAU case.

Figure H1. ZEV Sales Targets Over Time

8 We do not vary VMT across cases under the MHDV model for two primary reasons: (1) we use truck activity flows estimated from the FAF model, adjusted with estimates from the New York Metropolitan Transportation Council's NYBPM, and thus our model does not conduct vehicle routing or assignment; and (2) the strategies considered in the scenarios do not directly affect freight demand, and although there could be some changes in VMT due to charging and fueling detouring, these could potentially be minimal if the infrastructure is located at or near freight facilities.

The models indicate that electric vehicles will represent the largest share of ZEVs for short-haul heavy-duty and medium-duty trucks, while fuel cell vehicles will be the primary technology adopted in long-haul heavy-duty trucks. This is mainly because of estimated range limitations from battery sizes and weights. It remains unclear whether the market will be able to ramp up between now and 2030 to supply the number of vehicles required by the ZEV mandate as identified in our modeling (note that truck production capacity was not included in the modeling).

Finally, significant financial incentives will be required to achieve the desired ZEV adoption. The models estimate that for the most part, the various fees considered (carbon, copollutant, fee on internal combustion engine vehicles), and the existing BAU vehicle incentives programs (e.g., New York City Clean Truck, New York Truck Voucher Incentive Program) will not be enough. It is important to mention that the consideration of the LCFS credits and an increased fee (e.g., 10 percent) on internal combustion engines significantly reduce the level of incentives required in the CPC, though the sales target for Classes 2b–3 and 7–8 are also lower than in the SPC. Additional incentives will be needed for public and private charging and fueling infrastructure.

Appendix I. Greenhouse Gas, $PM_{2.5}$, and Precursor Emissions Results

Emissions of multiple types are expected to decline as a result of the CLCPA. That said, the different policy cases lead to significantly different emissions outcomes. For example, in 2030, CPC carbon emissions reductions are about 30 percent below BAU, while SPC carbon reductions are estimated to be about 54 percent below the BAU. The 2030 percentage reductions below the BAU for methane are even more dramatic in the SPC (91 percent reduction) compared with the CPC (31 percent reduction).

$PM_{2.5}$ precursors are also significantly affected by the different policy cases. The CPC creates estimated reductions below the BAU of 25 percent for SO_2, 18 percent for NO_X, and 42 percent for direct $PM_{2.5}$; the corresponding reductions under the SPC are 52 percent, 32 percent, and 75 percent. Table I1 lists statewide 2030 emissions for the three sectors we model under each case.

Table I1. New York Emissions Estimates, 2030, by Case and Sector

		BAU 2030	CPC 2030	CPC percentage reduction from BAU	SPC 2030	SPC percentage reduction from BAU
Electric power						
GHGs						
CO_2	**$MMTCO_2e$**	15.70	5.10	–68%	3.20	–80%
Methane	**$MMTCO_2e$***	10.08	3.36	–67%	1.68	–83%
$PM_{2.5}$ and precursors						
SO_2	**MT**	1,190.00	858.00	–28%	525.00	–56%
NO_X	**MT**	6,930.00	5,094.00	–26%	3,573.00	–48%
$PM_{2.5}$ (direct)	**MT**	1,423.00	554.00	–61%	280.00	–80%
Residential buildings						
GHGs						
CO_2	**$MMTCO_2e$**	36.60	22.20	–39%	3.10	–92%
Methane	**$MMTCO_2e$**	23.52	16.80	–29%	0.00	–100%

		BAU 2030	CPC 2030	CPC percentage reduction from BAU	SPC 2030	SPC percentage reduction from BAU
$PM_{2.5}$ and precursors						
SO_2	**MT**	181.00	109.00	–40%	16.00	–91%
NO_x	**MT**	2,883.00	1,598.00	–45%	286.00	–90%
$PM_{2.5}$ (direct)	**MT**	2,140.00	1,298.00	–39%	185.00	–91%
On-road transportation						
GHGs						
CO_2	**$MMTCO_2e$ (LDV)**	30.80	28.80	–6%	27.00	–12%
	$MMTCO_2e$ (MHDV)	12.90	10.90	–16%	10.60	–18%
Methane	**$MMTCO_2e$ (LDV)**	0.00**	0.00**	—	0.00**	—
	$MMTCO_2e$ (MHDV)	1.85	1.51	–18%	1.43	–23%
$PM_{2.5}$ and precursors						
SO_2	**MT (LDV)**	236.70	227.30	–4%	218.10	–8%
	MT (MHDV)	42.00	35.80	–15%	34.60	–18%
NO_x	**MT (LDV)**	757.80	732.90	–3%	711.00	–6%
	MT (MHDV)	18,000.00	16,000.00	–11%	15,000.00	–17%
$PM_{2.5}$ (direct)	**MT (LDV)**	111.10	108.20	–3%	104.60	–6%
	MT (MHDV)	542.70	496.90	–8%	487.60	–10%
Total* **						
GHGs						
CO_2	**$MMTCO_2e$**	96.00	67.00	–30%	43.90	–54%
Methane	**$MMTCO_2e$**	35.45	21.67	–39%	3.11	–91%

		BAU 2030	CPC 2030	CPC percentage reduction from BAU	SPC 2030	SPC percentage reduction from BAU
$PM_{2.5}$ and precursors						
SO_2	**MT**	1,649.70	1,230.10	–25%	793.70	–52%
NO_X	**MT**	28,570.80	23,424.90	–18%	19,570.00	–32%
$PM_{2.5}$ (direct)	**MT**	4,216.80	2,457.10	–42%	1,057.20	–75%

* In this document, we assign each ton of methane a CO_2 equivalent of 85 (except where otherwise noted). This is approximately seven times as large as the methane CO_2 equivalent of 12.9 implied by the US Environmental Protection Agency's new draft guidance (2022) on the social cost of greenhouse gases. That new draft guidance is based on extensive research (e.g., Carleton and Greenstone 2022; Rennert et al. 2022) guided by an expert panel convened by the National Academies of Sciences, Engineering, and Medicine (2017). This difference might be partially offset by the fact that recent studies focusing on small parts of the country suggest that natural gas methane leakage rates might be considerably larger than the national estimates that we and other modelers use (Chen et al. 2022; Lenox 2013). If so, those high leakage rates might persist through 2030.

** These upstream values appear as zero because of rounding; we include upstream methane from light-duty vehicles in our analysis.

*** The totals are the sum of emissions across the three sectors we model, not New York economywide totals.

I.1. Power Sector Detail

Reduced natural gas generation in both policy cases relative to the BAU leads to significant electricity sector emissions reductions in 2030. CPC policies reduce New York power plant NO_X and SO_2 emissions by smaller proportions than the other emission types because waste–fueled generation accounts for large portions of New York power plants' NO_X and SO_2 emissions, and the CPC policies do not appreciably change waste–fueled generation. Even in the baseline scenario results, waste-fueled generation accounts for more than half of New York power plants' NO_X and SO_2 emissions despite producing less than 10 percent generation as natural gas. The reduction of waste-fueled generation in the SPC is a significant contributor to the emissions reductions in that scenario.

Of all the emissions types in Table I1, $PM_{2.5}$ tends to have the most localized effects. Most harm from NO_X and SO_2 is from their formation of ozone (NO_X only) and particulate matter (NO_X and SO_2), but these "secondary" pollutants take time to form, so to a large extent they form miles (or hundreds of miles) downwind. The impact on their formation of $PM_{2.5}$ in New York State is covered by our air quality model.

I.2. Residential Buildings Sector Detail

Similarly, in the residential building sector, both GHGs and local air pollutants would decline significantly under all future scenarios because of reductions in fossil fuel (natural gas and diesel) use for heating. SPC reductions in both GHGs and local air pollutants are more than double those of the CPC (with 90–100 percent reductions from the BAU across the various emissions types).

These emissions changes are the result of reductions in the use of natural gas and heating oil (diesel), which are the result of different rates of uptake of electric heat pumps (see above). In the CPC, about half of New York households continue to use natural gas and diesel for heating, while in the SPC, more than 90 percent of households use heat pumps.

GHG emissions are driven by the extent of natural gas consumption. Methane emissions include leaks both in the distribution system and in homes (from gas stoves) as well as the upstream leakages associated with delivered natural gas.

I.3. Transportation Sector Detail

I.3.1. Light-Duty Vehicle Fleet

For LDVs, the CPC reduces CO_2 emissions by 6 percent and SPC by 12 percent below the BAU—the same as the fuel consumption reductions reported above. Methane (from incomplete combustion and upstream fugitive emissions associated with gasoline production and distribution) accounts for a trivial share of LDV GHG emissions. Consequently, GHG emissions are proportional to the carbon content of fuel and the fuel consumption that was reported above. Since the carbon content of fuel does not vary across the BAU and policy cases,[9] the GHG reductions are proportional to the fuel consumption reductions.

Compared with the BAU, the CPC and SPC reduce direct $PM_{2.5}$, NO_x, and SO_2 emissions by small amounts (3 to 8 percent across the two cases). The SPC does reduce emissions by about double the CPC, although again it is a small amount (from 4 percent in the CPC to 8 percent in the SPC for SO_2, for example; see Table 7 for more detail). The main policy driving this difference is the ZEV standards, since EVs do not emit these pollutants directly when running on electricity (the power sector modeling accounts for emissions caused by battery charging). The SPC achieves greater emissions reductions than the CPC because of the additional EVs, and to a lesser extent because of the copollutant taxes.

I.3.2. Medium- and Heavy-Duty Vehicle Fleet

For MHDVs, the CPC reduces CO_2 emissions by 16 percent and the SPC by 18 percent below the BAU (there are similar reductions in methane; see Table I1), primarily resulting from the penetration of ZEVs, with the SPC having a slightly larger share of ZEVs by 2030. Compared with the BAU, the CPC achieves a further reduction of 15 percent for SO_2, 11 percent for NO_x, and 8 percent for direct $PM_{2.5}$; the SPC reduces these emissions by 18, 17, and 10 percent, respectively.

9 The CPC includes a LCFS. However, by 2030 there is no change to the carbon content of gasoline, the primary fuel consumed by LDVs (the LCFS does change the carbon content of diesel fuel).

Appendix J. Location of Emissions Changes

Emissions changes are generally concentrated in populous areas, particularly for vehicles and residential sectors. Beyond population density, certain policies may affect certain geographies. For example, policies that are thoroughly means-tested may lead to greater emissions reductions in low-income areas than what is observed in the BAU. This section covers details for each sector about where emissions changes take place, to the greatest level of spatial detail possible. For simplicity of presentation, we restrict our discussions to direct emissions of $PM_{2.5}$, even though the models predict changes in NO_X, SO_2, and VOCs (and other pollutants). We focus on direct $PM_{2.5}$ emissions because they have the greatest impact on local air quality. The extent to which other pollutants combine to form secondary $PM_{2.5}$ is covered in the Air Quality Results section.

J.1. Electricity Sector

This study focuses on emissions changes in New York State. However, some models, including the electricity sector modeling, also calculate the effects of the policy differences between the CPC and SPC on power plant emissions outside New York. "Emissions leakage" is a consequence of some emissions reduction policies, including policies applied to the electricity sector. Emissions leakage occurs when emissions increase outside the state or country where the policy is adopted as a result of the policy. For example, an emissions price in one state can cause an increase in other states as production moves to where it is not subject to an emissions price.

However, the policies in SPC cause the opposite of emissions leakage: they cause power plant emissions in other states to decrease. They reduce non–New York electricity sector CO_2 emissions by 600,000 short tons, or by 28 percent as much as they reduce New York electricity sector CO_2 emissions. They reduce non–New York electricity sector SO_2 emissions by 3.6 million pounds, or nearly five times as much as they reduce New York electricity sector SO_2 emissions. And they reduce non–New York electricity sector NO_x emissions by 2.6 million pounds, or by 80 percent as much as they reduce NY electricity sector NO_x emissions.

This study is not the first to find that New York's electricity sector emissions reduction policies would reduce emissions outside the state as well (Shawhan et al. 2019), although this effect is a function of the type of policy. Again, relative to the CPC, the SPC has considerably higher emissions prices (accompanied by a concomitantly higher electricity border carbon adjustment), fewer New York nuclear generators, fewer fossil fuel peaker generators, and no new fossil fuel generators. These policies reduce emissions outside the state for two reasons. First, they increase New York's reliance on solar and wind generation, which in turn causes New York's generation and wholesale electricity prices to vary more from hour to hour across the year, even outside New York. This higher electricity price variability outside New York favors natural gas–fueled generators over coal–fueled generators. Second, the effects just described increase dispatchable, fossil fuel generation and generation capacity near New York, in New Jersey. That in turn reduces the need for dispatchable, fossil fuel capacity and generation in the next state to the west, Pennsylvania (see Figure 3). New Jersey does not have coal-fueled generators, but Pennsylvania does, so the shift from Pennsylvania to New Jersey reduces total emissions.

Figure J1 shows the location of estimated electricity $PM_{2.5}$ emissions changes in New York and surrounding states, under various policy scenarios. For the electricity sector, we include estimates for adjacent states for two reasons: (1) New York policy has a greater effect on out-of-state emissions in the electricity sector than in other sectors; and (2) electricity emissions get dispersed over a broader geographic area than are emissions from the other sectors we model because of the tall smokestacks at power plants. Given this, New York electricity emissions changes would affect air quality both in New York and in other states and Canadian provinces, and vice versa (depending on prevailing wind directions).

Figure J1. Direct $PM_{2.5}$ Emissions Differences, by Power Generator, 2030

Figure J1A. Change in Direct $PM_{2.5}$ Emissions, BAU vs. SPC

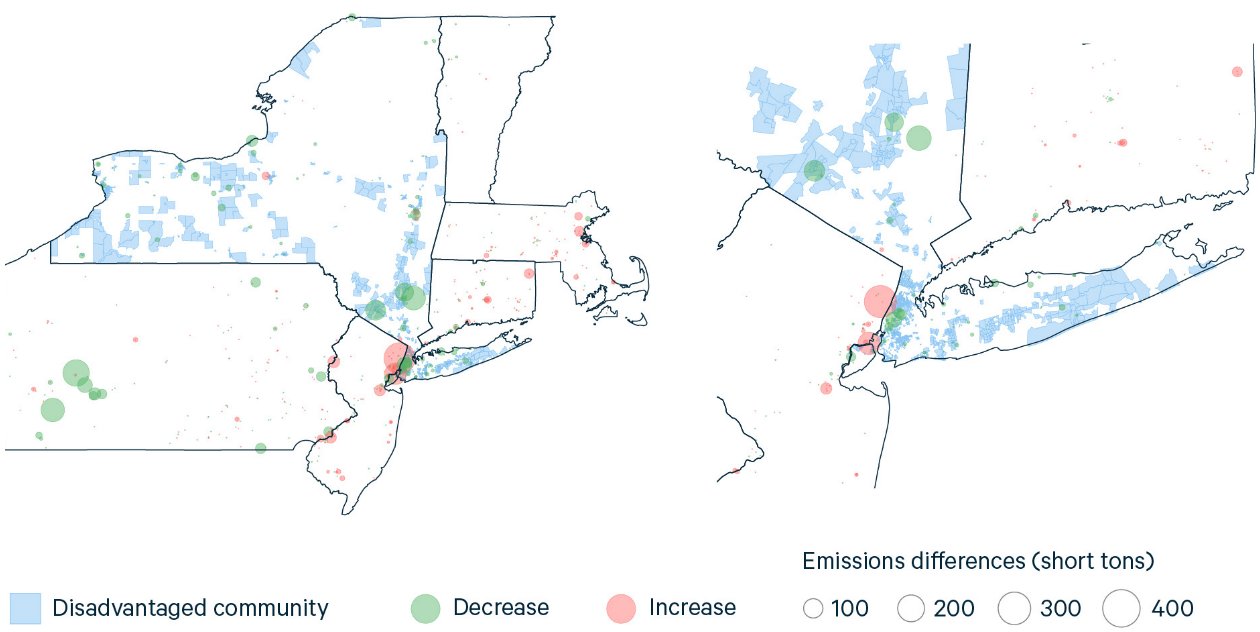


Figure J1B. Change in Direct $PM_{2.5}$ Emissions, BAU vs. CPC

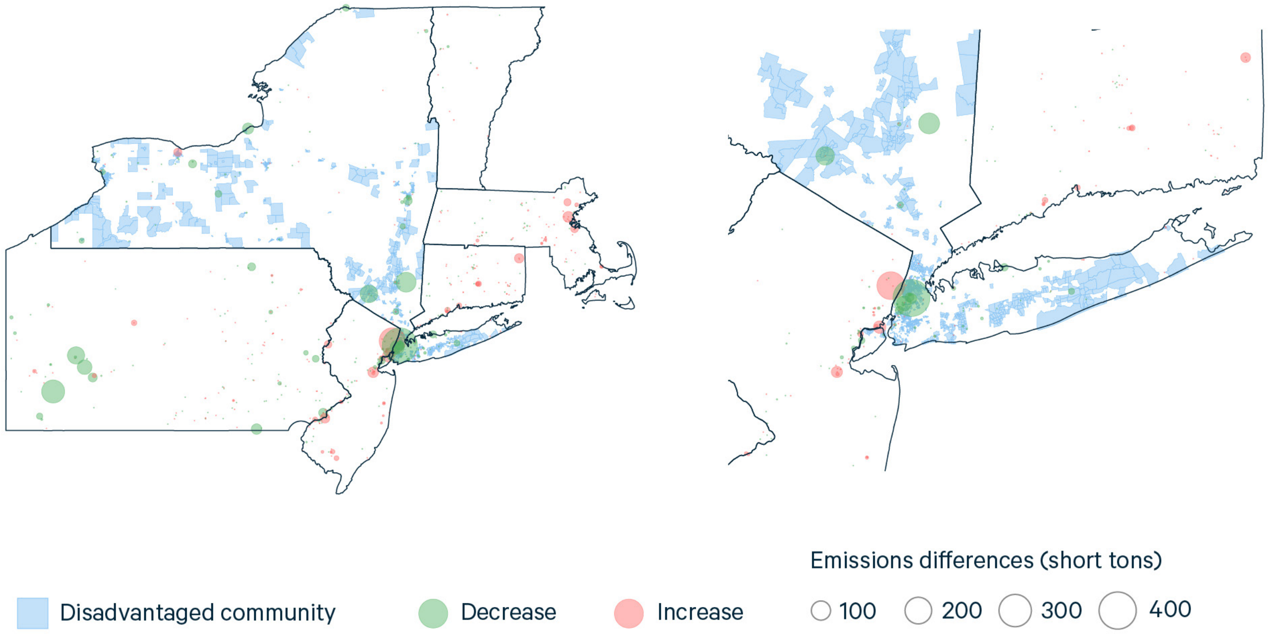


Figure J1C. Change in Direct $PM_{2.5}$ Emissions, CPC vs. SPC

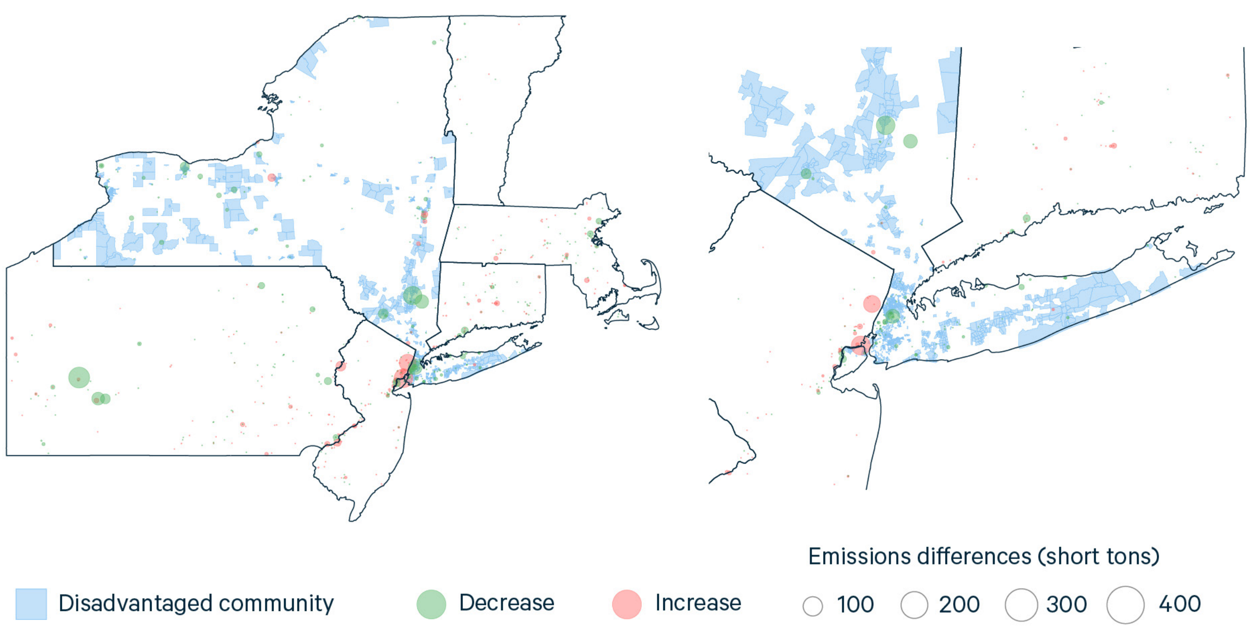


Figure J1 shows the power generating unit emissions changes in New York, New Jersey, Pennsylvania, Ohio, Connecticut, Massachusetts, and Vermont as a result of the differences between the policy cases. A green dot means emissions are lower in the policy case than in the BAU; a red dot means emissions are higher. The larger the dot, the greater the changes in emissions.

Just comparing the number of green and red dots, we can see that although most power-generating units in New York State decrease emissions (green dots) in both policy cases relative to BAU, the CPC results in a larger number of power-generating units that increase emissions (red dots)—only seven of the 348 generating units increase emissions in the SPC, compared with 64 in the CPC.[10]

Key Findings for Figure J1

- Although most of the power-generating units in New York decrease their emissions in both policy cases relative to the BAU (the green dots), the CPC results in a larger number of power-generating units that increase emissions (the red dots).
- In both policy cases, the largest decreases are at generating units close to or in New York City.
- In both policy cases, emissions increase and decrease at many generating units outside the state. Some of the largest increases (e.g., in New Jersey) occur at generating units that are close to and upwind of New York City. The largest out-of-state decreases occur at Pennsylvania coal generating units.
- Compared with the CPC, the SPC produces lower emissions at nearly every New York generating unit and also leads to greater out-of-state reductions (Figure J1C).

Emissions increases at some generating units allow greater emissions reductions at other units. One of the effects of emissions prices and caps is to shift generation from generating units with higher per kWh emission rates to generating units with lower per kWh emission rates. As a result, the generating units that are used more as a result of emissions prices (or higher emissions prices) tend to have low per kWh emissions rates.

Examining the size of the dots, we find that in both policy cases, the largest decreases in emissions are at power-generating units close to or in New York City. The concentration of emissions reductions in southeastern New York is beneficial for public health, since that is the most densely populated part of the state. New York City is also upwind of densely populated Connecticut and Rhode Island as well as the Boston metropolitan area. That further increases the benefits of emissions reductions in the New York City area.

10 Since there can be more than one generating unit at a given site, there may be emissions increases at fewer than seven and 64 sites. This is partially because some of the units with emissions increases may be adjacent to each other, and partially because a unit with an emissions increase may be next to one or more units with a larger emissions decrease.

Looking at the dots outside New York State, we see that in both policy cases, emissions both increase and decrease at many power-generating units outside the state. The largest increases are at generating units close to and upwind of New York City, and the largest decreases occur at Pennsylvania coal generating units that are also upwind of the city but farther away. Note that, as explained above, the only differences between the cases are New York policies and the EV sales mandates that several states plan to adopt together. As a result, any changes in emissions in other states are the result of New York policy and the collective action on ZEV mandates.

Table J1 shows the total $PM_{2.5}$ emissions increases and decreases in DACs and within a 10km buffer of DACs. For both cases, less than 6 percent of the $PM_{2.5}$ emissions increases within the 10km buffer zones originate from New York sources.

Finally ,in Figure J1C, the dots represent differences between SPC and CPC emissions. We see that for nearly every New York generating unit, emissions are lower for the SPC than the CPC. Only 14 of 348 generating units in the state have higher predicted $PM_{2.5}$ emissions in the SPC than the CPC. This striking result occurs because of the strict regulation on new fossil fuel generation in the SPC, as well as the higher price on carbon and copollutants.

Table J1. $PM_{2.5}$ Emissions Effects and New York DACs, SPC vs. CPC, 2030

	SPC	CPC
Emissions decreases in short tons (number of electricity-generating units)		
Direct $PM_{2.5}$ emissions decreases in DACs	–312.98 (126)	–166.63 (105)
Direct $PM_{2.5}$ emissions decreases within 10 km of DACs (NYS generators only)	–1154.67 (283)	–848.77 (231)
Direct $PM_{2.5}$ emissions decreases within 10 km of DACs (all states' generators)	–1156.05 (322)	–853.23 (270)
Emissions increases in short tons (number of electricity-generating units)		
Direct $PM_{2.5}$ emissions increases in DACs	11.71 (3)	16.34 (24)
Direct $PM_{2.5}$ emissions increases within 10 km of DACs (NYS generators only)	27.34 (5)	16.34 (57)
Direct $PM_{2.5}$ emissions increases within 10 km of DACs (all states' generators)	472.56 (28)	284.74 (80)

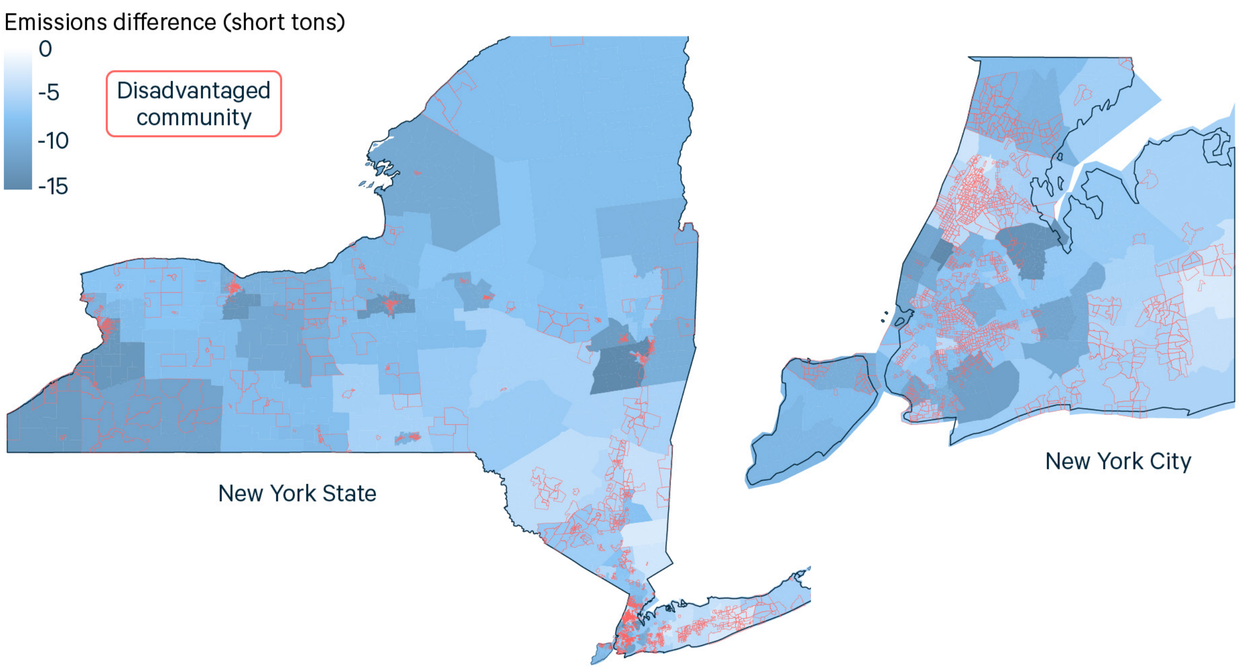
J.2. Residential Buildings Sector

Direct $PM_{2.5}$ emissions from residential heating are spatially modeled by public use microdata area.[11] In New York, PUMAs tend to be similar in size to counties, but in some areas—particularly around the densely populated metropolitan areas—PUMAs are smaller (more granular) than counties. Given the spatial scale, there is limited ability to derive direct $PM_{2.5}$ emissions estimates for the residential sector at the census tract level.

That said, we are able to observe broader trends that provide useful insights about local pollution exposure. The location of residential emissions has greater nexus with the health of colocated communities (compared with electricity generation) because these emissions tend to occur closer to the level where people are living (although some residential high-rise buildings may be a slight exception).

Our modeling shows that direct $PM_{2.5}$ emissions from residential heating decline in all New York PUMAs, under both the CPC and the SPC compared with the BAU. In the SPC, emissions reductions from the BAU are roughly uniform across the state. In the CPC, the eastern counties have relatively higher percentage reductions from the BAU compared with other counties (not shown).

Figure J2. Residential Home Heating Direct $PM_{2.5}$ Emissions from CPC to SPC (2030)



11 PUMAs are US Census Bureau–defined geographic delineation of population containing at least 100,000 people. For more information, see **https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html**.

Figure J2 compares SPC with CPC residential $PM_{2.5}$ results, by PUMA. Darker colors indicate greater emissions reductions. Note the modest change in direct $PM_{2.5}$ emissions in New York City relative to other parts of the state. This result is caused by the relatively high penetration of heat pumps in that region in the CPC, implying that there are few additional opportunities for heat pump penetration even with the larger subsidies in the SPC. In contrast, the generous subsidies for heat pumps in the SPC raise heat pump adoption rates upstate, where adoption in the CPC was relatively low.

Key Findings for Figure J2

- $PM_{2.5}$ emissions from residential home heating are consistently lower in the SPC than in the CPC.
- Because the geographic unit for modeling purposes is the PUMA, high-density areas do not necessarily see greater absolute reductions in emissions than low-density areas.
- The largest emissions differences between the CPC and SPC are upstate, where heat pump penetration is low until large subsidies are provided in the SPC.

J.3. Transportation Sector

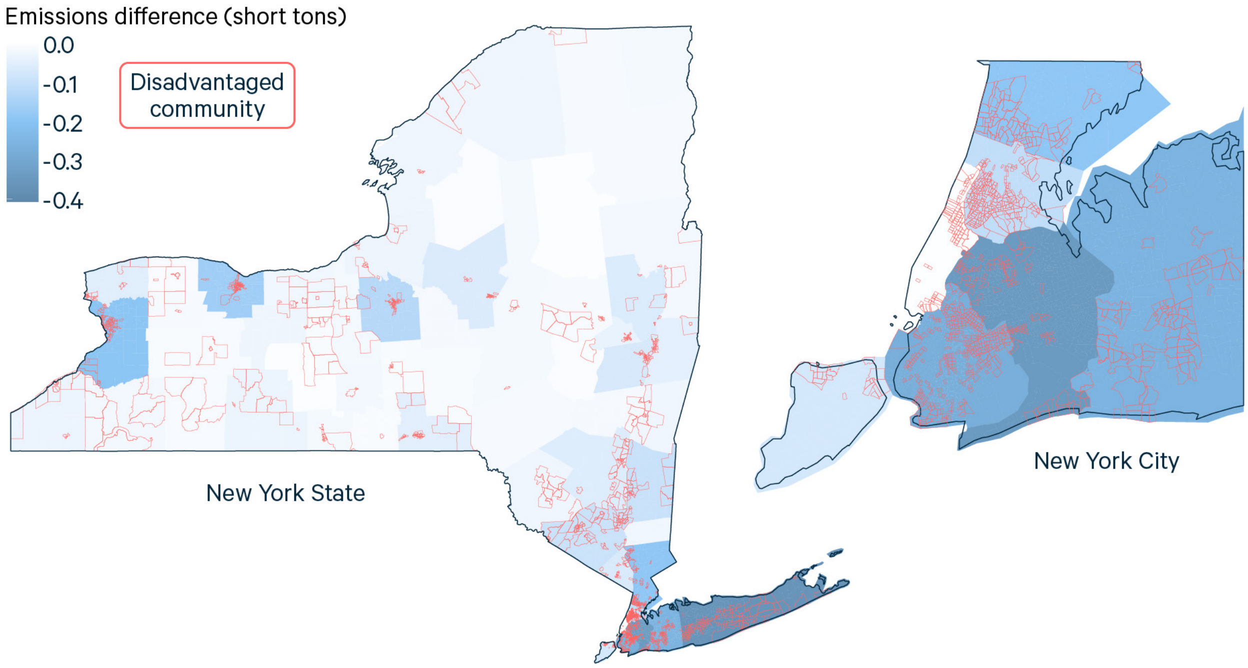
As noted above, we use two models to estimate emissions from light-duty vehicles and medium- and heavy-duty vehicles. Results are reported for LDVs and MHDVs. As with residential emissions, the location of transportation emissions (both LDV and MHDV) has significant nexus with the health of colocated communities (compared with electricity generation) because these emissions largely occur at the ground level, where people are living and breathing.

J.3.1. Light-Duty Vehicle Fleet

The light-duty vehicle modeling is performed at the county level, which is slightly less granular than PUMAs. There is therefore limited ability to assess unique impacts in each census tract (the level at which DACs are designated). That said, we are able to assess broader trends. Unlike the electricity sector, where emissions increase in some locations as a result of SPC and CPC policies, all counties in New York experience reductions in LDV $PM_{2.5}$ relative to the BAU as a result of the SPC and CPC policies.

We can also look at differences in emissions across the two policy scenarios. In Figure J3, the darker the color, the larger the emissions reductions for the SPC relative to the CPC. Not surprisingly, the darkest areas are in cities, where vehicles and their emissions are concentrated. And again, not surprisingly, the differences in SPC versus CPC emissions reductions are greatest in New York City.

Figure J3. Light-Duty Vehicle Direct $PM_{2.5}$ Emissions, 2030



Key Findings for Figure J3

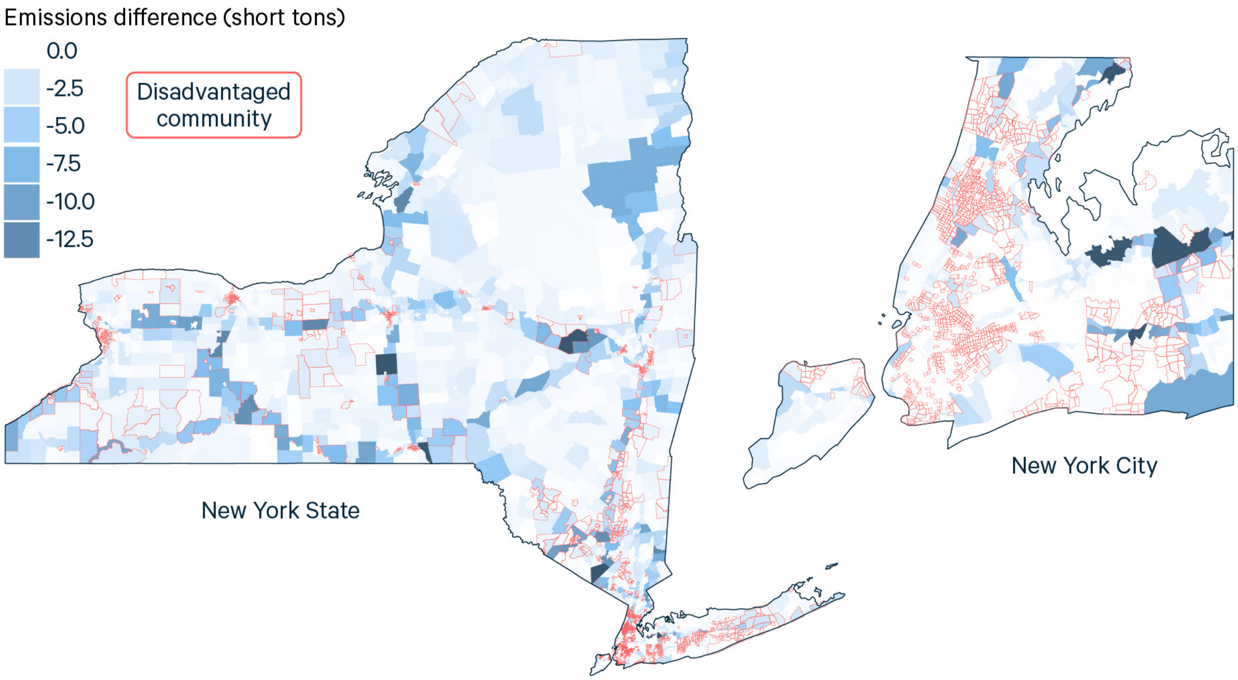
- $PM_{2.5}$ emissions from light-duty vehicles are consistently lower in the SPC, relative to the CPC.
- The areas of greatest improvement in the SPC have the highest population density, particularly the New York City area.
- The extent to which DACs experience increased benefits of $PM_{2.5}$ reductions is directly related to the concentration of DACs in urban areas.

J.3.2. Medium- and Heavy-Duty Vehicle Fleet

For the MHDV fleet, emissions are estimated for each major road segment ("network link") along the primary and secondary highway system in New York State. The length or geographic scope of individual network links varies. In this analysis of the location of emissions changes, $PM_{2.5}$ is displayed by census tract (by grouping network links within a given census tract). Most emissions concentrate in denser regions, especially the New York City metropolitan area.

Figure J4 compares direct $PM_{2.5}$ emissions in the CPC and SPC. The difference in emissions ranges between 0.4 and 4 percent reduction (with dark blue indicating a larger reduction). The SPC (mostly because of its higher ZEV sales requirement and faster sales ramp-up) generates a larger reduction across the state. Except for New York City, the map shows that these increases happen on intercity infrastructure. One of the main reasons for these results is the fact that the share of long-haul heavy-duty combination vehicles is larger on these network links; this is the segment that will experience a significantly lower penetration of ZEVs by 2030, and because of activity growth, it is thus not able to mitigate the emissions increase.

Figure J4. Medium- and Heavy-Duty Vehicle Direct $PM_{2.5}$ Emissions, 2030



Key Findings for Figure J4

- $PM_{2.5}$ emissions from medium- and heavy-duty vehicles are consistently lower by 1 to 4 percent in the SPC, relative to the CPC.
- The areas of greatest improvement in the SPC have the highest congestion, including major highways and New York City.
- Tracts with the greatest difference in emissions appear to be the non-DAC tracts in the New York City area.

Table J2 goes into more detail about emissions differences between the two policy cases by specific census tract group. We go beyond the DAC and non-DAC designations to identify communities that experience the greatest improvements from implementing the SPC over the CPC. We find that average $PM_{2.5}$ emissions differences between the two policy cases are consistently in favor of the SPC but are relatively modest, averaging around 1.5 percent. In terms of absolute $PM_{2.5}$ emissions differences, we find that non-DAC tracts experience greater improvement under the SPC. This is likely due to the fact that DACs as defined here do not take up the majority of space along major highways, where pollution reductions from medium- and heavy-duty vehicles are concentrated.

Table J2. Direct $PM_{2.5}$ EMissions Difference by Tract Type, CPC vs. SPC, 2030

Community type	Average $PM_{2.5}$ emissions Difference from CPC to SPC (short tons)	Average $PM_{2.5}$ emissions difference from CPC to SPC (percentage)
All tracts	–.003	–1.53%
Non–DAC tracts (65% of tracts)	–.004	–1.56%
DAC tracts (35% of tracts)	–.001	–1.48%
High exposure (top 10%)	–.003	–1.55%
High vulnerability (top 10%)	–.001	–1.47%
High elderly population (top 10%)	–.003	–1.48%
High historical $PM_{2.5}$ (top 10%)	–.001	–1.54%

Appendix K. Additional Results Context: Nonlinearities and Excluded Emissions

K.1. Nonlinearities

The relationship between NO_x and SO_2 and the creation of $PM_{2.5}$ is nonlinear, sometimes highly so. For our case, this relationship means that under the "wrong" conditions, reductions in NO_x emissions can lead to very small or even zero reductions in $PM_{2.5}$ concentrations and, in even more specialized conditions, increase $PM_{2.5}$ emissions. Again, we cannot precisely model this relationship for this project, but our investigation of the composition of $PM_{2.5}$ concentrations do reveal some nonlinearities.

Although reducing SO_2 and NO_x emissions indeed reduces SO_4^{2-}, NO_3^-, and associated NH_4^+, we see some increases in total secondary organic aerosol (SOA), showing the nonlinearity in inorganic aerosol and SOA formation. Lower SO_2 and NO_x would free more OH available for the oxidation of volatile organic compounds (VOCs), leading to more SOA formation.

As expected, SO_2 and NO_x decrease, but NH_3 increases because of less NH_4^+ formation (because of less SO_4^{2-} and NO_3^- to neutralize NH_4^+). Although both NO_x and VOCs decrease, the decrease in the former is greater, leading to increases in O_3 (which shows disbenefit of NO_x reduction), because O_3 is VOC-limited in New York State and O_3 titration is weaker because of lower NO_x emissions. In the VOC-limited regime, reducing NO_x would increase O_3 rather than decreasing it, leading to increases in $PM_{2.5}$ when the reduction in NO_3- is compensated by increases in other $PM_{2.5}$ composition, such as SOA.

This confirms that the nonlinearity pollution formation effect partly explains the smaller-than-expected reduction in $PM_{2.5}$ when the SPC is compared with the BAU. Effective reduction in $PM_{2.5}$ requires understanding of $PM_{2.5}$-precursor relations and $PM_{2.5}$ formation chemical regime, since $PM_{2.5}$ formation may be limited by any of the precursors (e.g., NO_x or VOCs or NH_3 or SO_2).

K.2. Modeling Choices

We model emissions changes in only a few of the sectors contributing to $PM_{2.5}$ concentrations. Beyond power plants, LDV, MHDV, ports, and home heating, the direct $PM_{2.5}$ and precursor emissions also come from industry, aviation, shipping (other than ports), commercial heating, waste management, and more. Agricultural emissions are another important sector, particularly for ammonia, which combines with SO_2 and with NO_x to form sulfate and nitrate aerosols, which count as $PM_{2.5}$ concentrations.

We model only 2030 emissions reductions. Many of the policies in the SPC and CPC take time to be fully implemented or to fully realize their emissions-reducing potential. An example is transport policies that affect only new-car purchases. Yearly turnover of the vehicle stock is only a fraction of that stock, so until the new-vehicle policies have been in effect for at least seven to 10 years, they will not make a huge dent in the transportation emissions.

We find that air emissions are already significantly reduced in the BAU case by 2030 compared with emissions in 2012, our baseline. This is partly for economic reasons and partly because of policy. The most prominent economic reason has to do with natural gas prices. During this almost 20-year period, coal plants continue to retire and are replaced by cheaper and cleaner natural gas generation, made possible by fracking, and by renewable generation, made possible by price declines and technology breakthroughs (themselves aided by tax credit policies).

Policies reducing $PM_{2.5}$ direct emissions and $PM_{2.5}$ concentration precursors have been a mainstay of federal air pollution policy since the Clean Air Act was passed in 1970. Since 2012 (our base year) there have been numerous policies to further reduce these types of emissions. In the auto and truck sectors, very tight emissions standards and the continual retirement of older, more polluting vehicles lead to significantly lower tailpipe emissions by 2030, even in the absence of additional policy. In the residential sector, the transition to natural gas furnaces in lieu of traditional oil furnaces significantly reduces $PM_{2.5}$ and SO_2 by 2030, even without additional policy. State-level policy, such as New York's decision to shut down peaker plants in high-density areas, also contributes. In our 2012 emissions inventory, the power sector emitted an estimated 39.3 ktons of SO_2, compared with an estimated 1.8 ktons in 2030 with no additional policy.

Table K1. Economy-Wide Emissions Changes in New York

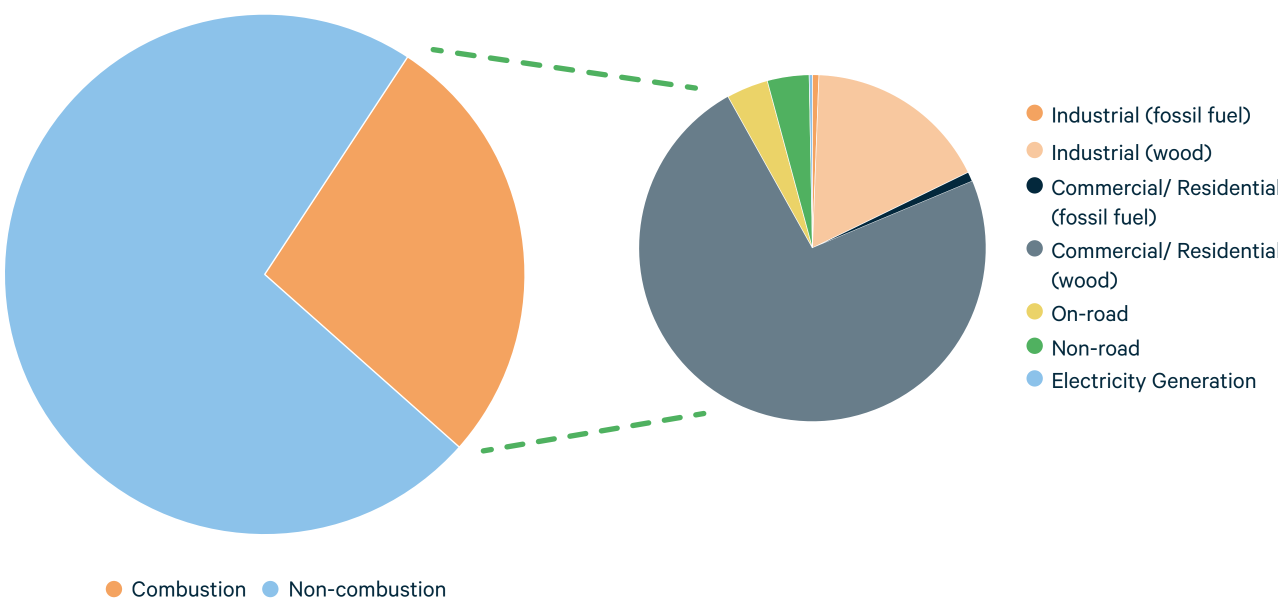
	Baseline (2012) to BAU 2030		BAU 2030 to SPC 2030	
Pollutant	Kt of pollutant	Percentage change	Kt of pollutant	Percentage change
CO	–722	–27%	–24	–1%
SO_2	–50	–35%	–5	–5%
NO_X	–123	–34%	–16	–7%
VOCs	–90	–17%	–1	~0%
$PM_{2.5}$	–10	–16%	–1	–2%
PM_{10}	0	0%	–2	0%

Because certain emissions changes are left out of our analysis, the actual percentage reduction in emissions becomes more misleading and difficult to interpret. Say that our modeling of emissions changes is capturing only half the relevant emissions inventory. As the other sectors are held equal, the share of emissions changes we cover by 2030 will be smaller than it was in 2012 (Table K1). For this reason we focus on absolute changes in economywide emissions and air pollution concentrations.

Our own air quality modeling is not suited to identifying the largest contributing sectors to $PM_{2.5}$ outside our modeled sectors. The Environmental Protection Agency's 2011 emissions inventory reveals that our modeled emissions changes cover approximately 50 percent of SO_2 emissions, 37 percent of $PM_{2.5}$ direct emissions, and 54 percent of NO_x emissions in 2011. Major contributors to emissions that we do not model include ambient dust, off-road vehicles, waste disposal, and industrial fuel combustion.

New York State's air quality analysis of the CLCPA impacts provides some helpful insights on future emissions (Energy and Environmental Economics 2022). It estimates that approximately 75 percent of the projected reference case $PM_{2.5}$ emissions are from "noncombustion sources," including dust or biogenic sources. Nearly all of the $PM_{2.5}$ emissions associated with combustion sources come from residential or industrial wood combustion, which we do not model. Figure K1 estimates the $PM_{2.5}$ emissions sources in 2025. Furthermore, the New York State analysis finds that many of the benefits associated with reduced power sector emissions are realized in 2040, which is beyond our modeling timeline.

Figure K1. New York Integration Analysis Sector-Level $PM_{2.5}$ Reference Case Emissions, 2025



Note: This data is available in Appendix G of the New York State integration analysis (E3 2022).

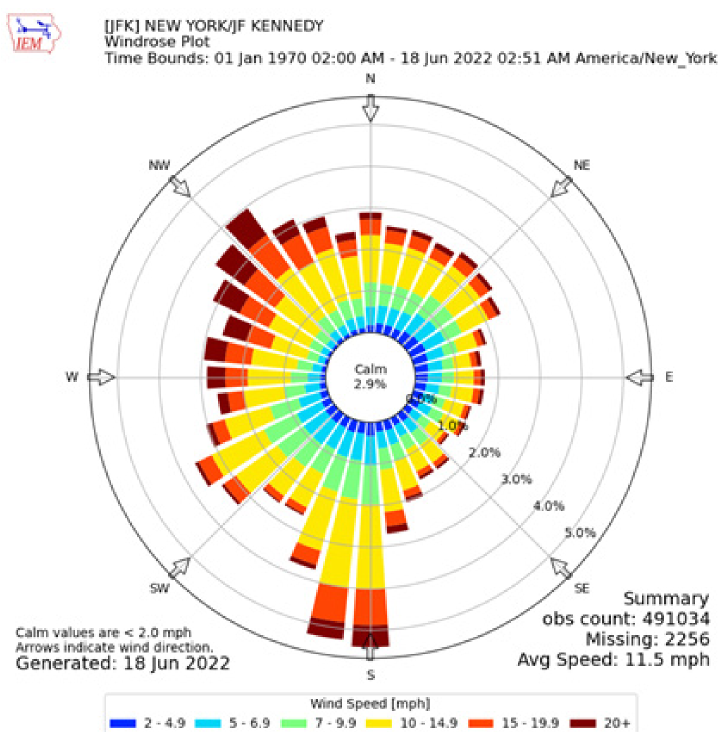
K.3. Traveling Air Pollution

Many factors contributing to $PM_{2.5}$ concentrations are beyond the ability of New York State policies to control. The largest factor might be termed background concentrations—the concentrations that do not have a cause in economic activity in the state. They are caused, for example, by fine dust picked up by the wind and by emissions from economic activity and natural causes in other states and Canada. Even emissions from China have shown up in the United States, so these emissions can travel long distances.

We can examine some of these traveling emissions through our power sector modeling. Whether chemically transformed or not, emissions move with the wind direction and speed. This means that emissions reductions upwind from a border with another state could improve air pollution in those states, but not necessarily in the emitting state, particularly when the emissions come from tall stacks, as in the power sector.

Figure K2 shows the wind “rose” (wind direction, frequency, and speed) for JFK airport. The winds from the south and northwest are the most frequent and strongest. This has two implications. At least some emissions from power plants along the eastern border are swept into Massachusetts and Connecticut, with emissions reductions benefiting those states. Second, emissions from power plants west and, most importantly, south of the border are swept into New York. This means emissions from Ohio, Pennsylvania, New Jersey, Delaware, and Maryland could all contribute to New York pollution in the summer. Although emissions reductions in those states benefit New York residents, energy generation and associated pollution increases in these bordering states can ameliorate $PM_{2.5}$ improvements in New York.

Figure K2. JFK Windrose



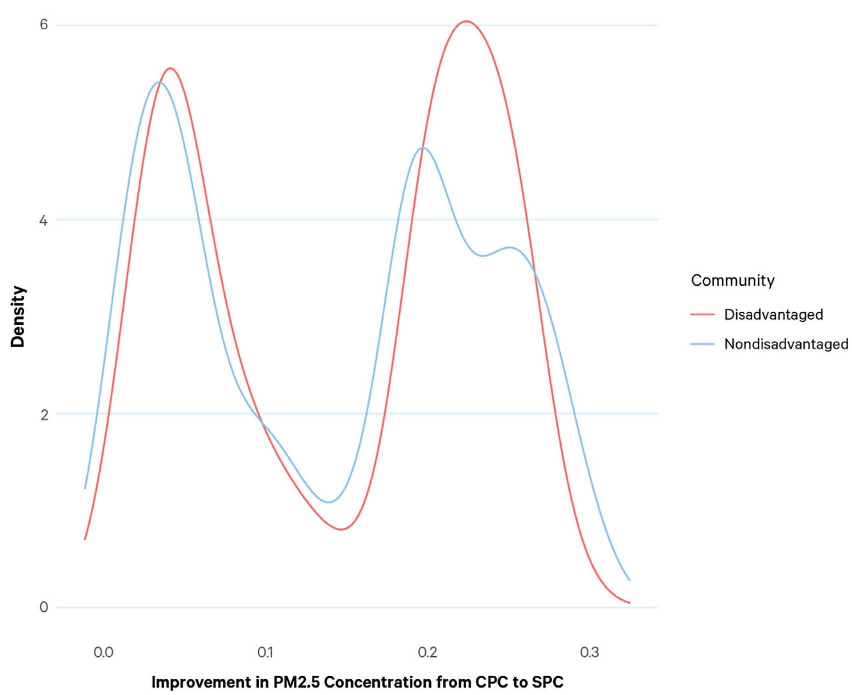
Given the resources available to this project we cannot precisely estimate how much of the benefits of NYS emissions reductions are being realized in NYS on net, but we can give a sense of the size of these emissions/concentrations cross-border flows. NYS power plants on the eastern border (See Figure 4) account for about 50-56 percent of total power sector emissions throughout the state (depending on the pollutant). And NYS power plant emissions are only between 3 and 9 percent of the emissions counting all the border states' power emissions. This indicates that some emissions improvements near the border of New York may be transported out of state, and some increased emissions in PA, OH, and NJ may be transported into the state.

Appendix L. Distribution of $PM_{2.5}$ Concentration Reductions by Scenario and DACs vs. Non-DACs

In the main text, we presented detailed maps (Figure 10) showing how $PM_{2.5}$ concentrations vary across the state for DACs and non-DACs associated with the two scenarios (CPC-BAU and SPC-BAU) and use the mean of the concentration reductions to quantitatively describe impacts across the scenarios for DACs and non-DACs. While the means are easy to interpret, they miss other features of the distribution of $PM_{2.5}$ concentrations changes across communities and scenarios. For instance, we could use the median of the various distributions, or various percentiles of the distributions. Rather than these limited measures, Figures L1 and L2 below simply show the entire distributions.

These distributions illustrate the frequency (or percentage) for which DAC (or non-DAC) communities experience a given concentration reduction in $PM_{2.5}$ as a result of the CPC scenario relative to BAU. In Figure L1, we depict two distributions, one for the disadvantaged communities (red) and the other the non-disadvantaged (blue). The frequency (the percentage of the DAC or the percentage of the non-DACs) is on the Y-axis and the concentration reductions in $PM_{2.5}$ from BAU to CPC is on the X-axis. Note that the X-axis legend shows a range of negative reductions from -0.05 μg/m³ (at the origin). Negative numbers represent increases in $PM_{2.5}$ concentrations as a result of a scenario. At the other end of the X-axis, the largest $PM_{2.5}$ concentration reduction experienced by any community for the BAU to CPC scenario is 0.10 μg/m³.

Figure L1. Distribution of $PM_{2.5}$ Concentration (μg/m³) Improvements from BAU to CPC

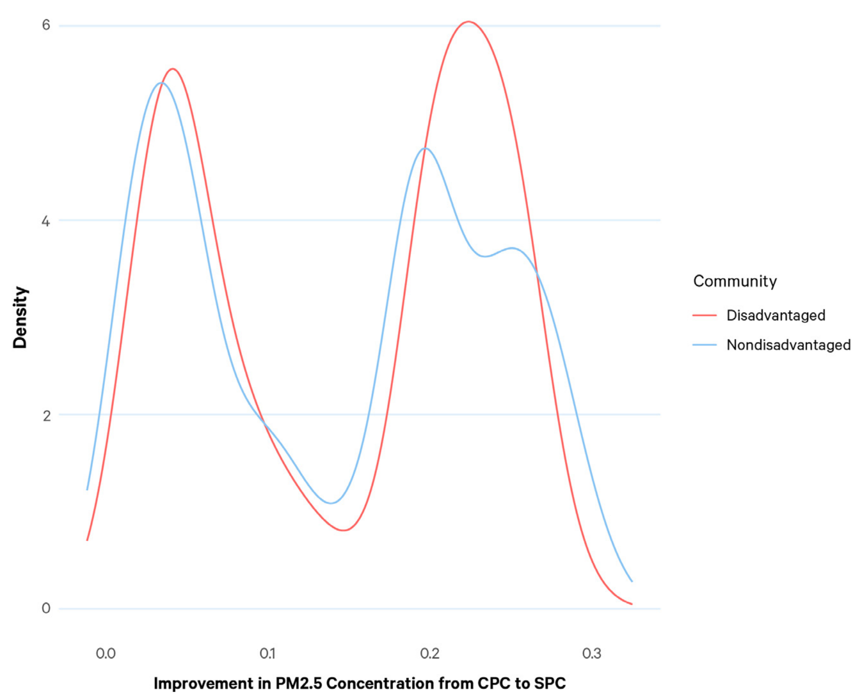


Turning to the red line for the DAC distribution, we see that most communities experience $PM_{2.5}$ reductions in the range of 0.02 to 0.05 µg/m^3 (the big hump in the red distribution). The non-DAC communities (blue line) are also experiencing reductions primarily in this range but there's also a hump representing a high percentage of non-DAC communities experiencing higher $PM_{2.5}$ reductions.

What we care most about is the difference in these two distributions for any given $PM_{2.5}$ concentrations. What we see is that the red line is lower than the blue line for PM increases. This shows that a greater percentage of non-DAC communities experience increases in pollution than the percentage of DAC communities. This is a good result for environmental justice. Of course, most communities experience reductions in $PM_{2.5}$ concentrations. Where the state scenario does well for DACs is where the big red hump is higher than the blue hump in the range of 0.02 to 0.05 µg/m^3. The big advantage to non-DAC communities is where the blue line is higher than the red line for the bigger $PM_{2.5}$ concentration reductions on the right-hand side of the figure.

Now let's turn to what happens with the stakeholder scenario. What is different about Figure L2 compared to L1? First, notice the scale on the X-axis. There are no communities experiencing $PM_{2.5}$ concentration increases and some communities experience reductions in $PM_{2.5}$ concentrations from BAU to SPC that are far larger than in the CPC scenario—a bit more than 0.4 µg/m^3. Thus, the SPC policies do more for both types of communities. Second, the shape of the distributions are different. Both are double-humped, with the humps about equal in size and shape for the DACs and the double humps for non-DACs looking similar to those in the state scenario.

Figure L2. Distribution of $PM_{2.5}$ Concentration (µg/m³) Improvements from BAU to SPC



These differences lead to the most important difference, which is that the red hump on the right side is so much higher than the blue hump (in the range of 0.2 to 0.3 µg/m^3. In this area a far higher percentage of DACs are experiencing these large $PM_{2.5}$ reductions compared to the percentage of non-DACs. Finally, as we saw for the state case, the very largest reductions in PM are experienced more frequently in the non-DAC communities, but the difference in frequency compared to DACs is not very large.

Figure L3 looks at the distribution of $PM_{2.5}$ concentration changes comparing the SPC to the CPC casers to make the above discussion graphically more explicit. Here we see very minor differences in the percentages of DAC and non-DAC communities experiencing $PM_{2.5}$ concentration reductions for the two scenarios. The exception is the relatively large $PM_{2.5}$ concentration reductions ranging from 0.20 to 0.27 µg/m^3, where a far higher percentage of DAC communities are represented compared to non-DAC communities for the SPC case.

Figure L3. Distribution of $PM_{2.5}$ Concentration (µg/m³) Improvements from CPC to SPC