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To cite this article: Eleanor M Hennessy *et al* 2024 *Environ. Res.: Infrastruct. Sustain.* **4** 035001

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ENVIRONMENTAL RESEARCH
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RECEIVED
1 December 2023

REVISED
14 May 2024

ACCEPTED FOR PUBLICATION
6 June 2024

PUBLISHED
8 July 2024

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PAPER

Pathways to zero emissions in California's heavy-duty transportation sector

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Keywords: transportation decarbonization, fleet turnover modeling, decarbonization pathways, health impacts, environmental justice, heavy-duty transport

Supplementary material for this article is available online

Abstract

California contributes 0.75% of global greenhouse gas (GHG) emissions and has a target of reaching economy-wide net zero emissions by 2045, requiring all sectors to rapidly reduce emissions. Nearly 8% of California's GHG emissions are from the heavy-duty transportation sector. In this work, we simulate decarbonization strategies for the heavy-duty vehicle (HDV) fleet using detailed fleet turnover and air quality models to track evolution of the fleet, GHG and criteria air pollutant emissions, and resulting air quality and health impacts across sociodemographic groups. We assess the effectiveness of two types of policies: zero emission vehicle sales mandates, and accelerated retirement policies. For policies including early retirements, we estimate the cost of early retirements and the cost-effectiveness of each policy. We find even a policy mandating all HDV sales to be zero emission vehicles by 2025 would not achieve fleetwide zero emissions by 2045. For California to achieve its goal of carbon neutrality, early retirement policies are needed. We find that a combination of early retirement policies and zero emission vehicle sales mandates could reduce cumulative CO_2 emissions by up to 64%. Furthermore, we find that decarbonization policies will significantly reduce air pollution-related mortality, and that Black, Latino, and low-income communities will benefit most. We find that policies targeting long-haul heavy-heavy duty trucks would have the greatest benefits and be most cost-effective.

1. Introduction

A rapid reduction in greenhouse gas (GHG) emissions is needed to mitigate global climate change. As the world's 5th largest economy, California contributes roughly 0.75% of global GHG emissions, and has ambitious climate targets including a goal of reaching economy-wide net zero GHG emissions by 2045 [1]. Transportation is the single largest contributor to GHG emissions in California, accounting for 38% of the state's total emissions. Of these, roughly a quarter are caused by the heavy-duty transport sector [2]. This amounts to 32 million metric tonnes (MTonnes) of CO_2 per year, or roughly the same annual emissions as New Zealand. To achieve zero emissions in the transportation sector, the state has primarily focused on selling new zero-emission vehicles (ZEVs). The Advanced Clean Cars II legislation requires that 100% of passenger vehicles and light trucks sold in the state be ZEVs by 2035, with interim sales targets along the way. The Advanced Clean Trucks (ACTs) regulation has similar, but less stringent sales targets for heavy-duty vehicles (HDVs), requiring 55% of Class 2b-3 vehicle sales, 75% of Class 4–8 vehicle sales, and 40% of Class 7–8 Tractor sales to be ZEVs by 2035 [3]. The Innovative Clean Transit (ICT) regulation requires public

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transit fleets to consist of only ZEVs by 2040 [4].

Other policies of relevance to our present work include the National Car Allowance Rebate System ('Cash for Clunkers') [5]; the Clean Cars for All program [6] at the state level; and the Carl Moyer On-Road Voucher Incentive Program [7]. All three programs provide incentives for retiring older, less efficient internal combustion engine (ICE) vehicles, but only the Carl Moyer program targets HDVs. All three programs allow for replacement of older vehicles with newer ICE vehicles. Li *et al* suggest the Cash for Clunkers program did not result in large emissions savings [8], and Naumov, Keith and Sterman suggest that emissions savings from these types of programs would be greater if vehicle replacements were limited to ZEVs [9].

In previous work, in other geographical and policy contexts, authors have studied the implications of similar policy instruments for the light-duty transportation sector [10, 11], but there has been limited work done on the heavy-duty sector [12]. Studies addressing the light-duty sector have focused on the representation of the stock and its turnover [9, 13–15]. Other authors, including Alarfaj *et al*, have studied the requirements for reaching a 100% ZEV passenger fleet in the United States by 2050, finding 100% of sales would need to be ZEV by 2020 [16]. Keith *et al* studied the implications of a repeal of the corporate average fuel economy (CAFE) Standards, showing that policy decisions have a lasting impact in the fleet due to slow turnover [14]. Others have explored additional options for decarbonization of passenger vehicle fleets, including various tax policies [17], light-weighting new vehicles [15], and reducing vehicle ownership and usage [18]. While there are limited studies assessing the implications of different policy instruments for the HDV sector, there have been numerous studies on technology options for HDV decarbonization. Some demonstrate the viability of HDV electrification [19–22], and others assess the use of hydrogen fuel cell HDVs [23–25]. Brown *et al* present various scenarios and policy options for achieving zero emissions in California's transportation sector (including both light-duty and heavy-duty vehicles), focusing on both adoption of electric vehicles and the use of zero carbon liquid fuels to achieve carbon neutrality in the heavy-duty sector [26].

In this work, we model the effectiveness of two policy instruments: ZEV sales mandates and accelerated retirements with different levels of stringency. We compare the effects of these policies to a business-as-usual (BAU) scenario aligned with projections by the state's primary regulator, the California Air Resources Board (CARB). For simplicity, we limit our analysis to replacing ICE vehicles with battery electric vehicles. We consider the tailpipe emissions from diesel and gasoline combustion, as well as the emissions associated with power generation required to charge the electric vehicles. We assume that the carbon intensity of California's grid decreases linearly to zero between 2019 and 2045 in accordance with the state's policies. Figure 1 shows an overview of our modeling approach.

We simulate a ZEV sales mandate for different onset years from 2025 to 2040. We assume that the ZEV mandate is such that by the onset year, all new vehicles sold will be ZEVs. Thus, for ZEV mandate year = 2025, for example, all new vehicle sales would be ZEVs from 2025 onwards, with the sales of ZEVs increasing linearly between 2019, our base year, and 2025. We simulate the effect of an early retirement policy with different onset years and for different vehicle ages (5 and 10 years old). For example, an early retirement policy with policy onset year 2025 and vehicle age 10 indicates that from 2025 onwards, all vehicles reaching age 10 or older would be retired from the fleet and replaced with ZEVs. While many retirement policies would reduce emissions to some degree, we focus on combinations of ZEV sales mandates and accelerated retirement policies that achieve the goal of zero emissions by 2045.

This work has the potential to directly inform climate policy in California as well as in other locations. Numerous states have adopted similar goals of carbon neutrality, including New York, Washington, and Louisiana with goals of net-zero GHG emissions by 2050; Maryland and Virginia with targets of net-zero GHG emissions by 2045; and Nevada with a goal of near-zero GHG emissions by 2050. Similar targets have been proposed in other countries as well. The European Union, for example, has a goal of carbon neutrality by 2050. While specific conditions will be different in each geographical context, transportation decarbonization will be a key component of most climate targets and accelerated retirement policies will likely be needed in other locations with large ICE vehicle fleets. The approach and findings presented in this study are relevant for governments at any level with a goal of decarbonizing the vehicle fleets within their jurisdictions.

2. Methodology

Figure 1 shows an overview of our modeling approach. We construct a detailed fleet turnover model disaggregated by vehicle age and fuel type and calculate the vehicle population, sales, and retirements in each year. In policy scenarios with accelerated retirements, early retirements are treated separately from natural retirements. In these scenarios, the second-hand vehicle price is used to estimate the cost of the early

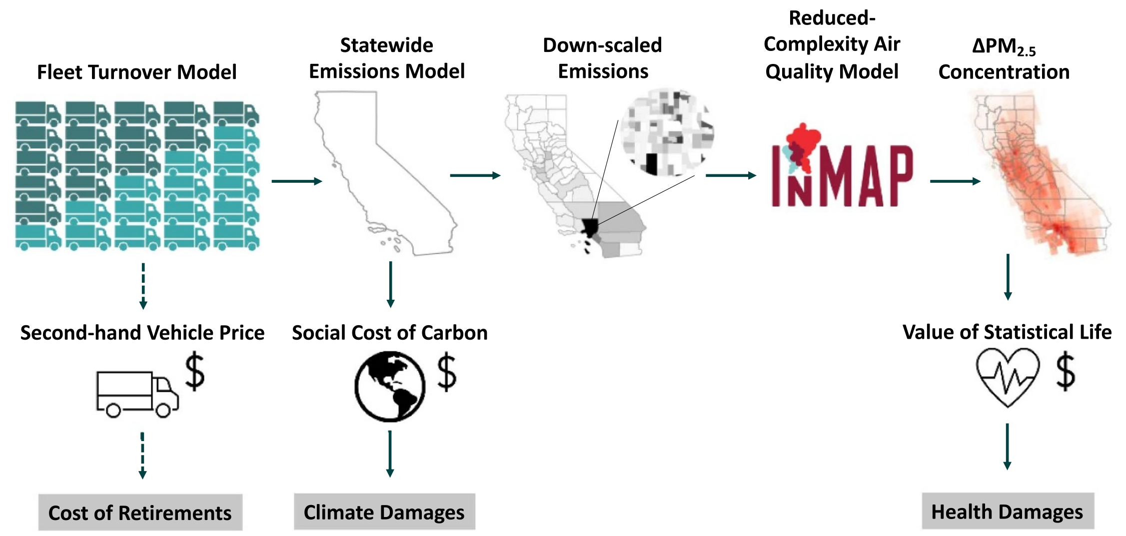

Figure 1. Modeling approach. A fleet turnover model is paired with an emissions model and reduced-complexity air quality model to determine CO_2 emissions and air quality impacts of different policy scenarios. CO_2 emissions are converted to climate damages using the social cost of carbon, and air quality impacts are used to estimate premature mortality and health damages, using the value of statistical life. Second-hand vehicle prices are used to estimate the cost of early retirements in some policy scenarios.

retirements. In all scenarios, statewide emissions of GHGs and criteria air pollutants are estimated based on age-specific fuel economy, vehicle miles traveled (VMT), and emissions factors from CARB's EMFAC database. Both tailpipe emissions and emissions related to electricity generation are included. Climate damages are estimated using the social cost of carbon (SCC). Criteria air pollutant emissions are downscaled to the block group level using county-level distribution of vehicle miles traveled and block group-level vehicle population distribution as of 2019. InMAP, a reduced complexity air quality model is used to determine the associated change in annual average $PM_{2.5}$ concentration and resulting mortality. Health damages are calculated using the value of statistical life (VOSL) from the US EPA.

2.1. Data sources

- Our main data source is CARB's EMFAC online emissions and fleet database [27]. The emissions component of the tool includes historical data and future projections of vehicle stock, VMT, and both GHG and criteria air pollutant emissions. We extract statewide data from 2019 to 2045, broken down by vehicle type, chassis model year, and fuel type. The fleet database contains historical data on vehicle fleet composition. We extract data on the number of vehicles of each type, chassis model year, and fuel type by census block group for 2019. Hereafter, 'model year' refers to chassis model year.
- We take current CO_2 emissions factors for electricity used for transportation from CARB's low carbon fuel standard [28].
- We use demographic data from the 2019 5 yr Estimates from the American Community Survey [29] at the census tract level to conduct our demographic analysis.
- We use consumption-based $PM_{2.5}$ concentration increase factors from Hennessy *et al* [30] to perform our air quality analysis for electric vehicles.

2.2. Stock and flow model

We model the evolution of the vehicle fleet from 2019 to 2045 using a stock and flow model. The model relates vehicle stock in the next year to vehicle stock, retirements, and sales in the current year. Vehicle stock is broken down by age, vehicle type, and fuel type. The relationship is defined in equation (1), where t represents the current year; $t+1$ represents the next year; $Q_{t+1,m,v,f}$ represents the stock of vehicles of type v, fuel type f, and model year m in year $t+1$; $Q_{t,m,v,f}$ represents the stock of vehicles of type v, fuel type f, and model year m in year t; $R_{t,m,v,f}$ is the retirement of vehicles of type v, fuel type f, and model year m in year t; and $S_{t,m,v,f}$ is the sales of vehicles of type v, fuel type f, and model year m in year t,

$$Q_{t+1,m,v,f} = Q_{t,m,v,f} - R_{t,m,v,f} + S_{t,m,v,f}. \tag{1}$$

We fix the total stock for each vehicle type in each year across scenarios, to allow for comparisons to be made across scenarios. We use total stock by vehicle type from CARB's projected stock in the EMFAC emissions database [27] as the total stock. CARB's vehicle stock forecasts are based on national vehicle sales growth trends from the annual energy outlook paired with county-level estimates of VMT from the California statewide travel demand model (CSTDM) [31], which is a multi-modal activity-based travel demand model [32]. Baseline projections include an increase in long-haul freight transport represented by an increase in heavy-heavy duty vehicle population and VMT (see figures S18 and S19 for BAU stock and VMT projections). Anticipated modal shifts are implicitly included via the CSTDM's multi-modal design.

Retirements are determined using survival profiles extracted from EMFAC, which specify the percentage of vehicles of a given vehicle type that survive to a specified age (see figure S13 for survival profiles for each vehicle type). We use CARB's projected vehicle stock by vehicle type for vehicle years with a model year of 2020 to calculate the survival profiles. For simplicity, we assume that the survival profile for a given vehicle type does not change throughout time, and that the survival profile for a given vehicle type is the same for all fuel types. Future work could incorporate variations in survival profiles for different fuel types and model years.

Sales are then calculated as the sales needed to make up for the loss in stock due to retirements to achieve the projected stock in the next year. We do not explicitly model the sale of used vehicles, and assume that all sales are new vehicles (age = 0). For each vehicle type, we specify the breakdown of sales by fuel type in each year as a percentage of total sales.

We include ten vehicle types in our study: two classes of light HDVs ('LHD1' and LHD2"); local medium HDVs ('T6'); long-haul medium HDVs, operating both within California and in other states ('T6 OOS'); local and long-haul heavy HDVs ('T7' and 'T7 OOS'); heavy HDVs operating in ports ('T7 Port'); buses, motorcoaches ('MC'); and motorhomes ('MH'). See table S1 for details.

2.3. ZEV sales mandate scenarios

To model ZEV sales mandates, we adjust the breakdown of sales by fuel type in each year. We assume that the percentage of ZEV sales increases linearly from 2019 to the year the sales mandate is implemented. We assume the relative distribution of the other fuel types remains the same. For simplicity in our analysis, we assume that all ZEV sales are battery electric vehicles, but the model has the capability to specify a split between hydrogen and electric vehicles. Future work could include scenarios with different types of ZEVs.

2.4. Accelerated retirement scenarios

To model accelerated retirement policies, we add a term, $E_{t,m,v,f}$ representing early retirements of vehicles of type v, fuel type f, and model year m in year t to equation (1), resulting in equation (2),

$$Q_{t+1,m,v,f} = Q_{t,m,v,f} - R_{t,m,v,f} - E_{t,m,v,f} + S_{t,m,v,f}. \quad (2)$$

The number of early retirements is determined by the retirement schedule, which specifies the year in which the policy takes effect (t_r, retirement year), and the minimum age of vehicles to be retired (a_r, retirement age). In the retirement year, all ICE vehicles whose ages are greater than or equal to the retirement age are forced to retire. In all subsequent years, vehicles that reach the retirement age are retired. This is shown in equation (3). In our analysis, we assume that early retirements of ICE vehicles are replaced with new sales of ZEV vehicles in the same year,

$$\forall t \geqslant t_r, f \in \{Diesel, Gasoline, Natural\ Gas\} : E_{t,a,v,f} = Q_{t,a \geqslant a_r,v,f}. \quad (3)$$

2.5. CO_2 emissions model

Once we have determined the vehicle stock in each year of our model, we calculate the associated tailpipe emissions using equation (4), where E represents annual GHG emissions for vehicles of a given age, vehicle class, and fuel type, Q represents vehicle stock, VMT represents annual vehicle miles traveled per vehicle for a given vehicle class and age, e_f represents GHG emissions per unit of fuel for fuel type f, and fe represents fuel economy for vehicles of a given age, vehicle class, and fuel type in the specified year. GHG emissions per unit of fuel are extracted from the EMFAC database [27],

$$E_{t,a,v,f} = \frac{Q_{t,a,v,f} \cdot VMT_{a,v} \cdot e_f}{fe_{t,a,v,f}}. \quad (4)$$

2.5.1. VMT

We include two options for calculating VMT in our model. The first is based on the age distribution of vehicles in the fleet and is unconstrained. The second is constrained by specified total VMT in each year.

Table 1. Tailpipe CO_2 emission factors.

Gasoline	Diesel	Natural gas
9.48 g gal^{-1}	11.19 g/DGE	8.65/DGE

2.5.1.1. Basic VMT mode

The total VMT is calculated based on the number of vehicles, the annual VMT of a new vehicle for the given vehicle class, and the VMT degradation factor, as shown in equation (5), where *VMT* is the VMT per vehicle for a given calendar year, model year, vehicle type and fuel type, *vmt* is the annual VMT by a new vehicle of type *v*, and *d* is the VMT degradation factor for model year *m* in year *t* for vehicle type *v*. Both the VMT degradation factors and new vehicle VMT are extracted from EMFAC [27] (see figure S14). We use this mode to calculate VMT in the BAU scenario,

$$VMT_{t,m,v,f} = vmt_v \cdot d_{t,m,v}. \tag{5}$$

2.5.1.2. VMT profile mode

If a stock profile is specified, a corresponding VMT profile is specified (fleetwide VMT per year for each vehicle type). We use this mode to calculate VMT in the sales mandate and accelerated retirement scenarios, using the VMT profile from the BAU. This allows for a more fair comparison across scenarios. Without this constraint, VMT in scenarios with early retirements would be higher than in other scenarios due to the influx of new electric vehicles to replace the old ICE vehicles they are replacing. For HDVs, VMT is tied to the service provided, and this increase in VMT would not be expected. In this mode, the VMT is first calculated as in the basic VMT mode, and then scaled to ensure total VMT in each year for each vehicle type matches the VMT in the VMT profile, as shown in equation (6), where VMT^{prof} is the total VMT specified in the profile for a given calendar year and vehicle type, and VMT^{adj} is the scaled VMT,

$$VMT^{\text{adj}}_{t,m,v,f} = VMT_{t,m,v,f} \cdot \frac{VMT^{\text{prof}}_{t,v}}{\sum VMT_{t,v}}. \tag{6}$$

2.5.2. Fuel consumption

Fuel consumption is calculated based on VMT and fuel economy, as showed in equation (7), where *FC* is fuel consumption (measured in gallons of gasoline, gallons of diesel, or diesel gallon equivalents, depending on the fuel type), and *FE* is the fuel economy by model year and vehicle type. We assume that fuel economy remains constant over the lifetime of a vehicle (i.e. remains constant across calendar years for a given model year). We extract data on fuel consumption and VMT for each model year from CARB's EMFAC database [27] and calculate effective fuel economy (see figure S15),

$$FC_{t,m,v,f} = \frac{VMT_{t,m,v,f}}{FE_{m,v,f}} \cdot Q_{t,m,v,f}. \tag{7}$$

2.5.3. Tailpipe CO_2 emissions

Tailpipe CO_2 emissions are estimated for diesel, gasoline, and natural gas vehicles based on fuel consumption and emissions factors derived from CARB's EMFAC model for each vehicle type.

Emissions factors used are shown in table 1.

2.5.4. Electricity generation CO_2 emissions

To estimate emissions associated with the use of electric vehicles, we estimate the emissions from the electricity generation required to charge the vehicles. California's electricity primarily comes from natural gas (43% of generation in 2019), renewables (32%), and large hydro (17%) [33]. As a result, charging vehicles from the electric grid will result in a small amount of additional emissions. In each year of the study, we multiply the total electricity consumption by the carbon intensity of the California grid. We assume that California's SB 100 Goals (carbon neutral electricity by 2045) [34] will be met, and assume a linear decrease in the carbon intensity of electricity from today's carbon intensity (82.92gCO_2e/MJ [28]) to zero in 2045.

2.6. Air quality and health impacts model

In addition to emitting CO_2, both ICE vehicles and the power generation facilities producing electricity required to charge electric vehicles emit criteria pollutants including nitrogen oxides (NO_X), sulfur dioxide (SO_2), volatile organic compounds (VOCs), primary fine particulate matter ($PM_{2.5}$), and ammonia (NH_3). These species react and form secondary $PM_{2.5}$ in the atmosphere and are transported downwind. We use

InMAP [35], a reduced complexity air quality model to estimate the annual average change in fine particulate matter due to emissions of these pollutants. InMAP uses a simplified representation of physical and chemical processes and transformations to map emissions of pollutants in one location to the change in annual average $PM_{2.5}$ concentration on a grid. InMAP uses a variable grid with higher resolution in more populated areas, which allows for reasonably accurate measures of exposure. As with all reduced complexity models, InMAP is less accurate than a traditional chemical transport model, but the reduced computational intensity allows for more spatial granularity and use in scenario analysis. Exposure to $PM_{2.5}$ is associated with health impacts including asthma and other respiratory diseases, cardiovascular diseases, and premature mortality [36, 37]. We estimate the mortality resulting from the increase in $PM_{2.5}$ concentrations due to tailpipe emissions and emissions associated with electric vehicle charging.

2.6.1. Statewide tailpipe emissions

We calculate criteria air pollutant emissions at the state level by vehicle type, model year, and fuel type. We extract emissions factors from CARB's EMFAC database by dividing total emissions by total fuel consumption for each fuel type, vehicle type, and model year. We then multiply by the fuel consumption from our model. We sum the emissions across vehicle ages and fuel types to attain the total annual emissions of each air pollutant for each vehicle type.

2.6.2. Block-group level tailpipe emissions

We downscale the statewide emissions to the census block group level to allow for the use of an air quality model to understand the air quality impacts of the emissions. We first distribute the statewide emissions to all counties in the state, by multiplying the statewide emissions by the percentage of statewide VMT that occurs in a given county for each vehicle type. We use county-level VMT data from the EMFAC database for 2019. We then distribute the county-level emissions to census block groups within each county using the vehicle population in each census block group as the weight. Block group vehicle populations are taken from EMFAC's fleet database for 2019.

2.6.3. Tailpipe impacts on $PM_{2.5}$ concentration

We use the modeled emissions to simulate the increase in $PM_{2.5}$ concentration caused by ICE vehicle criteria pollutant emissions by vehicle type. We use the InMAP Source Receptor Matrix (ISRM) [38] to map emissions in each block group to the change in $PM_{2.5}$ concentrations on a variable grid, ranging from 1 km $\times$ 1 km in densely populated areas to 48 km $\times$ 48 km in rural areas. We assume that pollutants are emitted at the centroid of each block group at ground level. We assume the distributions of VMT and vehicle population remain constant over the study period. Future work could explore the impact of changes to this distribution.

Rather than using the ISRM to calculate the change in $PM_{2.5}$ concentration caused by emissions in each year of the simulation for every scenario, which would be computationally expensive, we use the 2019 increase in $PM_{2.5}$ concentrations as a baseline, and scale the results in each year and scenario based on the annual NO_X emissions, as shown in equation (8), where $PM_{2.5v,s,y,x}$ is the increase in $PM_{2.5}$ concentration in grid cell x in scenario s in year y caused by vehicle type v, and $PM_{2.5v,BAU,2019,x}$ is the increase in $PM_{2.5}$ concentration in the same grid cell in 2019 in the BAU scenario. $NO_{Xv,s,y}$ represents the statewide NO_X emissions caused by vehicle type v in scenario s in year y, and $NO_{Xv,BAU,2019}$ is the NO_X emissions caused by vehicle type v in the BAU scenario in 2019. We choose to use NO_X emissions as our scaling factor as they are the largest contributor to the increase in $PM_{2.5}$ concentrations. To test that this approach is accurate, we use the ISRM to calculate the increase in $PM_{2.5}$ for all years in the BAU scenario for one vehicle type, and compare the resulting damages to the damages using our approach. The cumulative difference in health damages over the 25 years in the study is less than 5% (see figure S16). Note that this approach would not be appropriate if the distribution of VMT and vehicle population in counties and block groups was not held constant,

$$PM_{2.5\ v,s,y,x} = PM_{2.5\ v,BAU,\ 2019,\ x} \cdot \frac{NOx_{v,s,y}}{NOx_{v,BAU,\ 2019}}. \tag{8}$$

2.6.4. Electricity generation impacts on $PM_{2.5}$ concentration

To determine the impacts of electricity generation required to meet the demand of electric vehicles, we use consumption-based, geographically-specific $PM_{2.5}$ concentration increase factors by balancing authority (load-serving region of the grid) from Hennessy *et al* [30]. Using the same approach as for tailpipe emissions from ICE vehicles, we downscale the statewide electricity consumption in each year for each vehicle type to census block groups. We then overlay the block groups with balancing authorities [39], and sum the electricity consumption in each balancing authority. We then multiply the gridded increase in $PM_{2.5}$ concentration per TWh [30] by the electricity consumption in each balancing authority.

As with tailpipe $PM_{2.5}$ impacts, we first calculate a baseline gridded increase in $PM_{2.5}$, which we use to approximate the increase in $PM_{2.5}$ in each year in each scenario. Since most vehicle types do not have electric vehicles in 2019, we do not use 2019 as the baseline here, but instead use 1 TWh of electricity consumption statewide by each vehicle type. We then scale the gridded increase in $PM_{2.5}$ by the statewide electricity consumption. As with electricity-related CO_2 emissions, we also assume a linear decrease in the increase in $PM_{2.5}$ concentration per TWh of electricity consumption as the grid decarbonizes. While more precise estimates of the change in annual emissions could be made, they would have little impact on the overall results, given the smaller scale of electricity-related emissions compared to tailpipe emissions. Equation (9) shows the approximation, where $PM_{2.5}e_{v,s,y,x}$ is the increase in $PM_{2.5}$ in grid cell x from electricity consumption by vehicle type v, in scenario s in year y, $PM_{2.5}e^{\text{base}}{}_{v,x}$ is the baseline increase in $PM_{2.5}$ in grid cell x from 1 TWh of electricity consumption statewide by vehicle type v, $e_{v,s,y}$ is the statewide electricity consumption by vehicle type v in scenario s in year y, and p_y is the percent of 2019 $PM_{2.5}$ concentration in year y, assuming a linear decrease from 2019 to 2045,

$$PM2.5e_{\,v,s,y,x} = PM2.5e^{\text{base}}_{v,x} \cdot e_{v,s,y} \cdot p_y. \tag{9}$$

2.6.5. Premature mortality

Once we have determined the increase in $PM_{2.5}$ concentration caused by tailpipe emissions and electricity consumption in each year in each scenario, we calculate the associated premature mortality using equation (10), where M_x is the change in premature mortality, $M_x{}^0$ is the baseline all-cause mortality rate, β is the hazard ratio associated with exposure to an additional 10 μg m^{-3} of $PM_{2.5}$, and P_x is the population. We use a hazard ration of 1.06 from Krewski *et al* [40]. We assume that the demographics and population distribution remain constant over the 25 yr period of the study,

$$\Delta M_x = M_x^0 \left(e^{\frac{\ln(\beta)}{10}\Delta PM2.5} - 1 \right) \cdot P_x. \tag{10}$$

2.6.6. Demographic analysis

After determining the premature mortality in each grid cell, we merge the premature mortality outputs with demographic data from the American Community Survey at the census tract level [29]. We then calculate premature mortality by race and income, assuming that mortality within a grid cell is distributed according to the population distribution (e.g. if a grid cell has a 70% White population, 70% of the deaths will be attributed to Whites). We then calculate the statewide mortality per capita by race, ethnicity, and income by dividing the total number of deaths for each race/income/ethnicity by the total population of each race/income/ethnicity. We use U.S. Census definitions of race and ethnicity. 'Hispanic or Latino' includes people of any race identifying as Hispanic or Latino. Each race includes both Hispanic and non-Hispanic individuals (e.g. 'White' includes both 'White non-Hispanic' and 'White Hispanic' individuals. For simplicity, we refer to 'Hispanic or Latino' as 'Latino' in the remainder of the text. While a small fraction of air quality-related deaths occur in neighboring states, we limit this portion of the analysis to mortality and population occurring within California, where the vast majority of deaths occur, as including populations from other states would lead to misleadingly low values of mortality per capita.

2.7. Health and climate damages

To allow for comparison between the health and climate impacts of each scenario, we monetize both. To value the health damages, we use the VOSL, using the recommended value from the EPA [41] converted to 2020 dollars ($9.63 Million). To value the climate damages, we use the SCC in 2020 dollars. We use both the lower value previously recommended by the EPA ($51/tonne [42]) and the higher, recently adopted value of $190/tonne [43].

2.8. Retirement cost estimation

We use second-hand vehicle price as a proxy for the cost of retirement. We extract data from used vehicle sales databases [44, 45] for each vehicle type, and fit an exponential curve to the extracted data. We use the fitted curves to estimate the second-hand price of vehicles of each age by vehicle type. Figure S17 shows the estimated prices by age for each vehicle type. We also perform a secondary retirement cost estimation using new electric vehicle price for equivalent vehicles. For this analysis we use vehicle price data from California's Heavy-duty Vehicle Incentive Program [46].

2.9. Sensitivity analysis

To assess uncertainty in the results, we conduct a sensitivity analysis on three key parameters: VMT, vehicle survival, and electric grid emissions intensity. We run the model for each policy scenario while adjusting the

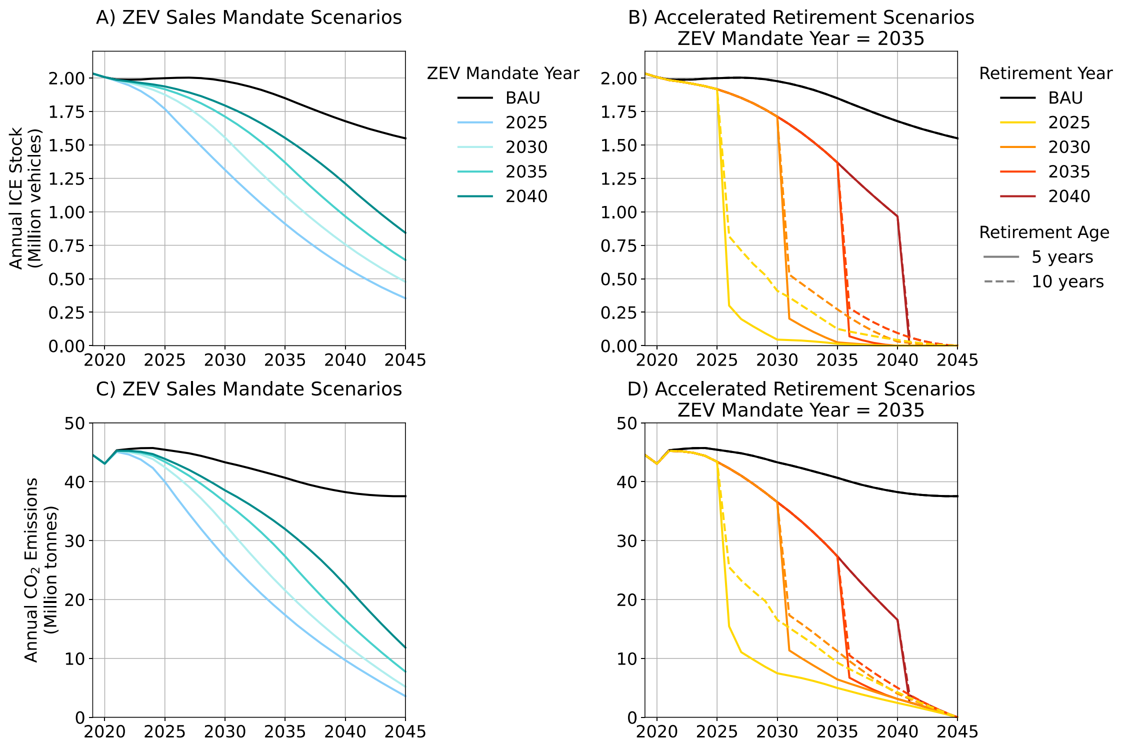

Figure 2. Annual ICE vehicle stock and CO_2 emissions in policy scenarios. CO_2 emissions include tailpipe emissions and emissions from electricity generation for electric vehicle charging. (A) and (C) show vehicle stock and CO_2 emission trajectories for ZEV sales mandate scenarios. The black line indicates the BAU scenario, and darker blue lines indicate ZEV sales mandates implemented in later years. (B) and (D) show trajectories for accelerated retirement scenarios implemented in addition to a ZEV sales mandate implemented in 2035. The black line indicates the BAU scenario, and the darker red lines indicate retirement policies implemented in later years. Solid lines indicate a minimum retirement age of 5 yrs, and dotted lines indicate a minimum retirement age of 10 yrs.

input parameters. To assess model sensitivity to VMT we increase the VMT in each year by 10% across all vehicle types. To assess model sensitivity to survival rates, we adjust the survival profiles for each vehicle type such that the median survival increases by 5 yrs. Finally, to assess the sensitivity to grid emissions intensity, we hold the CO_2 intensity and criteria air pollutant emissions intensity constant at current levels throughout the model period. For each scenario we report the total CO_2 emissions and the total air pollution-related mortality.

3. Results

3.1. Annual vehicle stock and CO_2 emissions

Annual ICE vehicle stock and CO_2 emissions decrease significantly in scenarios with ZEV sales mandates and accelerated retirement policies. Figure 2 shows the number of ICE HDVs in the vehicle stock, and total annual CO_2 emissions from all HDVs (including electric vehicles) between 2019 and 2045 under different policies. Figures 2(A) and (C) show the stock and emissions associated with a ZEV sales mandate where the initial year of policy implementation ranges from 2025 to 2040. Figures 2(B) and (D) show the stock and emissions in accelerated retirement scenarios. Each retirement scenario shown is in addition to a ZEV sales mandate implemented in 2035. We show results for a retirement age of 5 yrs and 10 yrs, and for policy implementation ranging from 2025 to 2040.

Under a no new policy scenario (BAU), representing current policy as of 2022, we observe a decrease in ICE HDVs from 2019 to 2045 due to fuel efficiency improvements and natural adoption of ZEVs. (see SI, figure S1). The annual CO_2 emissions under the BAU scenario decrease by 7 MTonnes from 2019 to 2045 as a consequence both of older, less efficient vehicles naturally aging out of the fleet, and moderate electrification of some vehicle types. Following the ACT regulation, which is accounted for in our BAU scenario, medium-heavy duty trucks (T6), light heavy-duty trucks (LHD1 and LHD2), and heavy-heavy duty trucks (T7, T7 OOS, and T7 Port) undergo meaningful electrification by 2045, as do buses, following the ICT regulation (see table S1 for a description of each vehicle type). The total vehicle stock is projected to increase from roughly 2 million vehicles in 2019 to 2.3 million vehicles in 2045, with roughly two thirds of the fleet being diesel vehicles (see figures S2–S11).

The implementation of ZEV sales mandates (figures 2(A) and (C)) leads to a rapid decrease of ICE vehicles and CO_2 emissions. However, even with an aggressive policy requiring 100% ZEV sales for HDVs starting in 2025 and sustained for every year thereafter, there would still be ∼354 thousand ICE HDVs on California roads in 2045, underscoring that a ZEV sales mandate alone will very likely not be sufficient for California to achieve its goal of carbon neutrality by 2045.

In contrast, the addition of an appropriate accelerated retirement policy would allow the state to meet its stated goals. Figures 2(B) and (D) show the evolution of the ICE heavy-duty stock and CO_2 emissions in selected accelerated retirement scenarios. All retirement scenarios shown are in addition to a ZEV sales mandate implemented in 2035 (the new policy in CA as of the recent Advanced Clean Fleets regulation) and assume that vehicles forced to retire early are replaced with electric vehicles. In all scenarios shown, the ICE vehicle stock and associated CO_2 emissions reach zero by 2045. We show four retirement years (the year in which the policy is implemented), and two retirement ages (the minimum age of vehicles forced to retire). Forcing younger vehicles to retire results in a quicker reduction in both ICE HDV stock and CO_2 emissions. Likewise, implementing the accelerated retirement policy sooner results in lower emissions. The ICE HDV stock decreases faster than CO_2 emissions due to emissions from electricity generation needed to meet the electricity demand from electric vehicles (see figure S12).

While a range of retirement ages were considered, 5 and 10 yrs were selected to demonstrate what would be necessary to reach a zero-emission fleet by 2045. If the state were to implement a ZEV sales mandate sooner, the minimum retirement age needed would be higher. The selected retirement ages are lower than typical retirement ages of HDVs, which range from 12 to 26 years across vehicle types based on the survival profiles used in our analysis. There is precedent for policies targeting the retirement of younger vehicles. In the nationwide Cash for Clunkers program, close to a quarter of vehicles traded in were 10 yrs old or younger [47]. However, Cash for Clunkers primarily targeted light-duty vehicles, and it is possible that targeting younger HDVs for retirement would be more challenging. This underscores the importance of beginning ZEV sales mandates sooner rather than later to reduce the need for retiring young vehicles in order to reach the state's emission goals.

3.2. Cumulative CO_2 emissions

While California's stated goal is reaching zero annual emissions by 2045, cumulative CO_2 emissions impact the state's overall contribution to climate change. Each decarbonization pathway results in different cumulative impacts. Figure 3 shows the cumulative CO_2 emissions from 2019 through 2045 in each policy scenario, including the BAU scenario, ZEV sales mandates beginning in various years, and accelerated retirement policies paired with ZEV sales mandates implemented in 2040 and 2035. Cumulative emissions are reduced by up to 64% in scenarios with the most ambitious policies. In the BAU scenario, 1100 MTonnes of CO_2 are emitted. 98% of these emissions come from ICE HDVs, while 2% come from electricity used in charging of the electric trucks. If a ZEV sales mandate were implemented in 2025, cumulative emissions would be reduced to 646 MTonnes of CO_2, with 11% coming from electricity generation. Removing the tailpipe emissions from ICE HDVs outweighs the added emissions from electricity generation, owing to the California grid's low carbon intensity. The earlier the ZEV sales mandate is implemented, the higher the emissions savings.

Implementing an accelerated retirement policy would further decrease cumulative emissions. Early retirement policies on top of a ZEV sales mandate in 2035 could save up to an additional 395 MTonnes of CO_2 between 2019 and 2045 (roughly 35% of BAU cumulative emissions). Retirement policies implemented prior to a ZEV sales mandate have a greater impact on emissions than those implemented after a ZEV sales mandate.

The minimum age of vehicles forced to retire has variable impact on cumulative emissions depending on the timing of the ZEV sales mandate and retirement policy. If the ZEV sales mandate is implemented at the same time or after the retirement policy, the age of retirement has very little impact. For a ZEV sales mandate and retirement policy both implemented in 2040, the difference in cumulative emissions between retiring ICE vehicles 10 yrs and older, and retiring ICE vehicles 5 yrs and older is only 12 MTonnes. In contrast, if the retirement policy is implemented before the ZEV sales mandate, the retirement age has a larger impact. For example, for a ZEV mandate implemented in 2040 and a retirement policy implemented in 2025, the difference in cumulative emissions from retiring vehicles 5 yrs and older and retiring vehicles 10 yrs and older is 125 MTonnes, equivalent to about 1/3 of California's annual GHG emissions. This dynamic is in part due to the assumption that vehicles forced to retire are replaced with ZEVs.

These results can be explained by the fleet turnover dynamics in each scenario. When a ZEV sales mandate is implemented first, vehicles that are naturally retired are replaced with ZEVs, and there are fewer ICE vehicles remaining in the fleet when the retirement policy is implemented. In contrast, when a

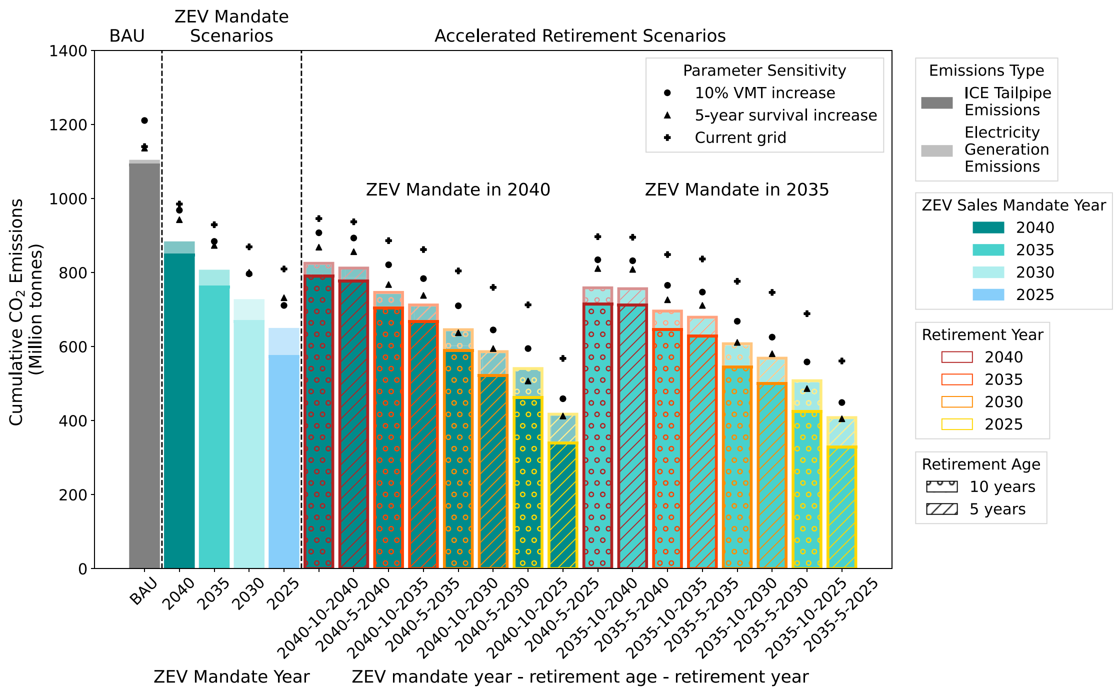

Figure 3. Cumulative CO_2 emissions across different policy combinations. The gray bar shows cumulative CO_2 emissions from 2019 to 2045 in the BAU scenario. The ZEV mandate scenarios section shows cumulative CO_2 emissions in scenarios with ZEV sales mandates only, where color indicates the year in which 100% of vehicle sales are required to be ZEVs. Darker colors correspond to later implementation of the sales mandate. The accelerated retirements section shows cumulative CO_2 emissions in scenarios with both ZEV sales mandates and accelerated retirement policies, with the first set of bars corresponding to a ZEV sales mandate in 2040, and the second set of bars corresponding to a ZEV sales mandate in 2035. The color of the bar indicates the year in which the ZEV sales mandate is implemented. The border color indicates the year in which the retirement policy is implemented, with darker colors corresponding to later retirement years. The pattern corresponds to the minimum age of vehicles to be retired, with lines indicating a retirement age of 5 yrs, and circles indicating a retirement age of 10 yrs. Across all scenarios shown, the transparency indicates the source of emissions, with opaque bars corresponding to tailpipe emissions and transparent bars corresponding to emissions from electricity generation required to meet the charging demands of electric vehicles in the fleet. The markers above the bars indicate the total cumulative CO_2 emissions in each scenario with changes to key input variables. Circles represent scenarios with a 10% increase in VMT, triangles indicate scenarios where median survival has been increased by 5 yrs for all vehicle types, and pluses represent scenarios where grid emissions intensity remains constant at current levels.

retirement policy is implemented first, a large number of ICE vehicles are still present in the fleet, and are forced to retire, resulting in a significant decrease in emissions due to the policy.

The total emissions in each scenario show mild sensitivity to key input parameters. Increasing VMT by 10% results in an 10% increase in CO_2 emissions across all scenarios relative to the baseline analysis. Increasing the median survival age by 5 yrs results in between a 6% decrease and a 13% increase in emissions depending on the scenario. Maintaining electricity emissions intensity at current levels results in a 3.5% increase in BAU emissions and up to 37.5% increase in emissions for policy scenarios relative to the baseline analysis due to the larger number of electric vehicles. Overall, while there is uncertainty in the magnitude of emissions in each scenario, the relative emissions of each scenario do not change, with ZEV sales mandates reducing emissions relative to the BAU, and accelerated retirement policies reducing emissions further. The sensitivity analysis suggests that the policy implications of the results are robust to changes in assumptions about electricity emissions intensity, vehicle miles traveled, and vehicle survival rates.

3.3. Air quality and health impacts

In addition to emitting CO_2, the use of HDVs results in an increase in fine particulate matter ($PM_{2.5}$), due to tailpipe emissions from ICE vehicles and emissions from electricity generators providing electricity to electric vehicles. As each vehicle type has different driving patterns, age distributions, and fuel type distributions, the associated air quality impacts vary by vehicle type. Figure 4 shows the increase in $PM_{2.5}$ concentration caused by emissions from each vehicle type in 2019. As we assume that the geographic distribution of VMT remains constant across all scenarios, the distribution of air quality impacts from tailpipe emissions does not change across scenarios, though the magnitude of the impacts varies. While a shift to electric vehicles results in an increase in air quality impacts near power plants, the electric vehicle damages are two orders of magnitude smaller than ICE vehicle damages. As a result, the change in

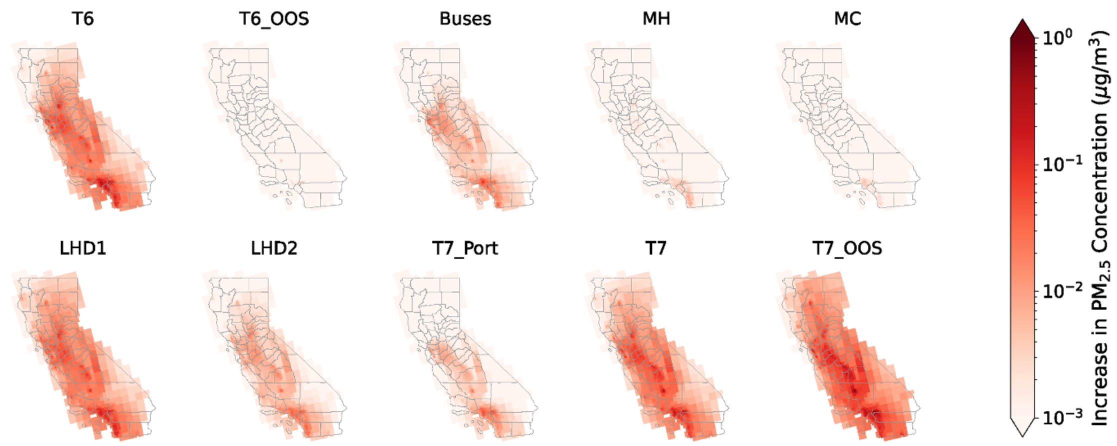

Figure 4. Change in annual average $PM_{2.5}$ concentration due to emissions from each vehicle type in 2019. Darker red indicates a larger increase in concentration. Change in $PM_{2.5}$ concentration includes primary $PM_{2.5}$ from tailpipe emissions and electricity generation emissions as well as secondary $PM_{2.5}$ from tailpipe emissions and electricity generation emissions of SO_2, NO_X, NH_3 and VOCs. Increase in concentration is shown on a variable grid, as produced by InMAP, ranging from 1 km × 1km in densely populated areas to 48 km × 48 km in rural areas. Emissions inputs are calculated at the census block group level.

distribution of impacts is negligible. Overall, the impact of HDV fleet emissions on $PM_{2.5}$ concentration is fairly low (generally less than 1 $\mu g\ m^{-3}$ increase in all parts of the state in 2019 for each vehicle type).

Large population centers see some of the largest impacts to air quality. The Southern portion of the state, in particular Los Angeles County and surrounding areas have the highest increases in $PM_{2.5}$ concentration across all vehicle types. The San Francisco Bay Area is impacted by medium-heavy duty trucks (T6), smaller light-heavy duty trucks (LHD1), and both local and long-haul heavy-heavy duty trucks (T7 and T7 OOS). The Northern part of the Central Valley is impacted by medium-heavy duty trucks (T6), buses, light-heavy duty trucks (LHD1 and LHD2), and heavy-heavy duty trucks (T7 and T7 OOS). The Los Angeles area and the Eastern portion of the Bay Area, where major ports are located, are impacted by heavy-heavy duty port trucks (T7 Port).

As with CO_2 emissions, cumulative air quality impacts, and the health damages caused by them, vary across scenarios. Figure 5 shows the number of cumulative deaths caused by exposure to $PM_{2.5}$ resulting from criteria air pollutant emissions from both ICE vehicles and electricity generation in selected scenarios. We do not separate the mortality from electric and ICE vehicles as the magnitude of mortality from electric vehicles is very small. From 2019 to 2045, air pollutant emissions from the BAU scenario result in over 8000 deaths. ZEV sales mandates would reduce the number of deaths by 13%–28% depending on which year the policy is implemented. The addition of an accelerated retirement policy would reduce the total number of deaths by 17%–57% for the scenarios shown.

As with CO_2 emissions, these results are impacted by uncertainty in model inputs. Increasing VMT by 10% across scenarios results in a 10% increase in cumulative mortality for all scenarios. Increasing the median survival age by 5 yrs results in an increase in mortality between 1.1% and 21.5% relative to the baseline analysis depending on the scenario. Holding electricity emissions intensity constant at current levels increases mortality by between 0.3 and 3.0% depending on the scenario, suggesting that uncertainty in grid emissions will have little effect on the health impacts of heavy-duty decarbonization policies. As with CO_2 emissions, while the magnitude of cumulative mortality varies as the model inputs are changed, the relative mortality across scenarios remains the same, suggesting that policy implications are robust.

3.4. Environmental justice implications

As shown in figure 4, the air quality impacts across the state are not uniform. Given that the population distribution is also heterogeneous, some demographic groups are impacted more than others. To assess these disparities, we combine gridded premature mortality with demographic data at the census tract level using a spatial overlay. Figure 6 shows the cumulative mortality per capita caused by each vehicle type in the BAU scenario. Figure 6(A) shows mortality per capita by household income. In general, households with low incomes experience more health damages, with the group with the highest mortality per capita being households making between \$10 000 and \$15 000 per year.

Figure 6(B) shows mortality per capita by race. Across nearly all vehicle types, Latinos are the most impacted group, followed by Blacks, with the exception of buses, for which Black populations are the most impacted group, followed by Latino populations. For most vehicle types, Asian populations have the

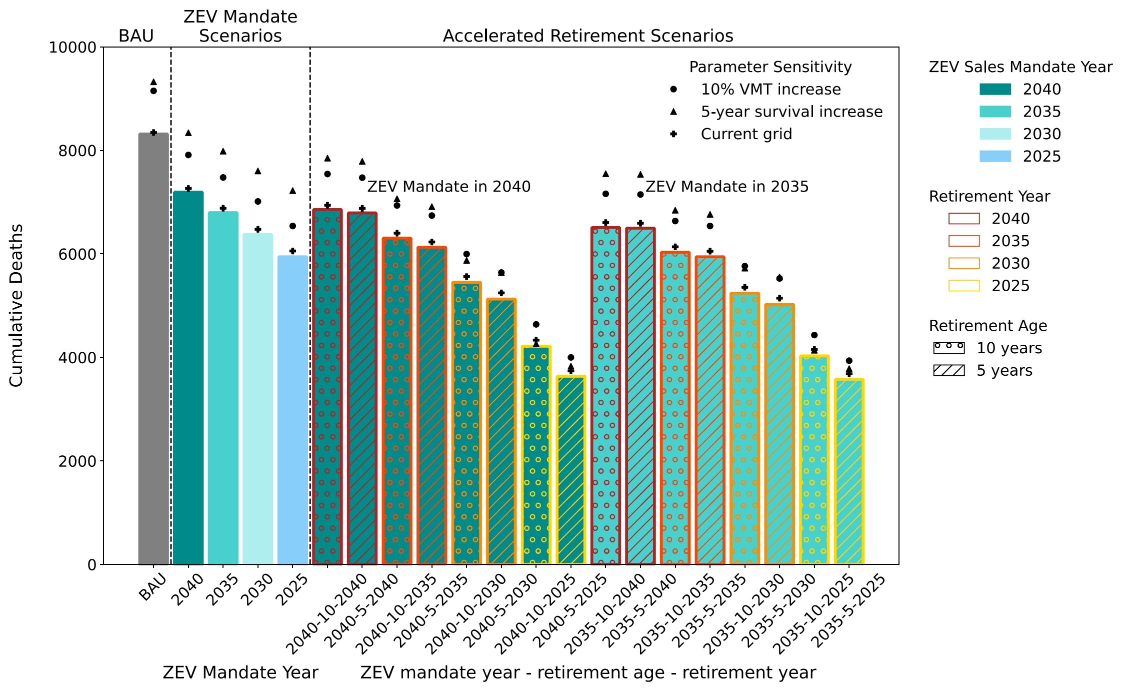

Figure 5. Cumulative deaths caused by exposure to $PM_{2.5}$ resulting from heavy-duty vehicle emissions in selected policy scenarios. Cumulative deaths include premature mortality in 2019 through 2045. The gray bar shows cumulative $PM_{2.5}$-related mortality from 2019 to 2045 in the BAU scenario. The ZEV mandate Scenarios section shows cumulative $PM_{2.5}$-related mortality in scenarios with ZEV sales mandates only, where color indicates the year in which 100% of vehicle sales are required to be ZEVs. Darker colors correspond to later implementation of the sales mandate. The accelerated retirement scenarios section shows cumulative $PM_{2.5}$-related mortality in scenarios with both ZEV sales mandates and accelerated retirement policies, with the first set of bars corresponding to a ZEV sales mandate in 2040, and the second set of bars corresponding to a ZEV sales mandate in 2035. The color of the bar indicates the year in which the ZEV sales mandate is implemented. The border color indicates the year in which the retirement policy is implemented, with darker colors corresponding to later retirement years. The pattern corresponds to the minimum age of vehicles to be retired, with lines indicating a retirement age of 5 yrs, and circles indicating a retirement age of 10 yrs. Mortality caused by both $PM_{2.5}$ associated with tailpipe emissions and $PM_{2.5}$ associated with electricity generation are shown together, as the $PM_{2.5}$ associated with electricity generation is negligible compared to the $PM_{2.5}$ associated with tailpipe emissions.

third-highest mortality per capita. The group with the lowest impacts varies by vehicle type. Long-haul HDVs (T7 OOS) impact Pacific Islander populations the least, while medium-heavy duty trucks (T6) and lighter light-heavy duty trucks (LHD1) impact Native American populations the least, and heavy-heavy duty trucks operating only within the state (T7) impact White populations the least.

For all races and incomes, long-haul heavy-duty trucks (T7 OOS) have the highest impact. This is due to these vehicles being driven more than other vehicle types as well as being less efficient and more polluting. As mentioned previously, while the magnitude of damages decreases in policy scenarios, the distribution of health damages remains the same as in the BAU. If vehicle electrification happens more quickly in some parts of the state than others, there would likely be changes in the distribution as tailpipe emissions would decrease faster in some locations than in others.

These results are driven by the geographic distribution of households and VMT. The disparities shown are likely underestimated as we are limited by our assumption that VMT is uniformly distributed across vehicles in each county, and vehicle population is distributed uniformly throughout each block group. Future work could incorporate higher resolution VMT estimates or pair this analysis with a traffic model to achieve more precise air quality and health estimates. Furthermore, our model does not track the age distribution of vehicles at the sub-state level. Older vehicles tend to be more polluting, but are driven less. While there is evidence that low-income households on average have older vehicles than high-income households [48], there is a lack of data on the relationship between income and vehicle age for HDVs. Future data collection efforts could enable an analysis of this relationship, and subsequent modeling efforts could incorporate this dynamic.

3.5. Cost-effectiveness of early retirements

In the previous sections, we have demonstrated that accelerated retirements will be needed to allow California to meet its climate goals. However, retiring vehicles that would have otherwise continued to be used has a cost. These vehicles still have value, and to prevent them from being resold in other states without

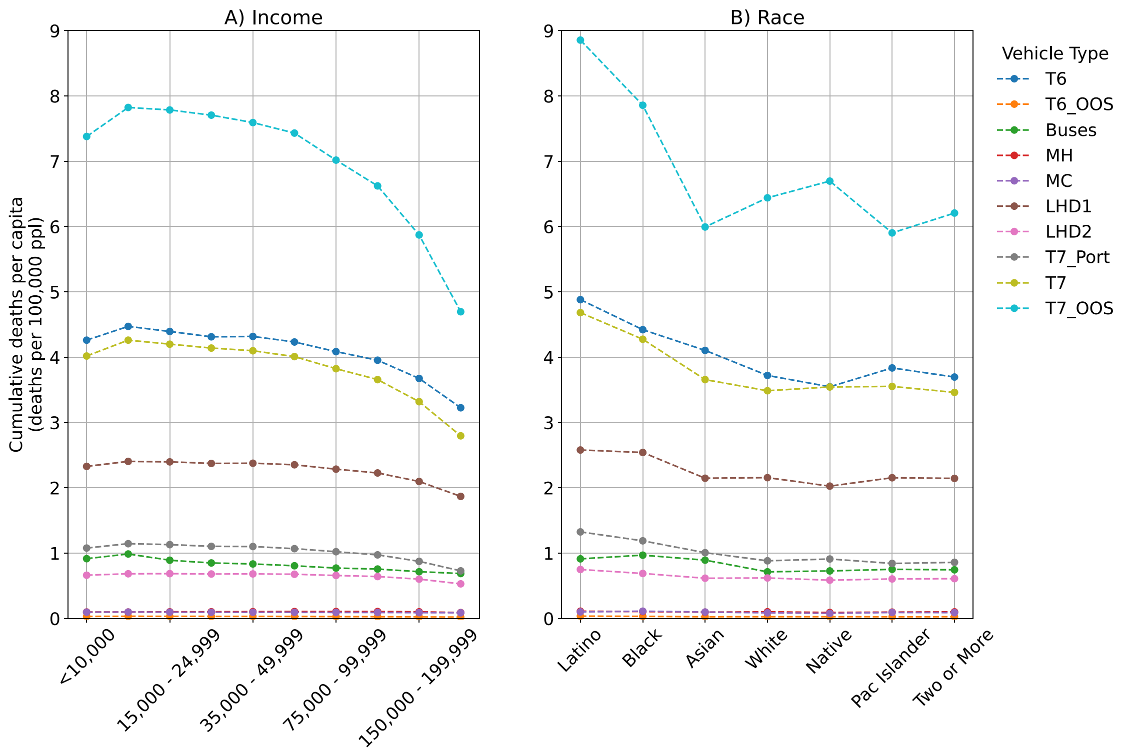

Figure 6. Cumulative mortality per capita by race and income in the BAU scenario. (A) shows cumulative mortality per capita by household income bracket and (B) shows cumulative mortality per capita by race and ethnicity. Each race and ethnicity indicated is representative of the population that is that race or ethnicity alone. The mixed-race population is represented by the two or more category. Latino refers to the census category'Hispanic or Latino'. Note that each race includes both Hispanic and non-Hispanic individuals of that race. The color of the lines and markers indicates the vehicle type whose emissions caused the mortality. Cumulative deaths per capita include all deaths in California from $PM_{2.5}$ exposure caused by vehicle emissions in 2019 through 2045. Mortality includes mortality related to tailpipe emissions and emissions from electricity generation.

such policies, owners would need to be compensated. In this analysis, we assume that vehicle owners would be compensated by the State an amount equal to the second-hand market value of the vehicle. This assumption is representative of an incentive program in which vehicle owners trade in their older vehicles for cash towards purchasing a new ZEV. We assume that all vehicles that are retired will be scrapped and will not be resold in other states or countries.

For simplicity, we treat the cost of compensation as a constant, though there is some evidence that second-hand market value may increase as the availability of ICE vehicles decreases. The literature suggests that increases in the price of new vehicles puts upward pressure on the price of used vehicles as they become more attractive [49]. Similar dynamics could play out in the presence of ZEV sales mandates as ICE vehicles become scarce, and used ICE vehicles become more valuable. Given the uncertainty around future second-hand market prices, we perform an additional cost analysis using new electric vehicle prices to estimate the cost of retirements. This would represent compensating vehicle owners for the purchase of a replacement vehicle, rather than for the removal of their current vehicle. We use new electric vehicle prices from the California Heavy-duty Vehicle Incentive Program total cost of ownership calculator [46]. Future work could incorporate changing value of used ICE vehicles into the cost of early retirements.

To identify feasible accelerated retirement scenarios, we perform a simple cost-benefit analysis. Figure 7 shows the avoided health and climate damages vs. the cost of early retirements for each early retirement scenario presented for each vehicle type. Figure 7(A) shows the retirement costs estimated based on used vehicle price, while figure 7(B) shows the retirement costs estimated based on new electric vehicle prices. The avoided damages are calculated relative to a ZEV sales mandate alone (e.g. a retirement policy in combination with a ZEV sales mandate implemented in 2035 is compared to the ZEV mandate implemented in 2035 alone). We monetize the avoided damages using two values of the SCC and the VOSL. Points above the dashed line indicate policies that have a net benefit, where the cumulative avoided damages exceed the cumulative cost of retirements. Those below the dashed line indicate that the costs outweigh the benefits. The lower estimate uses an SCC of \$51/tonne, and the higher estimate uses a value of \$190/tonne.

We first analyze the net costs using the second-hand market estimate. Using a SCC of \$51/tonne (recommended by the EPA until recently [42]), most policies have a net cost. Only policies targeting

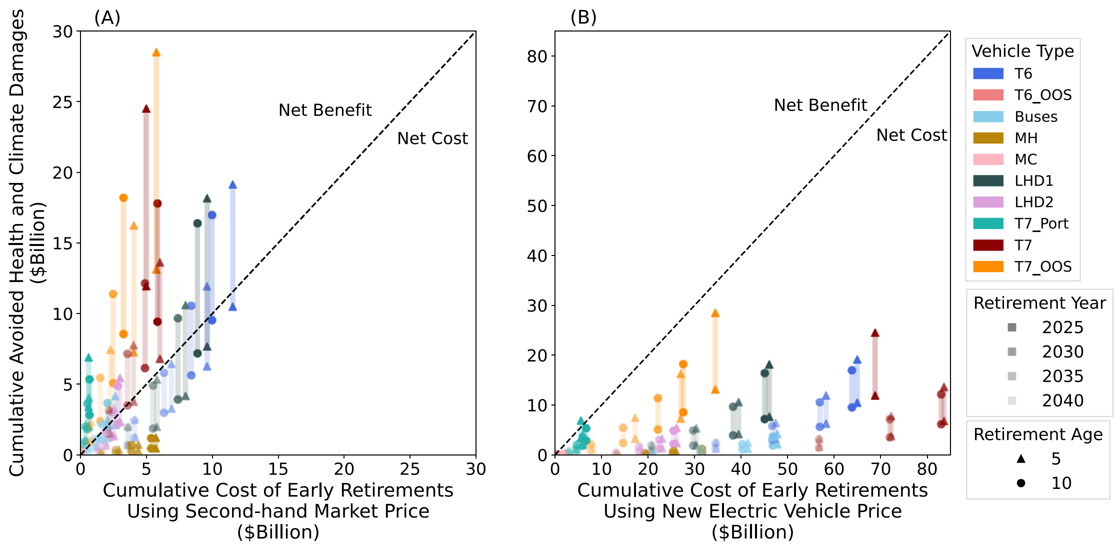

Figure 7. Avoided health and climate damages vs. cost of early retirements. Points above the line indicate a net benefit of retirements relative to a ZEV sales mandate-only scenario, and points below the line indicate a net cost. Lower estimates of avoided cost use SCC = \$1/tonne, and higher estimates use SCC = \$190/tonne. Both estimates use VOSL = \$9.63 Million. All retirement scenarios shown assume a ZEV mandate year of 2035. (A) shows cost estimates of early retirements using an age-specific second-hand market price of ICE vehicles of each vehicle type. (B) Shows cost estimates using the new electric vehicle price for each vehicle type. Color corresponds to vehicle type. Transparency corresponds to the year in which the retirement policy is implemented, with more transparent markers indicating a later retirement year. Marker shape corresponds to the minimum age of vehicles forced to retire, with triangles indicating a retirement age of 5 yrs and circles indicating a retirement age of 10 yrs.

heavy-heavy duty vehicles operating in ports (T7 Port) and long-haul heavy-heavy duty vehicles (T7 OOS) consistently have a net benefit. In addition, retiring long-haul heavy-heavy duty vehicles would have benefits outside of California which are not included here. For all vehicle types, the net benefit is highest for policies that are implemented sooner, and that target younger vehicles. This indicates that while retiring more vehicles is more expensive, the additional benefits of reduced health and climate impacts outweigh the additional cost.

If the EPA's current recommended SCC (\$190/tonne [43]) is used, policies have a net benefit for more vehicle types. In this case, all policies forcing the early retirement of port vehicles (T7 Port), long-haul trucks (T7 OOS), heavy-heavy duty trucks (T7), smaller light-heavy duty vehicles (LHD1), and medium-heavy duty trucks (T6) result in a net benefit. Additionally, policies with earlier retirement years targeting younger vehicles result in a net benefit for larger light-heavy duty vehicles (LHD2), and buses. The vehicle category with the greatest net cost is motorhomes (MH). This is likely due to their being fairly expensive, but having low mileage each year, resulting in relatively low emissions and little benefit from removing them from the road. These results may be an underestimate of the cost of retirements given the assumption of constant used vehicle price. Incorporating the dynamics of changing used vehicle prices in response to diminishing availability of ICE vehicles could result in higher estimates of retirement cost and reduce the number of policies that are cost-effective.

Estimating the cost of early retirements using the price of new electric vehicles that would replace the retired vehicles rather than the second-hand market price of the retired vehicles results in almost none of the policies being cost effective, regardless of the SCC used. This is due to the cost of new electric vehicles being much higher than the cost of used ICE vehicles. However, this analysis assumes the price of new electric vehicles remains constant, while in reality, prices may decrease as the market grows, which could lead to additional policy options being cost-effective.

4. Discussion

In this paper we have assessed a range of policy approaches to decarbonizing California's heavy-duty transportation sector. While ZEV sales mandates are effective at reducing emissions of both GHGs and criteria air pollutants and reducing the associated health and climate damages, it is clear from our analysis that they will not be sufficient for reaching zero emissions on the timeline desired by the state. Even with highly aggressive sales mandates beginning in 2025, which are likely infeasible under current technology and manufacturing constraints, 17% of today's ICE vehicle stock and 8% of annual CO_2 emissions would remain in 2045. Additional policy action in the form of accelerated retirement programs will be needed to reach zero emissions by 2045. In addition to allowing the state to meet its climate targets, the implementation of accelerated retirement programs along with ZEV sales mandates would further reduce cumulative GHG emissions and health damages, which disproportionately affect low-income communities and people of color. Early removal of vehicles from the fleet comes at a cost, as the vehicle owners would likely need to be compensated by the state to prevent resale of the vehicles out of state. Given the realities of budget limitations, policymakers may want to focus their efforts on vehicle types for which removal would be most cost-effective. Early retirement of long-haul heavy heavy-duty trucks, and heavy heavy-duty trucks operating in ports would have the greatest net benefit, along with the largest magnitude of reduced climate and health damages.

We have focused on fleet turnover as a means to achieving decarbonization, but there are other possibilities as well. Other studies have assessed the potential role of zero-carbon liquid fuels in reducing transportation emissions [26]. In its scoping plan, CARB proposes rapidly scaling up the production of liquid biofuels, renewable diesel, and biomethane to fulfill the liquid fuel requirements of remaining ICE vehicles rather than removing them from the road [50]. Similarly, in their report on achieving zero emissions in California's transportation sector, the Institute of Transportation Studies (UC-ITS) relies on biofuels to meet 40% of energy demand in the transport sector [26]. This would require a massive increase in the availability of low carbon liquid fuels. While these fuels may provide net zero GHG emissions, they still have tailpipe emissions of criteria air pollutants [51, 52], and as a result, strategies relying on them would not have the same health benefits as the strategies we have presented in this work.

Another factor we have not explicitly considered in this work is mode shifts in both passenger transport and freight transport. A shift from freight transport via trucks to rail or air travel could reduce the population and VMT of heavy HDVs. This in turn would result in fewer vehicles needing to be retired early in order to reach zero emissions in the on-road heavy-duty sector. However, the reduction in emissions in the on-road sector would likely be offset by an increase in emissions in the rail or aviation sectors unless these sectors are also fully decarbonized. Changes in personal transport could also have implications for fleet evolution in the heavy-duty sector. Policies incentivizing a mode switch from personal vehicles to public transit could increase vehicle population, VMT, and emissions of buses. Future work could explore these dynamics and assess decarbonization pathways and fleet turnover in the broader transportation sector including light-duty, heavy-duty, and non-road transport together.

Reaching zero emissions in the transportation sector will require California to meet its decarbonization targets in other sectors as well. While switching from ICE vehicles to electric vehicles would result in net benefits even with the current electric grid, if the grid is not fully decarbonized, there will still be health and climate damages associated with the transportation sector. To effectively decarbonize, the state must ensure that its policies in both sectors are aligned.

While this work is focused on California, similar approaches could be used to assess health and air quality implications of policy strategies in other geographic contexts. The fleet turnover model we have developed could be used directly in other areas to test ZEV mandates and early retirement policies given the availability of vehicle fleet data and could be adapted to test policies with different formulations. While other locations will have their own unique fleet characteristics and policy environments, the findings of this study will be relevant for locations with near-term climate targets and large existing vehicle fleets.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.11661099 .

Acknowledgments

The authors would like to thank the following entities for their generous support of this work: California Business Roundtable; California Cattlemen's Association; California Chamber of Commerce; California Manufacturers & Technology Association; California State Building and Construction Trades Council; International Brotherhood of Boilermakers; Stanford Center for Carbon Storage; Western States Petroleum Association. Prof. Azevedo Visiting Professorship at Nova SBE school is supported via a consulting assignment. This article is adapted from a chapter of the first author's PhD thesis at Stanford University.

Code availability

The model and code used to generate the results in this paper are available at https://doi.org/10.5281/zenodo.11661099.

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