Low-Carbon Transportation Incentive Strategies Using Performance Evaluation Tools for Heavy-Duty Trucks and Off-Road Equipment

Final Report

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Abstract

This report examines the market share of cleaner technologies and lower carbon intensive fuel use among heavy-duty vehicles (HDVs) and off-road equipment (ORE) to better understand how regulatory measures and incentive programs have and can affect the market. It also projects the uptake of technology for low-carbon transportation (LCT) and identifies the technical features that could potentially improve and optimize the energy demands of both HDVs and ORE under various operational conditions. The research team was led by Principal Investigator (PI) Professor Stephen Ritchie of the University of California, Irvine's (UCI) Institute of Transportation Studies (ITS), in collaboration with Professor Scott Samuelsen from UCI's Advanced Power and Energy Program. Research partners Dr. Bo Liu from the University of California, Los Angeles, (UCLA), Dr. Kanok Boriboonsomsin and Fuad Un-Noor from University of California Riverside (UCR), and Suman Mitra from the University of Arkansas (UARK).

In order to identify barriers to uptake of LCT, the research team conducted an analysis of existing market survey and real-world operation data of heavy-duty fleets and ORE participating in incentive programs. More incentive programs exist for HDVs; thus, lessons learned were extrapolated to OREs and that sector's unique challenges to increasing the market share of clean technology were identified. The project also examined incentive programs as a whole and quantified socioeconomic, environmental, and health impacts as a function of incentive dollars spent on clean technology adoption. Using the market data, as well as inputs from other research projects, this project delivered a tool that forecasts low-carbon transportation technology market penetration between 2020 and 2050 that considers incremental cost, projected availability of low-carbon fuel sources, estimated reduction of criteria pollutants, and GHG emissions. Finally, this project estimated the year in which low-carbon transportation technology solutions reach cost parity or market acceptance relative to conventional technologies without incentive program supports.

Executive Summary

Background

The transportation sector is California's largest emitter of oxides of nitrogen (NO_X) and greenhouse gases (GHGs) and off-road equipment (ORE) has become the largest source of NO_X emissions statewide. To meet federal health-based air quality standards and California climate change goals, including carbon neutrality by 2045, medium and heavy-duty trucks and ORE operating in California must transition to low-NO_X emission technologies coupled with advanced renewable fuels and to zero-emission vehicles where possible. The California Air Resources Board (CARB) has various policies aimed at reducing GHG emissions as well as toxic air pollutant emissions, including regulatory programs aimed at reducing GHG emissions as well as toxic air pollutant emissions of both on-road heavy-duty trucks and off-road equipment. CARB also has incentive programs to promote clean technology uptake and nudge markets toward full-scale technology transformation by bringing capital costs and the total cost of ownership for clean technologies into line with equivalent costs for conventional technologies. Investment in incentives can significantly impact market behavior, environmental and health outcomes, and the broader economy.

Objectives and Methods

The objectives of this study are to identify potential policy and incentive strategies that promote greater adoption of low-carbon transportation (LCT) technologies (zero and near-zero carbon and pollutant emissions) in the heavy-duty and off-road sectors. To do this, the research:

1. synthesizes current incentive programs and explores their effect on low-carbon transportation technology uptake among heavy-duty vehicles (HDV) and off-road equipment (ORE);
2. identifies existing and developing low-carbon technology and its applicability to heavy-duty on-road and off-road equipment applications, selecting the most important sectors to evaluate in more depth based upon their potential to reduce emissions and forecasting technology and fuel costs out to 2050 for conservative, moderate, and aggressive market scenarios;
3. explores the technical and behavioral factors governing the transition to low-carbon transportation through an analysis of existing literature and results from structured interviews conducted with heavy-duty and off-road equipment fleets in California;
4. develops an incentive program performance evaluation tool (PET) that employs a TCO-driven technology choice model to the evolution of fuel technologies in the fleet over time to quantify the emissions reductions, and ancillary benefits and cost-effectiveness of

low-carbon transportation incentive program designs targeting specific drayage, linehaul, and construction fleets of different sizes; and

5. using this tool, recommends incentive strategies by vehicle and vocation types for the sectors in which shifting to LCT will have the most impact toward meeting the State's emissions goals, forecasting low-carbon transportation technologies' attainment of cost parity or market acceptance relative to conventional technologies.

Results

The success of California's heavy-duty vehicle and off-road equipment transition to low-carbon transportation will hinge on effective deployment of both regulatory and incentive policy over the next decade. The adoption of the Advanced Clean Fleets (ACF) regulation has established a new playing field for HDV fleets operating in the State. Bringing the total cost of ownership of LCT HDV and ORE into parity is central to this successful outcome. Application of the Transportation Rollout Affecting Cost and Emissions (TRACE) model forecasts vehicle costs for diesel, natural gas, battery electric, and fuel-cell electric trucks and equipment out to 2050 across conservative, mid-, and aggressive market scenarios using a techno-economic approach that relates production volumes to cost reductions. These scenarios span potential ranges of both capital vehicle and equipment expenses as well as fuel costs that include California's Low Carbon Fuel Standard incentives. Results for off-road equipment analyzed estimated TCOs over time and suggest that incentive supports will be needed to maintain price parity between the zero-emission and diesel alternatives for the foreseeable future. Our findings applying the PET to evaluate for the on-road linehaul, drayage, and construction vocations with a range of incentive designs focused on duration of supports and caps tied to conventional technology costs show that cost parity can be reached by 2035, when the bulk of California's heavy-duty fleets will be required under the ACF to only bring zero-emission vehicles into operation. To achieve this, the results recommend an incentive design for CARB's incentive programs that gradually tapers from current (2023) levels down to zero by 2035. Unlike the current CARB incentives, our recommended design institutes caps on incentives to keep them under the incremental cost difference between ZEVs and their conventional counterparts. The costs of the selected design range from \$4.2B to \$5.3B for incentives through 2035, with the mid-market estimate at \$4.6B. This design results in C/E ratios of \$490,000, \$635,000, and \$3,184,000 per short ton of pollutant for our optimistic, mid-, and conservative market scenarios respectively. The optimistic and mid-market results fall within the high-value investment category guidelines under the CMAQ program whereas the conservative scenario ranks as a mixed-quality investment. To improve the likelihood of more favorable market conditions, policymakers should particularly focus on fuel costs as sensitivity results show that they have the most impact on the total cost of ownership driving the transition. Bringing down the cost of electric vehicle supply equipment (EVSE) also shows a notable impact on TCO, particularly if optimized charging is used to increase the ratio of trucks to EVSE.

Conclusions

The PET developed during this research is a flexible tool that builds on prior CARB-supported work from RD16011 contract 16RD011 (Mac Kinnon et al., 2020) to allow an analyst to represent, within a specific regulatory landscape, detailed incentive designs that are sensitive to a wide range of potential parameters, including location and jurisdiction, fleet characteristics such as vocation and size, as well as the relative costs of low-carbon and conventional fuels. This research demonstrated the PET's use to evaluate candidate incentive designs to support the LCT transition. However, improvements remain that can enhance the tool's effectiveness. These include continued improvements to the inputs to the PET, particularly on how incentives shape technology choices. On the off-road side, because the aggregate analysis of the PET doesn't fully account for the significant variety of equipment types and applications, we recommend continued research in this area to further refine the tool to better represent these details. On the on-road side, expansion of the PET's ability to model different procurement options beyond just purchase would allow the model to consider new business innovations such as truck-as-a-service that have the potential to facilitate the LCT transition, particularly for smaller fleets. The model could also be significantly enhanced if fleets were explicitly modeled as a synthetic population. This would allow for representation of both more complex decision-making processes that fleets undertake, as well as better representation of fleet-specific regulatory and incentive designs.

Introduction

California has long been an international leader in the effort to transition to low-carbon transportation. Over the past two decades, the State has advanced this goal through a series of executive orders and legislation. Executive Orders B-48-18[1] and N-79-20 set ambitious targets for the state to achieve carbon neutrality by 2045 that, among other things, sets the goal to achieve 100 percent of medium- and heavy-duty vehicles in the State be zero-emission by 2045 for all operations where feasible and by 2035 for drayage trucks. These executive orders build on earlier executive orders B-16-2012[2] and B-32-2013[3], which established goals for reducing greenhouse gas emissions from transportation.

There are also several legislative requirements that motivated the research described here. AB 32 (State of California, 2006) required the State to reduce its greenhouse gas emissions to 1990 levels by 2020 (a target that was met by 2016 CARB, 2022a). AB32's extension, SB 32 (State of California, 2016) established more aggressive targets, requiring a reduction of at least 40 percent below 1990 levels by 2030. Later updates to the AB32 scoping plan prioritized efforts to reduce emissions by promoting the use of zero-emission vehicles and reducing the carbon intensity of fuels (CARB, 2017e, 2022c). At the same time, SB 100 (State of California, 2018) set a goal for California to transition to 100 percent carbon-free electricity by 2045. It also increased California's renewable energy targets to 50% by 2025 and 60% by 2030. When coupled with increased electric vehicle use in transportation these grid improvements would multiply the carbon reductions achieved.

To help achieve these ambitious targets, The California Air Resources Board (CARB) has developed several regulatory programs and incentives to promote the deployment of Zero-Emission Vehicles (ZEVs) and low-carbon fuels in the transportation sector. The Low Carbon Fuel Standard (LCFS), was identified under the AB 32 Scoping Plan as an action measure (CARB, 2008a). It was first adopted in 2009 and today mandates a twenty percent reduction in Carbon Intensity (CI) of California's transportation fuel pool by 2030 (CARB, 2017d). The Advanced Clean Trucks (ACT) regulation (CARB, 2019a) requires manufacturers to increase the percentage of zero-emission vehicles (ZEVs) they sell in the state as part of California's broader goal to achieve 100 percent zero-emission truck and bus sales by 2045, as outlined in the state's Sustainable Freight Action Plan (State of California, 2016a). Related to the ACT regulation is the recently implemented Advanced Clean Fleets (ACF) regulation that requires State and local government fleets, drayage trucks, high priority fleets, and federal fleets to phase in medium- and heavy-duty ZEVs over time (CARB, 2020a).

[1] https://www.library.ca.gov/wp-content/uploads/GovernmentPublications/executive-order-proclamation/39-B-48-18.pdf
[2] https://www.ca.gov/archive/gov39/2012/03/23/news17472/index.html
[3] https://www.ca.gov/archive/gov39/2015/07/17/news19046/index.html

To offset the near-term costs of this transition, CARB and other agencies in the state offer incentive programs to promote clean technology uptake and nudge markets toward full-scale technology transformation by bringing capital costs and the total cost of ownership for clean technologies into line with equivalent costs for conventional technologies. However, designing clean technology incentives for HDVs and ORE is challenging because they operate in a wide variety of applications, engine sizes, and configurations. Due to the diverse nature of their operations, energy demands, and duty cycles, a one-size-fits-all incentive program will not effectively reduce emissions across the entire range of HDV and ORE applications. Additionally, many fleet operators may be unaware of incentive programs, or reluctant to adopt new technologies due to lack of infrastructure or financial support.

This project focused on developing a better understanding of how to coordinate these various regulatory and incentive policies for on-road HDVs and ORE. We built off work completed in prior CARB research identifying the most promising low carbon transportation (LCT) fuel pathways (Mac Kinnon et al., 2020), but whereas that earlier work focused mostly on the supply side of the LCT market, the focus in this project was to understand how the demand for LCT technology can be fostered through the effective application of policy, and incentives in particular. To answer this question, we structured the work around the development and application of an incentive program performance evaluation tool (PET) to evaluate how applying different regulatory and incentive policies can shape the heavy-duty vehicle market and help California attain its climate and equity goals in the coming decades. To do this, the PET estimates the costs and benefits of various low-carbon transportation technologies over time for specific high priority HDV vocations that include in-state linehaul, drayage, and construction, and various equipment types serving agriculture, industrial, and construction and mining applications[4].

Because of both its importance and requirements for general usability, the PET effectively established the requirements and scope for much of the supporting research conducted. The PET consists of (a) a TCO model that estimates costs by subarea in California for each HDV and ORE category for vehicle purchases in years from 2020 through 2050 under the influence of policy scenarios specified by the user, (b) a fleet turnover model that projects the evolution of the fleet during that time, and (c) an impact module uses the options from the turnover module to estimate emissions impacts and economic outputs from technology uptake. Figure 1 shows how the overall tasks in the project were structured to implement this approach and the organization of this report follows this structure.

[4] The reasons these vocations were chosen for analysis are discussed in Sections 2.4.1 and 2.5.1

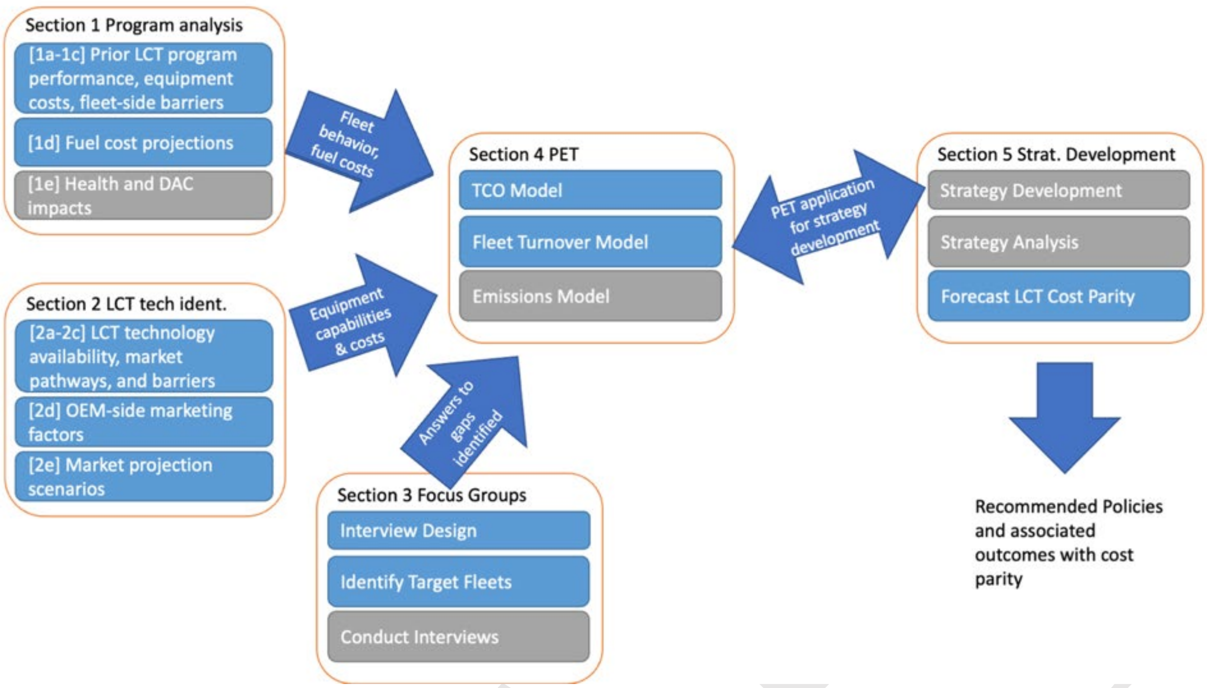

Figure 1. Task relationships

In Section 1 we review existing regulatory and incentive programs to draw insights about their influence of low-carbon transportation uptake in the HDV and ORE sectors. This review includes programs providing incentives for vehicle and/or equipment purchase. In Section 2 we discuss low-carbon technologies and their applicability to heavy-duty and off-road vocations. This includes our identification of low-carbon technology options that are applicable to heavy-duty and off-road vocations. We assessed the technology readiness level (TRL) of various low-carbon technologies including hydrogen fuel cells, battery-electric vehicles, and renewable natural gas. We also explored factors such as infrastructure requirements, maintenance costs, and operational feasibility for specific vocations.

Simultaneously with the work in Sections 1 and 2, we also conducted a set of interviews with fleets to gather their opinions on zero-emission technologies in both the on-road and off-road sectors. The interviews provided insights into the specific needs and challenges of fleets, which can be used to tailor incentive and regulatory program designs for evaluation with the PET. Section 3 looks at the technical and behavioral factors that will impede or foster the LCT transition by summarizing the literature, market status, and the opinions expressed by fleets during interviews regarding zero-emission technologies that were used to inform the development of the PET.

Section 4 details development of the PET based upon the inputs from the first three sections. We describe the PET's overall design, and detail for both the HDV and ORE, the implementation of the total-cost-of-ownership (TCO) module, the fleet turnover module, and the impacts module for assessing the cost effectiveness of low-carbon transportation programs. The TCO module estimates costs on an annual basis from 2020 to 2050 including vehicle costs, infrastructure costs, fuel costs, various incentives, and existing and planned regulatory policies. The fleet turnover module simulates turnover and forecasts future vehicle inventories by fuel type, incorporating specific regulatory requirements into the model. The impact analysis module quantifies fleet market shares over time, associated VMT by region, and resulting emissions reductions and employment benefits.

Finally, Section 5 describes our application of the PET to explore the regulatory and incentive policy space to identify a set of recommended incentive strategies for the on-road HDV space and evaluates their performance across economic and environmental metrics. The results forecast, for specific incentive program designs, the low-carbon transportation technology market penetration between now and 2050 in consideration of incremental cost, projected availability of low-carbon fuel sources, GHG emissions, estimated reduction of criteria pollutants, and associated employment benefits. These results offer guidance to CARB on how to structure incentive programs over the next two decades to support the ZEV transition as well as to demonstrate how the PET can be used for supplemental analysis going forward.

1 Regulatory and Incentive Program Synthesis and Analysis

The State of California has implemented many programs over the past several decades to reduce transportation-related emissions in California, including both criteria pollutants and GHG emissions. The domain is challenging, involving complex market dynamics that extend from the feedstocks supplying the energy sector to the fleets operating HDV and ORE. Due to its breadth and interconnectivity, this creates a challenging regulatory environment due the difficulty in understanding the impact of specific policies. This work focused on how regulation, and especially incentivization, can impact LCT uptake. As shown in Figure 2, CARB's Heavy-Duty Investment Strategy (CARB, 2021c) provides an overview of the State's strategy for public investment in LCT technology development and deployment from technology readiness level (TRL) 1 (feasibility) through 9 (market scale deployment).

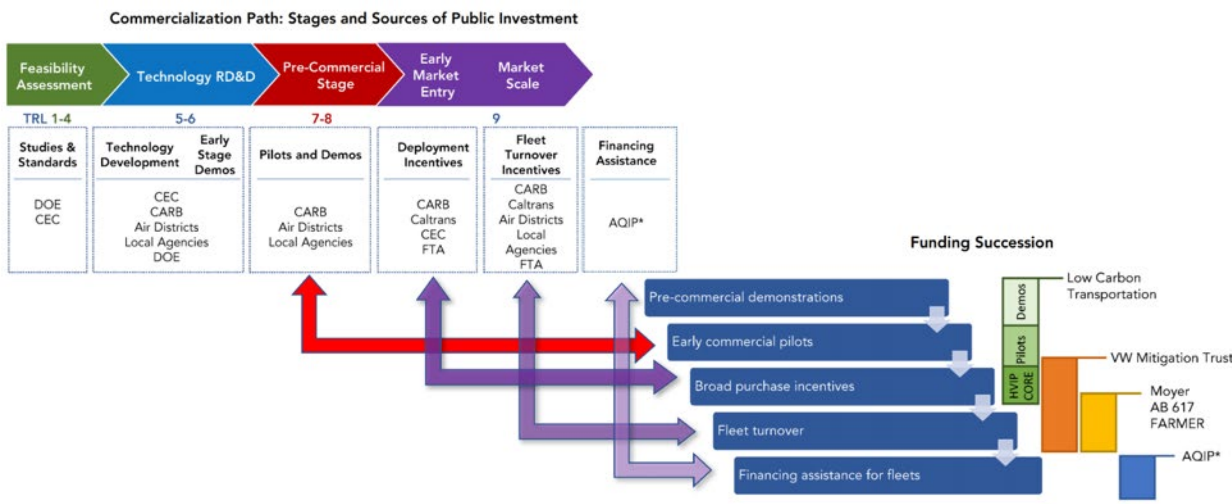

Figure 2. Types of incentive programs for technology development and deployment

Source: CARB Heavy Duty Investment Strategy (CARB, 2019b)

While this work targeted the policies surrounding TRL 7-9 that are designed to foster LCT technologies from the pre-commercial stage through market scale deployment, the primary focus was understanding market-scale (TRL 9) impacts of regulations and fleet turnover incentives. Toward this end we sought data that would help us characterize the causal relationship between incentives and uptake. Sections 1.1 through 1.6 describe our collection of data about existing programs and 1.6 details our efforts to characterize the prior performance of TRL 7-9 policy supports by looking at a case study of natural gas incentivization in the State. While we were unable to find definitive causal findings regarding the effectiveness of incentives and regulations, the review of existing incentive programs and regulations usefully informed the selection of future policies to represent in the PET for scenario analysis.

1.1 Existing early-market incentives and fleet turnover incentive programs

To explore the impacts of existing incentive programs we focused on identifying reports and data for incentive programs in California, focusing on three categories identified in CARB's 2021-22 Heavy-Duty Investment Strategy (CARB, 2021c): pre-commercial incentives that will be in the InfoShed database, early-market incentives focusing on deployment support, and fleet turnover incentives. We separately consider on-road HDV and ORE programs below.

1.1.1 On-road heavy-duty vehicle incentive programs

Our review of existing regulatory and incentive programs used a variety of sources, including the results from CARB contract 16RD011 (Mac Kinnon et al., 2020) and a literature search for new or planned programs that are relevant to California. Table 1 summarizes the programs and regulations identified for consideration. These include incentive programs operated by CARB, other state agencies, regional air districts, as well as federal initiatives.

Table 1. Existing regulatory and incentive programs identified for analysis.

Type	Fleet	Source	Program	Stage	Vehicle or Infrastructure	Notes
Incentive	HDV	Bay Area AQMD	Mobile Source Incentive Fund program	Market scale fleet turnover	Both	
Incentive	HDV	CARB	Hybrid and Zero-Emission Truck and Bus Voucher Incentive Program (HVIP)	Early market deployment	Vehicle	
Incentive	HDV	CARB	Advanced Tech. Freight Demonstration and Pilot Commercial Deployment	Pre-commercial pilot or demo	Both	CALSTART Infoshed will collect this data
Incentive	HDV	CARB	Low-NO_X Engine Incentives		Vehicle	
Incentive	HDV	CARB + All 35 AQMDs	Carl Moyer Memorial Air Quality Standards Attainment Program (1998))	Market scale fleet turnover	Vehicle	Replacement, new purchase, repower, and retrofit trucks to reduce near-term emissions; scrappage required
Incentive	HDV	CARB; CPCFA	Truck Loan Assistance Program	Market scale fleet turnover	Vehicle	
Incentive	HDV	CEC	Clean Transportation Program[5]	Early market deployment	Both	Formerly the Alternative and Renewable Fuels and Vehicle Technology Program

[5] Formerly the Alternative and Renewable Fuel and Vehicle Technology Program

Type	Fleet	Source	Program	Stage	Vehicle or Infrastructure	Notes
Incentive	HDV	CEC	Electric Program Investment Charge Program (EPIC)		Infrastructure	EV charging and vehicle-to-grid power transfer infrastructure
Incentive	HDV	CPUC	Transportation Electrification (Senate Bill 305)		Infrastructure	
Incentive	HDV	Sacramento AQMD	Sacramento Emergency Clean Air and Transportation (SECAT) truck replacement program	Market scale fleet turnover	Vehicle	Closed
Incentive	HDV	Sacramento AQMD	Community Clean Freight Truck Solicitation	Market scale fleet turnover	Vehicle	Closed
Incentive	HDV	San Diego County APCD	Response to UCI Institute of Transportation Studies (ITS) inferred they had their own incentive program for HDVs			
Incentive	HDV	San Luis Obispo County APCD	Response to ITS referenced provision of AB923 funding.			
Incentive	HDV	SCAQMD	SCAQMD AB 2766 Motor Vehicle Subvention Program	Market scale fleet turnover	Vehicle	Some discussion of cost-effectiveness metrics.[6]
Incentive	HDV	SCAQMD	SCAQMD Clean Fuels Program	Pre-commercial pilot or demo	Both	Annual reports available
Incentive	HDV	SCAQMD	SCAQMD Technology Advancement Program	Early market deployment	Both	
Incentive	HDV	SCAQMD	SCAQMD Mobile Source Air Pollution Reduction Review Committee funding		Both	Includes various programs

[6] http://www.aqmd.gov/docs/default-source/transportation/ab2766-motor-vehicle-subvention-fund-program/ab2766-resource-guide.pdf

Type	Fleet	Source	Program	Stage	Vehicle or Infrastructure	Notes
Incentive	HDV	State Treasurer's Office	CA Alternative Energy and Advanced Transportation Financing Authority			Annual reports available. Not direct vehicle incentivization. Includes various programs
Incentive	HDV	U.S. DOE	Zero-Emission Drayage Truck Development and Demonstration	Pre-commercial pilot or demo	Vehicle	Closed. Not direct vehicle incentivization
Incentive	HDV	U.S. DOE	Efficient Class 8 Trucks		Vehicle	
Incentive	HDV	U.S. DOE	SuperTruck Initiative	Market scale fleet turnover	Vehicle	Not direct vehicle incentivization
Incentive	HDV	U.S. DOE	U.S. Department of Energy Clean Cities Program (Reduce petroleum use)		Both	Not direct vehicle incentivization
Incentive	HDV	U.S. DOE (EERE)	Vehicle, Bioenergy, and Fuel Cell Technology Offices support electric vehicles and petroleum displacement			
Incentive	HDV	U.S. Federal Transit Administration	Zero Emission Research Opportunity (ZERO); research, demo, testing & evaluation of zero-emission and related tech. for public transportation		Both	
Incentive	HDV	U.S. Federal Transit Administration	Low or No Emission Vehicle Program, competitive funding for states and transit agencies to purchase or lease of zero or near zero-emission transit buses		Both	
Incentive	ORE	CARB	Clean Off-Road Equipment		Both	

Type	Fleet	Source	Program	Stage	Vehicle or Infrastructure	Notes
			Voucher Incentive Project (CORE)			
Incentive	ORE	CARB	Funding Agricultural Replacement Measures for Emission Reductions (FARMER)		Vehicle	
Incentive	HDV	CEC	Vehicle-to-Grid Incentive and Funding Programs		Infrastructure	
Regulation	HDV	Sacramento Metro AQMD	Adopted Rule 1003 (Reduced-emission Fleet Vehicles/Alternative Fuels) in 1994; but, never implemented it; need to research Rule 1003 further.		Vehicle	
Regulation	HDV	SCAQMD	SCAQMD Fleet Rules (Rule 1186.1, 1191-1196)		Vehicle	
Regulation	HDV	CARB	Truck and Bus regulation		Vehicle	
Regulation	HDV	CARB	Advanced Clean Trucks (ACT) regulation		Vehicle	
Regulation	HDV	CARB	Advanced Clean Fleets (ACF) regulation		Vehicle	

As shown in Figure 3, we used available reports to characterize each program across the following dimensions to create a taxonomy of programs for targeted analysis:

- Policy type: we're interested in **incentives**, which will reduce the capital or operating costs or **regulations**, which generally will mandate changes in the fleet technology.
- Fleet: either on-road HDV or off-road equipment.
- Source: the agency offering the program and, if possible, the underlying source of the funding.
- Stage: incentive programs can be targeted at different stages of technology readiness.
- Program focus: We're interested primarily in programs targeting vehicle/equipment, infrastructure, and fuels.

- Availability of data: whether data is available to evaluate past program performance, and what performance analysis has been completed.

This taxonomy supported the selection of programs for further analysis in terms of cost-effectiveness and other performance metrics. It also identifies potential correlative and causal relationships between regulation and incentives and LCT uptake, discussed later in Section 1.6, and which tie into the PET (Section 3.5) for assessing fleet response to proposed policy actions.

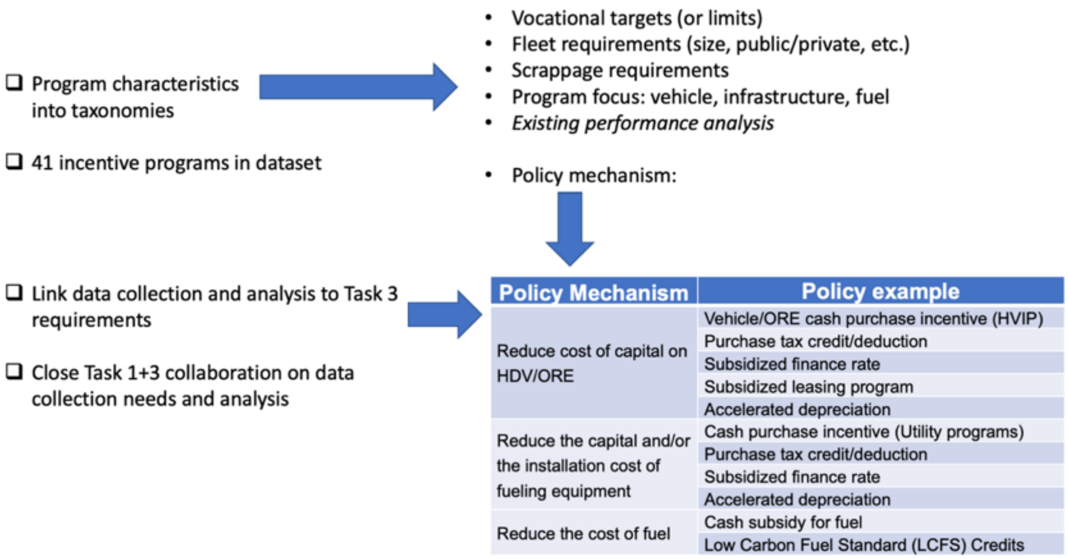

Figure 3. Programmatic data collection process and task linkages

For the programs selected for analysis, in addition to assessing prior program performance, our interest was also identifying characteristics of these incentive programs so that they can be represented in our later analysis. For incentive programs we needed information that will allow us to model how the incentives are allocated across the fleet population. Programmatic characteristics that potentially could be modeled include:

- Incentive amounts available, which may vary by fleet characteristics.
- Eligibility requirements:
    - Vocational targets (or limits)
    - Fleet requirements (size, public/private, etc.)
- Scrappage requirements (which impact residual values)
- Other limits
    - Maximum amounts: programs often limit the incentives beyond their maximums, which is usually a function of the incremental cost of the alternative technology over the conventional fuel.

- Stacking: programs often have specific rules about whether and how incentives can be used alongside other sources of funding. These rules may produce additional limits on funding.
- Total amount of funding available: programs typically have maximum funding in a given calendar or funding year. When this total is reached no more incentives can be paid out.
- Likely timeframe for the program to be active: no programs have unending funding and all can be expected to sunset at some point.

For regulations the primary concern for our purposes is to determine what restrictions and include:

- What technology restrictions are being implemented?
    - Fuel/technology requirements on new equipment, for example fuel type (the pending Advanced Clean Fleets regulation, CARB, 2020a) or emissions limits (the Omnibus Regulation CARB, 2021b).
    - Requirements for retirement of specific technologies (e.g., the Truck and Bus Regulation, CARB, 2008b).
- Who do the restrictions apply to?
    - For fleet rules this includes characteristics such as fleet vocation, size, geography, and other factors that determine who is subject to the rules.
    - Regulations may apply to other entities, such as manufacturers.
- What is the timing of those restrictions, which may differ by fleet, region, vocation, and other factors?

In the following subsections, we consider the most relevant programs identified in Table 1 across the above dimensions to determine which can be and should be represented in the PET. In this review, we also considered whether specific programs or program types could be represented by general programmatic categories in the tool rather than being represented individually. This is in part because it is difficult to predict the existence and form of specific future programs. For modeling purposes, one solution is to represent existing programs with known or expected operating horizons (which may only be a few years or less in some cases) and then beyond that represent general programmatic classes.

1.1.1.1 Hybrid and Zero-Emission Truck and Bus Voucher Incentive Program and Low NO_X Engine Incentive Program

The Hybrid and Zero-Emission Truck and Bus Voucher Incentive Program (HVIP) and Low NO_X Engine Incentive Program (CARB, 2023a) is a market transformation program that incentivizes the purchase of zero-emission heavy-duty trucks and buses in California using purchase vouchers. The funding is provided on a first come, first served basis. Its first funding year was FY 2009-10 and as of May 2023 $986M in funding had been allocated to the program with $281M implemented to that date[7]. In FY 2022/23, the total funding for HVIP was $587.7M, of which:

- $265M was available for standard HVIP
- $157M was targeted for drayage fleets
- $135M was set aside for public school buses
- $70M for zero-emission transit buses
- $35M for innovative small e-Fleets

HVIP funding amounts for zero-emission trucks are structured to include bonuses from baseline funding amounts for small fleets and DACs, as well as for hydrogen vehicles. Notable features of HVIP that should be considered in our modeling of incentive programs include:

- Individual fleets are limited to 30 voucher requests per year, or 50 if they are drayage operators;
- The number of unredeemed vouchers allocated for purchase of vehicles from a given manufacturer at any point in time is limited to 100;
- Fleet size is explicitly considered in the incentive design:
  - From 2024, fleet size includes all vehicles inside or outside of California;
  - Small fleets with 10 or fewer MHD receive a +15% adjustment to the base voucher amount;
  - Large fleets from 101-500 vehicles receive a -20% adjustment and those with 501 or more trucks receive a -50% adjustment;
  - From 2023, very large fleets over 500 vehicles have additional requirements that they must purchase more than 30 vehicles in a year before they become eligible for any vouchers and the trucks purchased with HVIP vouchers must be domiciled in disadvantaged communities.

[7] https://www.caclimateinvestments.ca.gov/clean-truck-and-bus-vouchers

As the primary vehicle incentive mechanism for CARB it is central to the work in this project. More details about incentive funding amounts and design are provided in the PET policy design discussion in Section 5.4.

1.1.1.2 Carl Moyer Memorial Air Quality Standards Attainment Program

The Carl Moyer Memorial Air Quality Standards Attainment Program (Carl Moyer Program) provides grant funding for cleaner-than-required engines, equipment, and other sources of air pollution. The Carl Moyer Program is implemented as a partnership between CARB and California's 35 local air districts. CARB works collaboratively with the air districts and other stakeholders to set Guidelines and ensure the Program reduces pollution and provides cleaner air for Californians.

Of specific interest to this project is On-Road Heavy-Duty Voucher Incentive Program (VIP),[8] which provides funding opportunities for fleet owners with 10 or fewer vehicles to quickly replace, their older heavy-duty diesel or alternative fuel vehicles to zero-emission. Air Districts have the discretion to set certain local eligibility requirements based upon local priorities. Fleet owners may be eligible for funding to replace the existing vehicle(s) to be scrapped. The notable features of this program are:

- It is limited to small fleets
- It has a scrappage requirement
- Funding available in 2023 ranges from $20,000 to $520,000 and depends on the documented utilization of the vehicle being replaced and whether it is domiciled in an environmental justice area or community with a priority population.

1.1.1.3 California's Beneficiary Mitigation Plan (VW settlement)

California's Beneficial Mitigation Plan[9], also known as the VW settlement, funds projects that mitigate the excess NO_X caused by Volkswagen's use of illegal software "defeat devices" in diesel passenger vehicles sold in the U.S. and California in a way that furthers California's clean air goals. The plan includes funding for a range of zero-emission vehicle and infrastructure projects including a $90 million allocation for class 8 freight and port drayage trucks. The relevant specific features of this program include:[10]

- Existing vehicle must be scrapped.
- New vehicle must be a zero-emission vehicle.

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[8] https://ww2.arb.ca.gov/sites/default/files/2023-01/Final%202023%20VIP%20Guidelines%2010123%20ADA.pdf

[9] https://ww2.arb.ca.gov/sites/default/files/2018-07/bmp_june2018.pdf

[10] https://xappprod.aqmd.gov/vw/zero-emission.html

- Funding cap per entity: 10% ($2.7 million)

1.1.1.4 Proposition 1B Goods Movement Emission Reduction Program

The $1 billion Proposition 1B: Goods Movement Emission Reduction Program (Prob 1B)[11] is being implemented in California's four priority trade corridors to reduce freight pollution and the associated health risks. Of the $1 billion authorized, $938 million has been allocated for CARB to award to local agencies that in turn offer incentives to diesel equipment owners to upgrade to cleaner technologies, with the explicit goal of achieving early or extra emission reductions not otherwise required by law or regulation. Prop 1B funding is available for a range of freight-related project types including locomotives, marine, and infrastructure, but the heavy-duty trucks component is most relevant for our work. The details vary by air district, but the Bay Area Air Quality Management District's (BAAQMD) guidelines are representative. BAAQMD funds diesel truck in the cleanest available technology for California-based fleets that:

- replace an existing engine in a class 7 or 8 truck that was manufactured in 2009 or earlier;
- primarily haul commercial freight, bulk, or goods for sale or for purchase on the major CA trade corridors;
- meet minimum utilization levels (20,000 miles/year for class 7-8 trucks).

Funding levels for the most recent solicitation range from $20,000 for an engine repower up to $200,000 for a fully zero-emission truck.

1.1.2 Off-Road Equipment Programs

Various funding programs are available for off-road equipment replacements as well. We summarize them in the following sections.

1.1.2.1 Funding Agricultural Replacement Measures for Emission Reductions: FARMER (CARB)

Agriculture is one of the most diverse industries in California, employing around 160,000 pieces of off-road, diesel-fueled, mobile agricultural equipment, in addition to on-road and stationary equipment. New engine manufacturer standards are not sufficient to curb emissions from this sector to the mandated federal standards. Natural turnover of diesel equipment to cleaner/zero-emission ones are also unlikely to meet the goals. This is because the equipment often operate for several decades due to seasonal use, equipment durability, lower operating cost, and higher purchasing price. Operators thus tend to procure new equipment when necessary. Incentives and funding programs are thus essential in this field.

[11] https://ww2.arb.ca.gov/sites/default/files/2020-07/Final%20Prop.%201B%20June%202015%20Guidelines%20ADA%20Version%202020.pdf

The FARMER program is aimed at reducing GHG and criteria emissions from the agricultural sector by providing necessary funding for harvesting equipment, heavy-duty trucks, agricultural pump engines, tractors, and other equipment used in agricultural operations. $135 million was awarded to CARB for this purpose from fiscal year 2017-2018, by the State Legislature and it has since received an additional $132 million for 2018-2019, $65 million during 2019-2020, $212.58 million in 2021-2022 and $150 million in 2022-2023.[12] At the time of this report, a total $685.6 million in FARMER funding has been deployed since inception.

The funding guidelines were developed by CARB, working in conjunction with local air districts and stakeholders, and were first approved in March 2018. This program aimed at meeting the Legislature's directives on reducing agricultural sector emissions through grants, rebates, and other financial incentives, while meeting the State's emission reduction goals. Under FARMER, funds are allocated to local air districts to administer with 80% of the grant allocated to the San Joaquin Valley Air Pollution Control District, because of its high equipment population, high concentration of emissions, high proportion of disadvantaged communities, and it being in extreme nonattainment with National Ambient Air Quality Standards for ozone. The funding is distributed among other districts based on their portion of farm equipment emissions and air quality attainment status. Air districts under this grant use their funding on a suite of projects that would turn over older vehicles, equipment, and engines used in agricultural operations.

$347.6 million of this project has been implemented to date. Agricultural utility terrain vehicles and tractors/harvesters have been the most engaged types. Other equipment types include agricultural trucks and irrigation pump engines. Table 2 shows the project implementation statistics at time of publication.

Table 2. Implementation categories of the FARMER program

Equipment type	Implemented projects	% investment
Tractors/harvesters	4,812	82
Agricultural trucks	289	7
Agricultural utility terrain vehicles	2,878	10
Irrigation pump engines	78	1

Source: FARMER Program Infographic[13]

While the FARMER program has primarily targeted replacing older diesel engines with cleaner ones, it increasingly targets electrification where feasible. For example, it mandated UTVs with less than 25 hp to be replaced with zero-emission ones. Districts were also allowed to develop and fund demonstration projects with CARB approval.[14] The most recent updates to the FARMER program now funds some limited applicability electric tractors under the new zero-emission agricultural tractor program.[15]

[12] https://ww2.arb.ca.gov/resources/documents/farmer-program-guidelines
[13] https://ww2.arb.ca.gov/sites/default/files/classic/ag/agincentives/outreach/farmerinfographic.pdf
[14] https://ww2.arb.ca.gov/resources/documents/farmer-program-october-2019-additional-project-categories
[15] https://ww2.arb.ca.gov/resources/documents/farmer-program-april-2022-additional-project-categories

1.1.2.2 Clean Off Road Equipment Voucher Incentive Project: CORE (CARB)

First started in 2017-2018, the Clean Off Road Equipment (CORE) Voucher Incentive Project provides first-come, first-served vouchers to specific zero-emission off-road freight equipment. Voucher amounts under this program are designed to cover the cost difference between prices of ICE equivalents to the ZE technology. Increased incentives are offered for equipment in disadvantaged communities. Federal, state, or local entities, local air districts, non-profit organizations, vehicle incentive projects as well as air quality projects were eligible for this program. The aim was to provide streamlined voucher services to fleets ready to acquire zero-emission equipment so that they could receive funding to support the higher cost of those equipment. At the time of this report the program has funded over $200 million in equipment vouchers.

1.1.2.3 Surplus Off-Road Opt-In for NO_X Program: SOON (CARB)

The SOON program funded large fleets of off-road diesel vehicles to procure cleaner heavy-duty engines that are commercially available at that time. The eligible purchases included NO_X exhaust retrofits (CARB approved aftertreatment devices), equipment replacement, and repowers (replacing in-use engine with a new, cleaner one).[16] Fleets having a statewide cumulative horsepower of over 20,000 hp were required to apply for this program. Other criteria for this mandatory participation were operation within respective air district and having higher than 40% Tier 1 and Tier 0 vehicles as of 2008. Fleets below the 20,000 hp threshold could participate in the program voluntarily.[17]

1.1.2.4 Carl Moyer

The Carl Moyer program mentioned for on-road vehicles in Section 1.1.1.2 also included off-road objectives for replacing, repowering, and retrofitting older off-road equipment. Like FARMER, it is administered through the air districts with the small air districts are lumped into one allocation called the Rural-Allocation Pool (RAP). It helped in commercializing the cleanest technologies available during the program timeline. It also focused on reducing air pollution in disadvantaged and low-income communities through the program. Eligible projects under this program relevant to off-road equipment were as follows[18]:

- Off-road: construction, agricultural, cargo handling, marine engine, locomotive, ship-side shore power
- Infrastructure

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[16] http://www.aqmd.gov/home/programs/business/business-detail?title=off-road-diesel-engines&parent=vehicle-engine-upgrades
[17] http://www.aqmd.gov/docs/default-source/aqmd-forms/moyer/moyer_offrdag_pps.pdf?sfvrsn=40
[18] http://www.aqmd.gov/docs/default-source/aqmd-forms/moyer/moyer_overview_pps.pdf?sfvrsn=38

Like FARMER, for vehicles and equipment, Carl Moyer is a scrap-and-replace program and funding amounts are based on cost-effectiveness and maximum percentage of equipment cost.

1.1.2.5 Local Programs

The funding provided by programs such as FARMER and Carl Moyer result in locally administered programs. For instance, the San Joaquin Valley Air Pollution Control District (SJVAPCD) funds equipment replacement and agricultural trade-up programs using a mixture of FARMER, Carl Moyer, and other funds. This program targets self-propelled, mobile, off-road diesel equipment and tractors having 25 or more horsepower.

The SJVAPCD programs give a glimpse of the utilization process of grant money allocated by the overarching programs such as FARMER – which grant a certain amount to the air districts. For this program, the SJVAPCD adopted a horsepower-based grant allocation, where equipment was awarded a certain amount of money based on their type and horsepower rating.

1.2 Infrastructure funding

One of the significant costs associated with zero-emission trucks and off-road equipment is the need for refueling or charging infrastructure. We identified the major sources of infrastructure funding as the California Energy Commission (CEC) as well as the various electric utilities.

1.2.1 CEC's EnergIIZE

Starting in 2022, the CEC's EnergIIZE Commercial Vehicles program has been designed to speed up the deployment and installations of electric charging and hydrogen refueling stations for MD/HD ZEV. The program offers funding through four "lanes" targeted as follows:[19]

- EV Fast Track Funding Lane (first-come, first-served): Intended for applicants/commercial fleets who have a zero-emission vehicle in the fleet or have a purchase order, and need funding for the necessary charging infrastructure.
- Hydrogen Funding Lane (competitive): Intended for commercial fleets or station owners seeking to deploy hydrogen refueling infrastructure for MD/HD zero-emission vehicles.
- EV Jump Start Funding Lane (competitive): Intended for applicants/fleet users located in a disadvantaged or low-income communities, and who meet other equity criteria. This lane provides a longer application window for applicants as well as technical assistance.
- EV Public Charging Lane (competitive): Intended for applicants interested in deploying publicly accessible charging infrastructure for battery-electric MD/HD vehicles.

[19] https://www.energy.ca.gov/proceeding/energy-infrastructure-incentives-zero-emission-commercial-vehicles-energiize

Available funding amounts for each lane are shown in Table 3 along with specific characteristics of each.

Table 3. CEC EnergIIZE infrastructure funding levels for 2023

	EV Fast Track	EV Jump Start	Public Charging Station	Hydrogen Fueling
Type of Application	First come, First Served	Competitive	Competitive	Competitive
Maximum incentive offering	50% of hardware, warranty, network, and software costs	75% of hardware, warranty, network, and software costs	50% of hardware, warranty, network, and software costs	50% of hardware, warranty, network, and software costs
Eligible for milestone payments	Yes	Yes	Yes	Yes
Maximum project cap	$500,000	$750,000	$500,000	$3,000,000

Source: Energiize: (CEC, 2022). Milestone payments allow for funding to apply to eligible costs incurred throughout the lifecycle of the infrastructure project.

EnergIIZE incentives notably cover installation costs as well as equipment.

1.2.2 Utility incentives

We also collected information on utility-level commercial EVSE infrastructure incentives for the following utilities: Burbank/Glendale (BUGL),[20] Los Angeles Department of Water and Power (LADWP),[21] Pacific Gas and Electric (PGE),[22] Southern California Edison (SCE),[23] San Diego Gas and Electric (SDGE),[24] Sacramento Municipal Utility District (SMUD).[25] These incentives range from $3,000 to $125,000 per vehicle (Figure 4) and are for the purchase of charging equipment. Rules and regulations vary with the utilities.

[20] https://www.burbankwaterandpower.com/leadthecharge

[21] https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB746832&RevisionSelectionMethod=LatestReleased

[22] https://www.pge.com/en_US/large-business/solar-and-vehicles/clean-vehicles/ev-charge-network/ev-fast-charge.page

[23] https://www.sce.com/evbusiness/chargeready

[24] https://www.sdge.com/business/electric-vehicles/power-your-drive-workplaces

[25] https://www.smud.org/en/Going-Green/Electric-Vehicles/Business

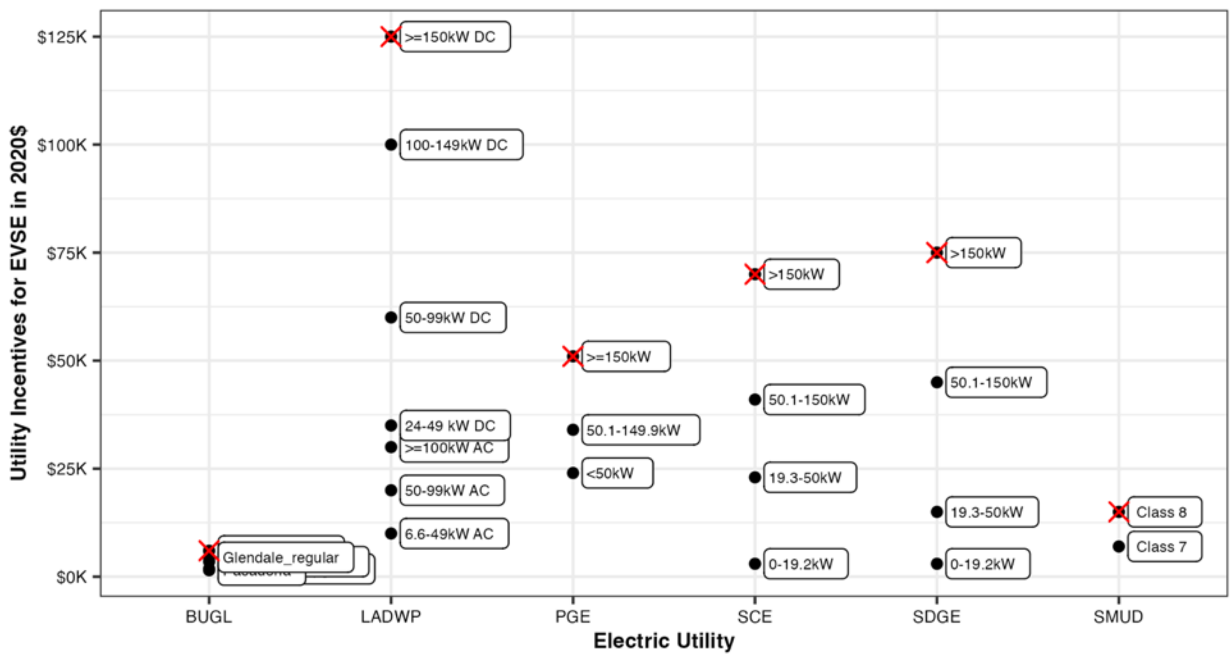


Figure 4. Utility-level incentives for EVSE

Source: Utility incentives were obtained from published utility incentive programs. Incentives are offered for a range of EVSE sizes and types. For the baseline case, the PET assumes that the class 8 vocations modeled will install 200kW DC chargers, which qualify for the largest incentives available at each utility as indicated by the red cross in the figure. BUGL=Burbank/Glendale; LADWP=Los Angeles Department of Water and Power; PGE=Pacific Gas and Electric; SCE=Southern California Edison; SDGE=San Diego Gas and Electric; SMUD=Sacramento Municipal Utility District.

1.3 On-road heavy-duty vehicle regulations

One of the most powerful tools available to the State to achieve cleaner heavy-duty transportation is through regulation. In this work we are most interested in regulations that mandate truck retirements or alter or restrict the available choices of new truck purchases.

1.3.1 Truck and Bus Regulation

The Truck and Bus Regulation was adopted in December 2008 and established the compliance schedule shown in Table 4 to retire trucks not meeting updated emissions standards.

Table 4. Truck and bus regulation heavy-duty vehicle compliance schedule

Engine Model Year	Compliance Date Install PM Filter by	Compliance Date 2010 Engine by
1993 & older	N/A	January 1, 2015
1994 – 1995	N/A	January 1, 2016
1996 – 1999	January 1, 2012	January 1, 2020
2000 – 2004	January 1, 2013	January 1, 2021
2005 – 2006	January 1, 2014	January 1, 2022
2007 or newer	January 1, 2014 if not OEM equipped	January 1, 2023

Source: (CARB, 2008b)

For our purposes, this means that any fleet turnover modeling needs to be able to represent forced retirements of older diesel trucks based upon this schedule.

1.3.2 Advanced Clean Trucks Regulation

The Advanced Clean Trucks (ACT) regulation was approved in 2019 (CARB, 2019a) and establishes a manufacturers ZEV sales requirement whereby OEMs selling more than 500 vehicles per year in the State must sell a specific fraction of zero emission trucks as shown in Table 5.

Table 5. Advanced Clean Trucks ZEV sales percentage schedule

Model Year	Class 2b-3 Group	Class 4-8 Group	Class 7-8 Tractors Group
2024	5%	9%	5%
2025	7%	11%	7%
2026	10%	13%	10%
2027	15%	20%	15%
2028	20%	30%	20%
2029	25%	40%	25%
2030	30%	50%	30%
2031	35%	55%	35%
2032	40%	60%	40%
2033	45%	65%	40%
2034	50%	70%	40%
2035 and beyond	55%	75%	40%

Source: (CARB, 2019a)

Compliance with ACT is governed by a credit/deficit scheme starting in 2024. Exceeding the target generates credits while failing to meet the target generates deficits. Credits can be banked into future years (for 5 years, starting in 2024). Deficits can be resolved by selling more ZEVs or by purchasing credits.[26]

Because ACT establishes supply-side targets, it is challenging to represent in a demand-side model of vehicle purchases over time. ACT may impact the relative costs of diesel and ZEV trucks as the market reacts to the regulation, but the potential magnitude of those impacts are unknown at this time. Furthermore, without explicitly modeling OEMs, it is difficult to see how you could represent ACT impacts in a demand-side model. As such, while we note the ACT regulation, we don’t intend to consider it in this work.

1.3.3 Advanced Clean Fleets Regulation

Unlike ACT, the Advanced Clean Fleets Regulation (CARB, 2023b) has several components. First, it has a **manufacturer sales mandate**, stating that manufacturers may sell only zero-emissions medium- and heavy-duty vehicles in California starting in 2036. Second, it places

[26] https://rmi.org/understanding-californias-advanced-clean-truck-regulation/

ZEV powertrain restrictions on new vehicles for specific fleet categories. The mechanisms are detailed, but they can be summarized as:

- **Drayage fleets**: Starting in 2024, any new drayage trucks placed into service must be zero emissions. Furthermore, all drayage trucks entering seaports and intermodal railyards are required to be zero-emissions by 2035. Therefore this is both a choice set restriction (starting in 2024) and a retirement mandate (starting in 2035).

- **High priority and federal fleets**. High priority fleets are those fleets that either have more than $50 million in annual revenue or operate 50 or more trucks. These fleets have two options:
    1. **Model Year Schedule**: Fleets must purchase only ZEVs beginning 2024 and, starting January 1, 2025, must remove internal combustion engine vehicles at the end of their useful life, as specified in the regulation.
    2. **ZEV Milestones Option**: Fleets can meet ZEV targets as a percentage of the total fleet shown in Table 6, starting with vehicle types that are most suitable for electrification.

Table 6. ACF ZEV milestones option

Percentage of vehicles that must be ZEVs	10%	25%	50%	75%	100%
Milestone Group 1: Box trucks, vans, buses with two axles, yard tractors, light-duty package delivery vehicles	2025	2028	2031	2033	2035+
Milestone Group 2: Work trucks, day cab tractors, pickup trucks, buses with three axles	2027	2030	2033	2036	2039+
Milestone Group 3: Sleeper cab tractors and specialty vehicles	2030	2033	2036	2039	2042+

Source: CARB ZEV Milestones Option fact sheet[27]

- **State and local agencies**. California State and local government fleets must have 50 percent of vehicle purchases must be zero-emissions beginning in 2024 and 100 percent of vehicle purchases must be zero-emissions by 2027.

These regulations impact both the retirement schedule for fleets as well as the powertrains available for specific purchases and must be considered in our modeling. Furthermore, the high-priority fleets criteria includes fleet size, which makes representing fleet size in our modeling an important consideration.

[27] https://ww2.arb.ca.gov/resources/fact-sheets/advanced-clean-fleets-regulation-zev-milestones-option

1.4 Off-Road Equipment Regulations

Off-road equipment is regulated by CARB via a number of application-specific programs. Here we highlight those regulations most relevant to this project, where we chose to focus on specific equipment categories in the OFFROAD database that are most amenable to ZEV operations including agricultural tractors, cargo handling equipment, and construction and mining equipment (see Section 2.5.1 for more information on this selection). Thus, this summary excludes marine regulations, transport refrigeration units, and locomotives. CARB recently summarized relevant regulations as follows: [28]

- Cargo Handling Equipment: Cargo handling equipment "is any motorized vehicle used to handle cargo or perform routine maintenance activities at California's ports and intermodal rail yards and includes yard trucks (hostlers), rubber-tired gantry cranes, container handlers, and forklifts." Existing regulations, such as the Large Spark-Ignition (LSI) Engine Fleet Requirements Regulation[29] have established emissions standards for current equipment since 2006. CARB is considering amendments to existing rules to include the transition to 100% zero-emission operations starting in 2026.
- Zero-Emission Forklifts: Forklifts are used in many different industrial sectors but are most prevalent in manufacturing and at freight facilities, such as warehouse, distribution centers, and ports. CARB is in the process of developing a regulation for Board consideration in 2024 to increase zero-emission forklift deployment throughout the State.[30]
- Off-Road New Compression-Ignition Engines: CARB uses the Off-Road Compression-Ignition Certification Program to certify off-road compression-ignition engines to the applicable emissions standards and other requirements contained in the California regulations and test procedures for off-road compression-ignition engines and equipment.[31] CARB staff is working on Tier 5 standards for off-road, land-based diesel engines around in 2025, with an implementation target of 2028.[32] The Tier 5 standards would apply to engines used in farming, construction, and industrial applications. Though these are not zero-emission requirements, they would affect the baseline, non-ZEV case for modeling purposes. In this project, our expectation is that these regulations would be reflected in the EMFAC emissions rates.
- Finally, the In-Use Off-Road Diesel-Fueled Fleets (Off-Road) Regulation: The Off-Road Regulation "reduces NOx and PM emissions from diesel-fueled off-road fleets operating

[28] https://ww2.arb.ca.gov/sites/default/files/2020-11/ZEV_EO_Off-Road_Fact_Sheet_111820.pdf
[29] https://ww2.arb.ca.gov/our-work/programs/large-spark-ignition-lsi-engine-fleet-requirements-regulation/about
[30] https://ww2.arb.ca.gov/our-work/programs/zero-emission-forklifts/about
[31] https://ww2.arb.ca.gov/our-work/programs/road-compression-ignition-certification-program/about
[32] https://ww2.arb.ca.gov/our-work/programs/tier5/about

in California and zero-emission technology may be used to comply."[33] CARB is approved amendments in October 2023 that will achieve additional reductions.

CARB's existing regulations for off-road equipment is currently less aggressive than the on-road regulations summarized previously with respect to explicit zero-emission restrictions. This is partly due to more limited regulatory authority in the off-road space and also a function of the more complex diversity of equipment types than the on-road space. The takeaway for this research is that modeling should focus on maximizing the flexibility for representing diverse regulatory and incentive strategies in the off-road space to allow staff to consider unique designs that may target specific sectors through a combination of regulation (where feasible) and incentives on both the manufacturing and fleet sides.

1.5 Representing incentive programs and regulatory policy in the PET

Mac Kinnon et al. (2020) offer a number of recommendations for CARBs HDV incentive programs. Several of them urge CARB to streamline their programs to provide better consistency in both implementation and the information that is provided about them. They also recommend simplifying the guidelines to reduce the burden of applying. However, this must be balanced against making the programs too lax so as not to achieve their intended benefits through emissions reductions. Two recommendations from this report are particularly relevant to this project. First, following Di Filippo et al (2019), they recommended:

> *"AVOID MAKING INCENTIVES MORE GENEROUS THAN NECESSARY. Incentives must consider the Total Cost of Ownership ("TCO") to ensure that the incentives provided are not overly generous. If the incentives are too generous, the number of new vehicles able to take advantage of the incentives will be too low. As more eligible vehicles enter the market, incentive levels will have to be continually reviewed and potentially reduced as initial purchase costs decline" (Mac Kinnon et al., 2020, p. 233).*

This is a notable recommendation that can and should be assessed in the PET. The tool should allow for caps to be placed on incentives and to provide a mechanism for the analyst to alter those caps as part of an incentive design. Minimally, the tool should implement what caps do exist already, such as limits on stacking incentives so that the total incentive dollars do not exceed the differential cost of the alternative-fuel technology and the conventional technology. A more nuanced design should be considered in the PET that places caps based upon TCO. Though this may be difficult to implement in practice it could illuminate how such a policy might save public dollars. Once programs are implemented, the extent to which programs are over/under subscribed can provide evidence for adjusting amounts over time.

The second relevant point was:

[33] https://ww2.arb.ca.gov/our-work/programs/use-road-diesel-fueled-fleets-regulation/about

"Requiring scrappage of old vehicles means owner must give up the potential resale value of the old truck, making the decision to participate in the Carl Moyer Program more difficult. More drivers might be willing to replace their trucks earlier if they could realize the resale value of their old truck rather than scrapping it. Assuming their old truck replaces an even older truck, allowing resale of the old truck might still result in a win-win situation. (Mac Kinnon et al., 2020, p. 233).

To support analysis of scrappage requirements (or lack thereof) it is clear that the PET should specifically include residuals based upon estimates of value degradation as a function of vehicle age (e.g., Figure 5) and assumptions of first owner vehicle life. These can be removed selectively in the model to consider their impact on TCO and choice.

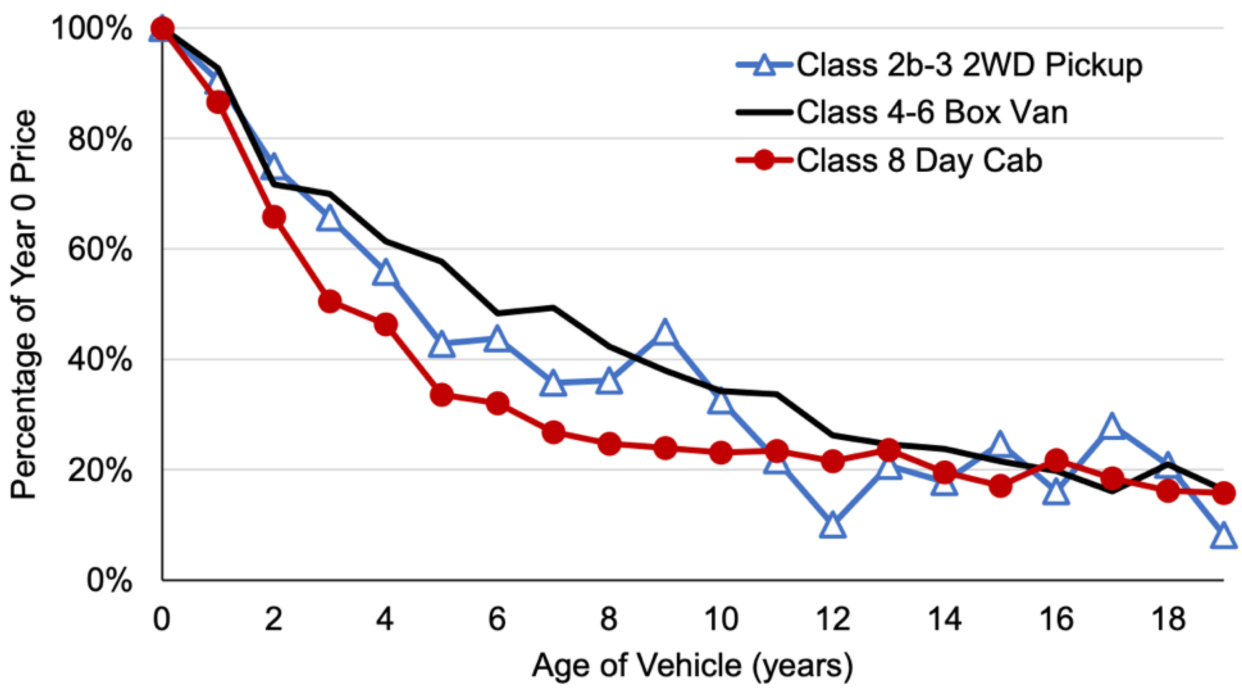


Figure 5. Residual values over time as a percentage of the original price

Source: Advanced Clean Fleets – Cost Workgroup Cost Data and Methodology Discussion Draft (CARB, 2020b)

1.6 Cost data clearinghouse: the Infoshed

As originally conceived in the proposal for this research, the Data Clearinghouse was referenced as an external project funded by CARB that would serve as a repository for all incentive program data obtained to support this project, with an intention to populate the clearinghouse with data collected. After project kickoff, the Data Clearinghouse was recharacterized as a datastore, called

InfoShed, but was earmarked for pre-commercial demonstration and early commercial pilot projects only.[34]

To ensure the data collected by InfoShed could serve as a future datastore for the PET, the research team engaged with CARB staff and CALSTART to consult on the InfoShed data structures and API for access. The team identified data deemed necessary for supporting its retrospective program analysis and the development of the PET as shown in Table 7. These requirements were shared with CARB and the CALSTART team to guide the development of the InfoShed schema. Specific emphasis in this request was placed on the collection of vehicle costs, operational and maintenance costs, and infrastructure costs for baseline internal combustion engine (ICE) vehicles. Another critical input identified was how VMT changes during and beyond the demonstration period. Besides asking for average mileage (under vehicle performance data category of the InfoShed), capturing the VMT changes will help researchers better understand changes in costs over time.

Table 7. Data needs passed to CALSTART InfoShed team

Low-carbon vehicles		ICE vehicles	
Category	**Data type**	**Category**	**Data type**
Vehicle	Acquisition cost Year of acquisition Annual registration fee Annual non-liability insurance Annual maintenance costs Maintenance frequencies over time Annual repair costs Repair frequencies over time Annual VMT VMT changes during the demo period Expected VMT changes over the remaining of its lifetime Annual down time (hours) Annual hours of operation Vehicle lifecycle (years) Battery or engine lifecycle (years) First owner life (years) Residual value	Vehicle	Acquisition cost Year of acquisition Annual registration fee Annual non-liability insurance Regulatory compliance costs Annual maintenance costs Maintenance frequencies over time Annual repair costs Repair frequencies over time Annual VMT VMT changes during the demo period Expected VMT changes over the remaining of its lifetime Annual down time (hours) Annual hours of operation Vehicle lifecycle (years) Engine lifecycle (years) First owner life (years) Residual value

[34] Though the distinctions are a bit fuzzy, CARB staff noted that demonstration projects are pre-commercial (vehicle/equipment does not have approvals to legally be available for sale) [whereas] in pilots projects the vehicle/equipment either already be legal approvals available for sale or must obtain them.

Low-carbon vehicles		ICE vehicles	
Category	**Data type**	**Category**	**Data type**
Fueling infrastructure	Equipment acquisition cost Year of acquisition Site construction costs Equipment installation costs Equipment configuration (plug-in/overhead/wireless) Back-up power storage costs Annual maintenance costs Maintenance frequencies over time Annual repair costs Repair frequencies over time Annual down time (hours) Annual hours of operation Equipment lifecycle (years) EVSE power (kW) or H2 fueling throughput Smart charging software costs	Fueling infrastructure	Equipment acquisition cost Year of acquisition Site construction costs Equipment installation costs Annual maintenance costs Maintenance frequencies over time Annual repair costs Repair frequencies over time Annual down time (hours) Annual hours of operation Equipment lifecycle (years)
Fuel	Annual fuel costs Demand charges (if any)	Fuel	Annual fuel costs

Toward the end of this project, the InfoShed datastore began to be populated with pilot project data. By the end of 2022, InfoShed had data on a total of 351 distinct vehicles, which are summarized by vocation and vehicle type in Table 8. Of these, 151 represented off-road equipment, 88 were buses (school or transit), 15 were class 4 delivery vehicles, and 97 were class 8 (i.e., GVWR over 33,000 lbs) HDV. Purchase cost data was available for 170 vehicles and maintenance cost estimates were available for 126 vehicles.

Table 8. Summary of vehicle and equipment in the InfoShed database at the end of 2022

Vocation	Vehicle Type	Unknown fuel	Battery-electric	CNG engine	CNG hybrid-electric	Diesel hybrid-electric	Fuel Cell	Total
Unknown	unknown	2						**2**
Unknown	Other		1					**1**
CHE	Forklift		2					**2**
CHE	Other		1			2		**3**
Drayage	HD truck		7			2		**9**
Fixed-route	Transit bus		13	3		1		**17**
Freight	Forklift		5					**5**
Freight	Heavy-duty Truck						10	**10**
Freight, Local	Box Truck		10					**10**
Freight, Local	Debris Hauler		1					**1**
Freight, Local	Forklift		34					**34**

Vocation	Vehicle Type	Unknown fuel	Battery-electric	CNG engine	CNG hybrid-electric	Diesel hybrid-electric	Fuel Cell	Total
Freight, Local	Heavy-duty Truck		6					**6**
Freight, Local	Medium-duty Step Van		20					**20**
Freight, Local	Other		9					**9**
Freight, Local	Top Handler		2					**2**
Freight, Local	Yard Tractor		38					**38**
Freight, Long haul	Heavy-duty vehicle	5						**5**
Freight, Regional	Heavy-duty Truck		35		2			**37**
Heavy-haul locomotive	Other		2					**2**
Long Haul	Heady-duty Truck		15					**15**
Nonroad, Industrial/MH	Other		25					**25**
Nonroad, Industrial/MH	Yard Tractor		5				1	**6**
Parcel Delivery	Medium-duty Step Van		15					**15**
School Bus	School Bus		27					**27**
Transit Bus	Transit Bus		25				25	**50**
Total		**7**	**298**	**3**	**2**	**5**	**36**	**351**

A range of additional data is available as well that could be valuable for supporting cost and performance analysis of LCT equipment options. However, InfoShed was still maturing during this project and the late availability of this data meant that we were unable to use it directly in our analysis. However, as this dataset scales and matures, it has the potential to be a calibration source for models of HDV and ORE costs.

1.7 Performance of Existing Incentive Programs

To analyze the effect of existing regulatory and incentive programs on vehicle markets, we collected data on incentive programs in the state. The broad goals here were (1) to identify metrics of success that can be incorporated in our incentive program analysis tool, and (2) to conduct a case study on incentive program performance from the available data that could inform how regulatory and incentive programs can influence uptake of low-carbon technologies.

1.7.1 Cost-Effectiveness Analysis

An assessment of cost-effectiveness indicators was conducted to be used for assessing existing programs. Federal Highway Administration (FHWA) developed their cost-effectiveness calculation method for Congestion Mitigation and Air Quality Improvement (CMAQ) program, aiming to assist States and project sponsors in using their CMAQ funding in a more efficient way to reduce vehicle emissions and traffic congestion. Five kinds of emission pollutants including CO, particulate matter (PM2.5 and PM10), NO_X and VOCs (CARB started using the term ROG to replace VOCs used by US EPA to measure organic gases in 1995) were considered when measuring the emissions. Project types in CMAQ program were rated as having either strong, mixed, or weak cost-effectiveness by summing the median cost-effectiveness across the pollutants listed (Pildes et al., 2020). FHWA classified projects associated with HDVs and OREs in CMAQ program as follows, based on analyzing broad empirically nationwide data.

- Strong C/E (median cost < \$ 2.8M/ton): Diesel Engine Retrofit, Intermodal Freight Facilities and Programs
- Mixed C/E (\$ 2.8M/ton ≤ median cost < \$ 8.8M/ton): Natural Gas Re-Fueling Infrastructure, Electric Vehicle Charging Stations
- Weak C/E (median cost ≥ \$ 8.8M/ton): HDV Replacements

Table 9. CMAQ cost effectiveness levels for various pollutants

Project Types	Project C/E	Strong C/E Pollutants	Mixed C/E Pollutants	Weak C/E Pollutants
Diesel Engine Retrofit	Strong	CO, NO_X, VOCs	PM	-
Intermodal Freight Facilities and Programs	Strong	CO, NO_X, VOCs	PM	-
Natural Gas Refueling Infrastructure	Mixed	CO, NO_X	VOCs, PM	-
EV Charging Stations	Mixed	CO, NO_X	VOCs, PM	-
HDV Replacement	Weak	-	CO, NO_X	VOCs, PM

Source: (Pildes et al., 2020)

In the context of CMAQ program, FHWA defines cost-effectiveness as:

$$\mathrm{C/E} = \frac{\text{project total cost (\$)}}{\text{emission reduction (lbs/yr)} * \text{project lifetime (yr)}} \qquad \textbf{Eq. 1}$$

Funded by the federal CMAQ program, CARB and Caltrans improved the cost-effectiveness calculation method by incorporating the capital recovery factor (CRF) in the guideline to Motor Vehicle Registration Fee program (Burmich, 2005), which suggested the cost-effectiveness calculation as:

$$\frac{\mathrm{C}}{\mathrm{E}} = \frac{\text{annualized funding} * \mathrm{CRF}}{\text{emission reduction}(\mathrm{ROG} + \mathrm{NO_x} + \mathrm{PM10})} \qquad \textbf{Eq. 2}$$

with

$$\text{CRF} = \frac{(1+i)^n(i)}{(1+i)^n - 1} \qquad \textbf{Eq. 3}$$

Here, i and n represent the discount rate and project life, respectively.

In the 2017 guideline revisions to the Carl Moyer program, CARB further modified the cost-effectiveness calculation as (CARB, 2017a):

$$\frac{\text{C}}{\text{E}} = \frac{\text{potential grant amount} * \text{CRF}}{\text{annual weighted emission reduction}(\text{ROG} + \text{NO}_\text{x} + 20 * \text{PM10})} \qquad \textbf{Eq. 4}$$

$$\begin{aligned} &\text{Annual weighted emission} \\ &\qquad = (\text{activity emission} + \text{deterioration emission}) \\ &\qquad * \%\ \text{operation in CA} \end{aligned} \qquad \textbf{Eq. 5}$$

Specifically, the major revisions for the cost-effectiveness calculation in this updated version assigning higher weights to the pollutant PM than the ROG and the NO_X as the PM has been shown to have more negative impacts on the environment and health, and taking the emissions from engine deterioration and fraction of activity conducted in CA.

From this review, we recommend generating programmatic cost-effectiveness analysis that stresses the identified core themes while adding some additional considerations as follows:

1. Besides emission reduction and the marginal effect of the incentive, evaluating the co-benefits of incentives for clean vehicles and infrastructure is important when estimating the grant amount.
2. The operation time or activity percent within the State should be included in cost-effectiveness analysis if the funds are strictly granted within the state only.
3. CRF, as it links with CPI (consumer price index) in each year, is an important parameter in cost-effectiveness calculation especially for the long-lasting projects;
4. If applicable, taking the deterioration problems into account is recommended as it will result in extra emissions other than vehicle operations over time;
5. The cost-effectiveness analysis should explicitly consider specific pollutants based on the project attributes, higher weights are recommended for pollutants with mixed or weak cost-effectiveness comparative to pollutants with strong cost-effectiveness.

1.7.2 Project performance evaluation metrics

In the *Fiscal Year 2019-2020 Funding Plan on Clean Transportation Incentives* (CARB, 2019c), CARB proposed metrics with both qualitative and quantitative assessments that could be used to evaluate the effectiveness of different types of programs. CARB continues to update these metrics to be more detailed in the in each version of its fiscal year funding plan (CARB, 2021c).

The metrics (CARB, 2019c, 2020c), shown in Table 10, evaluate the programs from three different perspectives: public health, technology evolution, and the building of green economy. For each perspective, there are some short-term metrics, which are feasible at the current stage, and some metrics that are proposed for evaluating long-term performance of the program. This project is focusing on current metrics, with an eye toward computing future metrics where data is available. Identification of data sources is still a work in progress.

Table 10. Summary of CARB evaluation metrics

Criteria	Current Metrics	Future Metrics
Public health	Quantifying emission reductions & identifying the occurrence locations	Long-term benefits
Tech evolution	Quantify how investments in commercially available techs are accelerating consumer acceptance and decreasing the production costs. Collecting observations that technologies from one application are being transferred to and used in others. The number of HVIP vouchers requested each year by type of advanced techs.	Tracking the number of suppliers for core components and growth over time
Building the green economy	Tracking the total purchase price and co-funding on HVIP-funded vehicles Qualitative information on the expanding supply chains for advanced technology components	Quantifying the number of HVIP-eligible manufacturers has increased over the lifetime of the program (10 years)

To fulfill the SB 1204 requirements requiring that performance criteria and metrics are established for deployment incentives, CARB specified additional performance criteria for evaluating heavy-duty projects funded through AQIP, California Clean Truck, Bus, and Off-Road Vehicle and Equipment Program, or both (CARB, 2019d). These metrics are summarized in Table 11.

Table 11. CARB evaluation metrics for SB 1204 compliance.

Criteria	Specific Assessments
Potential for statewide and local emission reductions and health benefits	Near-term reductions in both GHG and criteria emissions Long-term reductions in GHG and criteria emissions Emission reductions in non-attainment areas Emission reductions in and benefiting disadvantaged communities
Potential for technology viability	Cost parity compared to conventional technologies Reliability and durability in chosen application Ability to transfer technology to other vehicle or equipment types Fueling infrastructure support Ability to integrate renewable fuels
Broad market acceptance	Ability to leverage additional public and private funding Collaboration between multiple entities Ability to address market barriers

Source: California Air Resource Board (CARB, 2019d)

These two sets of metrics evaluate the performance of effectiveness for the heavy-duty projects in three overlapping domains including emissions reduction/health benefits, technology development, and economy/market penetration. For evaluation of heavy-duty projects in this project, we have merged the above into the proposed performance evaluation metrics in Table 12, with focus on quantitative assessment.

Table 12. Proposed performance evaluation metrics for incentive program assessment

Metric Domain	Specific Metric
1. Market penetration	Total purchase price and number of cleaner vehicles
	Market growth of core tech suppliers and supply chain over time
	Operator's, fleet owner's and consumer's attitudes or perceptions toward cleaner vehicle technologies;
2. Emission reduction and health benefits	Determine the pollutants and computational methodology for emission reductions and co-benefits (i.e. health, ...);
	Cleaner vehicles/technologies market projection in the future;
	Vehicle activity maps (i.e. used to identify priority/disadvantaged communities, ...);
3. Technology evolution and viability	Cost drops in commercially available technologies;
	Expenditure savings on research of relevant technologies;
	Fuel savings and re-fueling infrastructure support;

The incentive program performance evaluation tool will seek to represent incentive impacts on (1) total purchase price and how that shapes the number of the zero-emission fuels in the market over time through a TCO and fleet turnover model. Modeling market supply-side market growth is represented by our technology cost projections (discussed in more detail in section 1.6). Directly representing changes in fleet owners' perceptions would require detailed survey data that does not currently exist. The tool will also represent (2) the emission reduction and associated co-benefits of greater LCT penetration. These benefits will be spatially resolved to allow for assessing impacts on disadvantaged communities. For (3), cost drops can be represented in our technology cost projections. Supplemental data, such as that being collected in

InfoShed can improve these projections going forward as more longitudinal data becomes available. Projections of savings on research expenditures is beyond the scope of our modeling effort but should be tracked over time if possible.

1.7.3 Exploring the relationship between incentives and sales of HDVs

The incentive performance evaluation tool will need to forecast how fleets will respond to relative prices for different fuels in the HDV and ORE market. Very few research papers have covered the topic on identifying the correlations between government incentives and sales of HDVs, many existing works have discussed how incentives have motivated the purchasing and market penetration of alternative fuel vehicles, including battery-electric vehicles (BEV) and fuel-cell electric vehicles (FCEV). Though the ideas and methodologies behind these prior studies are potentially relevant to the study of HDVs.

In a review of the use incentives and regulations globally, Zhou et al. (2015) 1.6 found that national and regional incentives can play an important role in plug-in electric vehicle (PEV) markets across different countries including the U.S., China and western European countries. Specifically, the positive influences identified include:

- Government incentives have strongly stimulated the sales growth (both financial incentives like subsidies, tax credits, and non-financial incentives like free parking, free high-occupancy vehicle lane access, free license plate) of PEV;
- Setting numerical sales targets could accelerate market penetration of PEV;
- Both emission-related regulations and user-related regulations have positive impacts on PEV sales

However, not all financial purchase incentives have worked effectively in promoting the growth of HEV, PHEV and BEV markets. By exploring the literature broadly, Hardman et al. (2017) attributed the limitations of those incentives to three main reasons:

- Gas or petrol price and household income are better correlated to HEV purchasing in some areas;
- Consumers are not aware of the incentives available to them;
- Access to infrastructure, locality to major cities are more important factors for some consumers

To quantify the correlations between the incentives and purchase of LDVs, the widely used methods are summarized below based on existing literature (Javid & Nejat, 2017; Jenn et al., 2018; Narassimhan & Johnson, 2018):

- Qualitative discussion / basic statistical analysis;
- OLS regression / hedonic regression / linear regression;

- Discrete choice model / multinomial logit model / basic logit or probit model

As the purposes and scopes vary between different studies, the variables differ. But the categories and the ideas behind the variable selections are very similar among all studies (Bjerkan et al., 2016; Javid & Nejat, 2017; Jenn et al., 2018; Narassimhan & Johnson, 2018; Sierzchula et al., 2014). The common variables considered in these studies include:

- Vehicle-related (e.g. cost, vehicle categories and characteristics, fuel/engine types)
- Consumer-related (e.g. socioeconomics of household, demographics and travel behavior indicators of individual buyers)
- Context-related (e.g. energy price, manufacturers density, charging infrastructure accessibility, population density)
- Incentive-related
    - Financial incentives: purchase credits/rebates, and fleet credits
    - Non-financial incentives: free parking, high-occupancy vehicle access, inspection exemption, registration fee deduction/waive, EVSE, and TOU rates

However, the transferability of these concepts derived from household vehicle purchase behavior to that of firms purchasing heavy duty vehicles or equipment is difficult to justify. It is likely that the broad variable categories identified above will play a role in the uptake of LCT in HDV and ORE fleets, but the relative importance of these variables as well as the characterization is likely to differ. Furthermore, organizational decision-making in fleets is more complex than that of households because organizations can have a variety of structures to make decisions. This means that the "consumer" variables will likely be distinct from those for households (Bae et al., 2020; Sierzchula et al., 2014).

We obtained data from multiple incentive programs administered by CARB and other agencies on incentives and funding provided for vehicle purchases for the following programs to explore the relationship between incentives and alternative fuel vehicle uptake:

- Carl Moyer Program[35]
- AB 32 Cap and Trade funding
- Proposition 1B Goods Movement Emission Reduction Program[36]
- California Energy Commission (CEC) Clean Technology Program Natural Gas Vehicle Incentive Project
- InfoShed (Section 1.6)

[35] https://ww2.arb.ca.gov/our-work/programs/carl-moyer-memorial-air-quality-standards-attainment-program
[36] https://ww2.arb.ca.gov/our-work/programs/proposition-1b-goods-movement-emission-reduction-program

However, our conclusion is that there are not sufficient data at this time for a causal analysis because the way in which programs were implemented did not include sufficient variation. In the future this could be rectified by program managers coordinating with behavioral economists at CARB to implement pilot programs that are designed to identify the causal effects of the program as well as refine the program's approach before it is scaled.

In addition, attempting to formulate a causal model based upon fleet purchase behavior in an immature market is problematic. This is particularly true for class 8 ZEV HDVs, which are just emerging from the pilot stage. Indeed, the data obtained from the InfoShed is exclusively from pilot programs that have not reached market scale.

For the purposes of our project, the inability to generate a causal model of HDV and ORE fuel choice from the available data means that we need to identify an alternative formulation to be able to operationalize a forecasting model. Ultimately, the key to developing a useful choice model for forecasting LCT uptake is to strike a balance between the limitations of the available data and the need for a model that is flexible enough to capture the complex interactions between regulations, incentives, and vehicle technology choices.

We searched the literature for available models that might be adapted, with the criteria that it needed to be able to estimate fuel choice splits based on TCO. Toward this end we identified the Global Analysis Change Model (GCAM), which is "a dynamic-recursive model with technology-rich representations of the economy, energy sector, land use and water linked to a climate model that can be used to explore climate change mitigation policies including carbon taxes, carbon trading, regulations and accelerated deployment of energy technology" (Bond-Lamberty et al., 2022). GCAM is a multi-sector model, but it does directly model the fuel choice splits in the heavy-duty sector using a modified logit model (Bond-Lamberty, 2022). After considering the available alternatives we decided that adapting this GCAM choice model would account for the limitations of the available data by building on an existing framework and calibrating the choice model to fit to observed shares in the base year. The specifics of this process are discussed later in Section 4.1.5.

2 Low-Carbon Technology Identification and Applicability to Heavy-Duty and Off-Road Vocations

2.1 Information, data gaps, and existing barriers

This section provides a synthesis of current data gaps and existing barriers related to technology and cost/production limitations from the current state-of-knowledge for the HDV and ORE sectors. Low carbon fuel technologies considered in this study include natural gas, renewable diesel, battery electric, and fuel cell electric. Vocation-specific barriers are being considered for the categories listed in Table 13.

Table 13. Vocations considered in this review

On-Road Vocations	Off-Road Vocations
Drayage	*Agriculture equipment*
Linehaul	*Cargo handling equipment*
Short Haul	Ship-to-shore cranes
Long Haul	Rubber-tired gantry cranes
Construction	Top-picks
	Side-picks
	Yard tractors (on-dock, off-dock)
	Construction

The team conducted a literature review to identify previously identified barriers. A summary of barriers discussed in the literature are presented in Table 14.

Table 14. Previous Reviews of Low-Carbon On-Road and Off-Road Technologies and Deployment Potential

Reference	Scope	Barriers/Factors Affecting Deployment
(Hunter et al., 2021)	Alternative fuel vehicles	Cost, performance (dwell, payload)
(Xu et al., 2020)	Hydrogen refueling stations	Cost, vehicle availability, hydrogen supply, policy and regulations
(Ajanovic & Haas, 2020)	Hydrogen and fuel cell electric vehicles	Cost, policy
(Trencher et al., 2020)	Fuel cell electric vehicles	Production cost, performance, infrastructure cost and availability, low-cost renewable hydrogen, vehicle availability, policy
(Anderhofstadt & Spinler, 2019)	Alternative fuel vehicles	Most relevant: Vehicle reliability and charging/fueling infrastructure availability; 34 factors affecting deployment
(Blynn & Attanucci, 2019)	Bus electrification	Capital cost, infrastructure cost, operational complexity, policy

Reference	Scope	Barriers/Factors Affecting Deployment
(Smith et al., 2019)	Medium- and heavy-duty electric vehicles	Cost, vehicle performance (ability to meet duty cycle), reliability, powertrain/vehicle lifetime, battery weight, infrastructure, thermal management, high voltage components
(Y. Zhang et al., 2019)	Fleet alternative fuel vehicles	Cost, performance, vehicle availability
(Globisch et al., 2017)	Commercial BEV fleets	Consumer uncertainty
(Dominković et al., 2018)	Alternative fuel vehicles	Range, payload capacity
(Birky, Laughlin, Tartaglia, Price, & Lin, 2017)	Medium-duty, heavy-duty, off-road, rail, aircraft, marine	Sustained power demand, daily energy demands, operation in extreme environments, consumer uncertainty, vehicle performance and availability (scaling production)
(Birky, Laughlin, Tartaglia, Price, Lim, et al., 2017)	Plug-in electric (PHEV, BEV) Class 2B-3	Design and performance limitations, range, payload capacity, reliability, customizability, driving schedule adjustments (due to charging)
(Brotherton et al., 2016)	Electric trucks	Cost, poor vehicle quality and support, infrastructure (planning, cost) and operational constraints in extreme climates
(Moreda et al., 2016)	Off-road: tractor and agricultural machinery	High torque requirements, power/weight ratio, energy density
(Sierzchula, 2014)	Fleet electric vehicles	Consumer uncertainty
(Tran et al., 2013)	Alternative fuel light-duty vehicles	Cost, infrastructure
(Whyatt, 2010)	Natural gas light-duty and heavy-duty vehicles	Vehicle cost, local fueling infrastructure (public access)

Renewable diesel is a drop-in fuel replacement for conventional diesel, and therefore the limitations for widespread deployment are mostly associated with the cost and improving/scaling production pathways. Natural gas is also a mature fuel used for heating and power generation with a statewide natural gas system to supply these end uses. The main limitations of natural gas are related to vehicle cost and local fueling infrastructure (Whyatt, 2010). Of the two zero-emission vehicle technologies, BEVs have a greater number of vehicle models commercially available but have range and cargo-carrying limits (Çabukoglu et al., 2018). FCEVs have much faster refueling times and have less impact on cargo capacity, volumetrically and by-weight (Çabukoglu et al., 2019). Both MHD-ZEV types have additional areas of improvement including vehicle and infrastructure availability (Y. Zhang et al., 2019), reliability, cost, and vehicle performance (Birky, Laughlin, Tartaglia, Price, & Lin, 2017).

The medium-, heavy-duty, and off-road sectors encompass commercial vehicles and equipment which range in function and application. These sectors rely heavily on diesel fuel, with some vocations relying on gasoline and natural gas, see Figure 6 and Figure 7 (CARB, 2017c). Identifying baseline fuel demand is important in understanding vehicle requirements and current operational behavior of on-road and off-road vehicles and equipment, as well as the emissions reduction potential of adopting low-carbon technologies both cumulatively and by vehicle type.

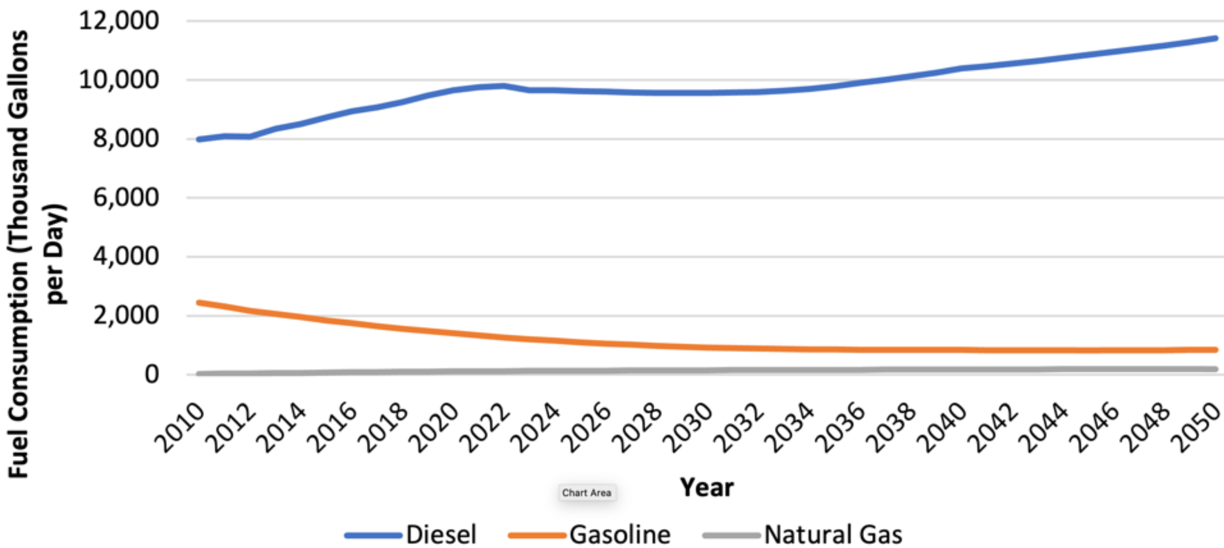


Figure 6. Projected Medium- and Heavy-Duty Daily Fuel Consumption Baseline 2010-2050
Source: data from CARB's Vision Model

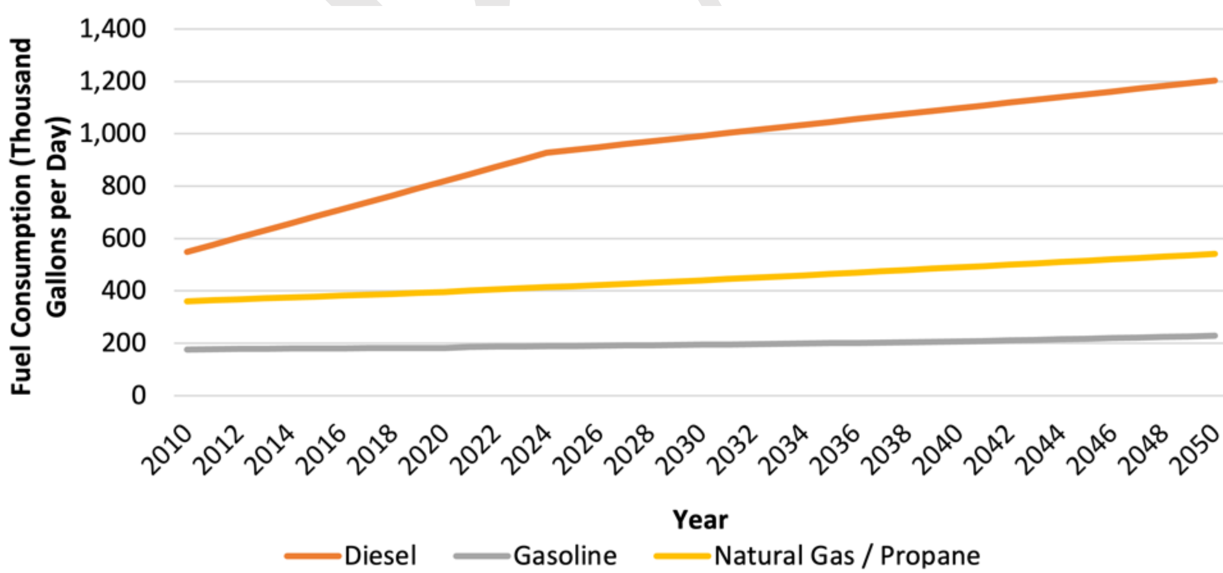


Figure 7. Projected Off-Road Vehicle Daily Fuel Consumption Baseline 2010-2050
Source: data from CARB's Vision Model

Under the CARB on-road baseline scenario, gasoline demand is spread across class 2B-8 vehicles and natural gas use is only used by solid waste collection vehicles. Under the off-road baseline scenario, gasoline, natural gas, and propane are used exclusively for forklifts, mostly in industrial applications. The off-road diesel demand is distributed across many applications, as presented in Figure 8, showing data from CARB's Vision Model, Off-road, Forklift, and Ground Support Equipment Module (CARB, 2017c). Construction and mining equipment are the largest off-road consumers of diesel, particularly, tractors, loaders, backhoes, and off-highway trucks. Converting off-road equipment to zero-emission options will depend on ZEV technology suitability to meet duty cycle demands as well as cost.

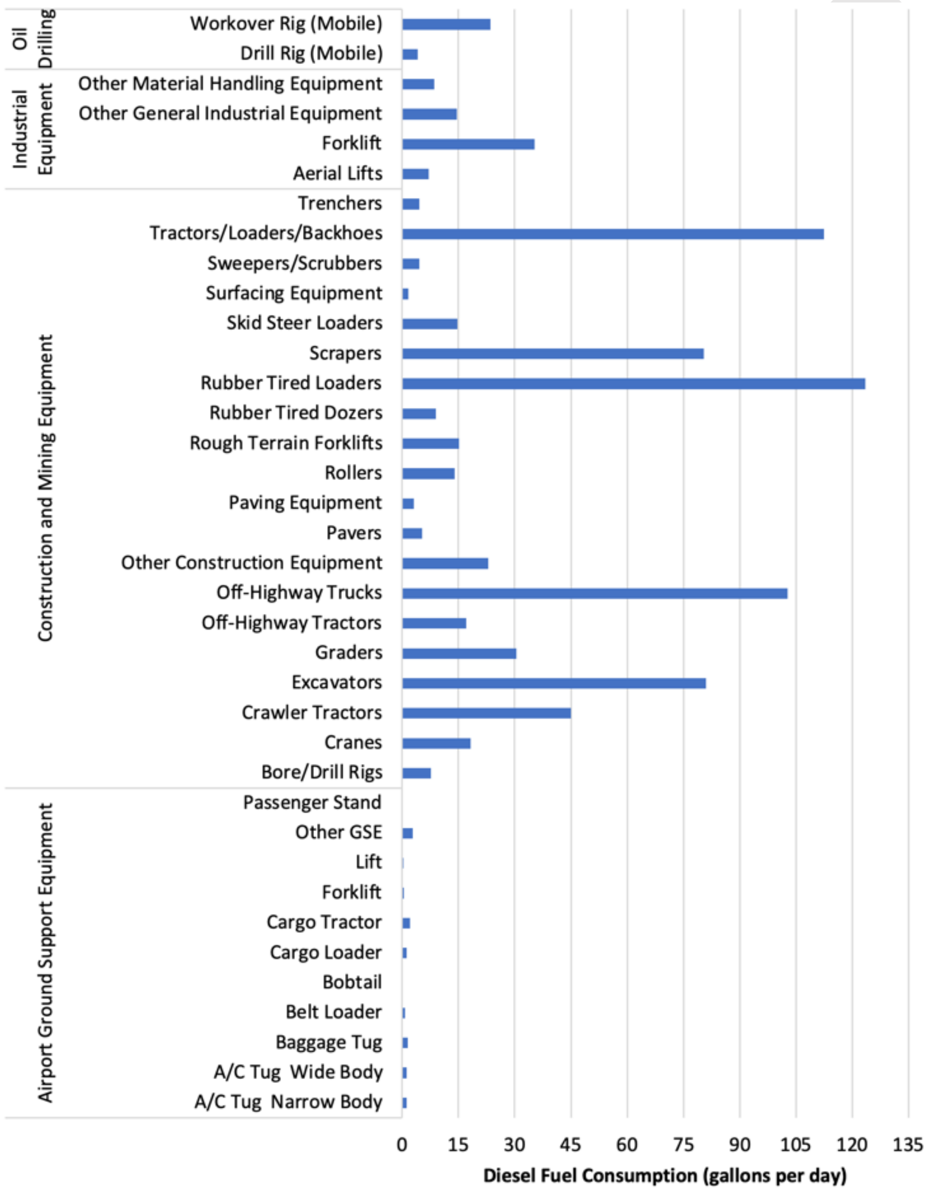


Figure 8. Projected Diesel Fuel Consumption by Off-Road Category in California for 2020
Source: CARB's VISION model

2.2 Low-carbon transportation technology markets and their transferability

Between 2019 and 2020, the number of on-road MHD-ZEV models commercially available increased from 95 to 169 and from there has grown to over 800. Through 2019, most of the model growth was medium-duty trucks and transit, but between 2019 and 2023 notable growth in ZEV heavy-duty truck models has occurred.

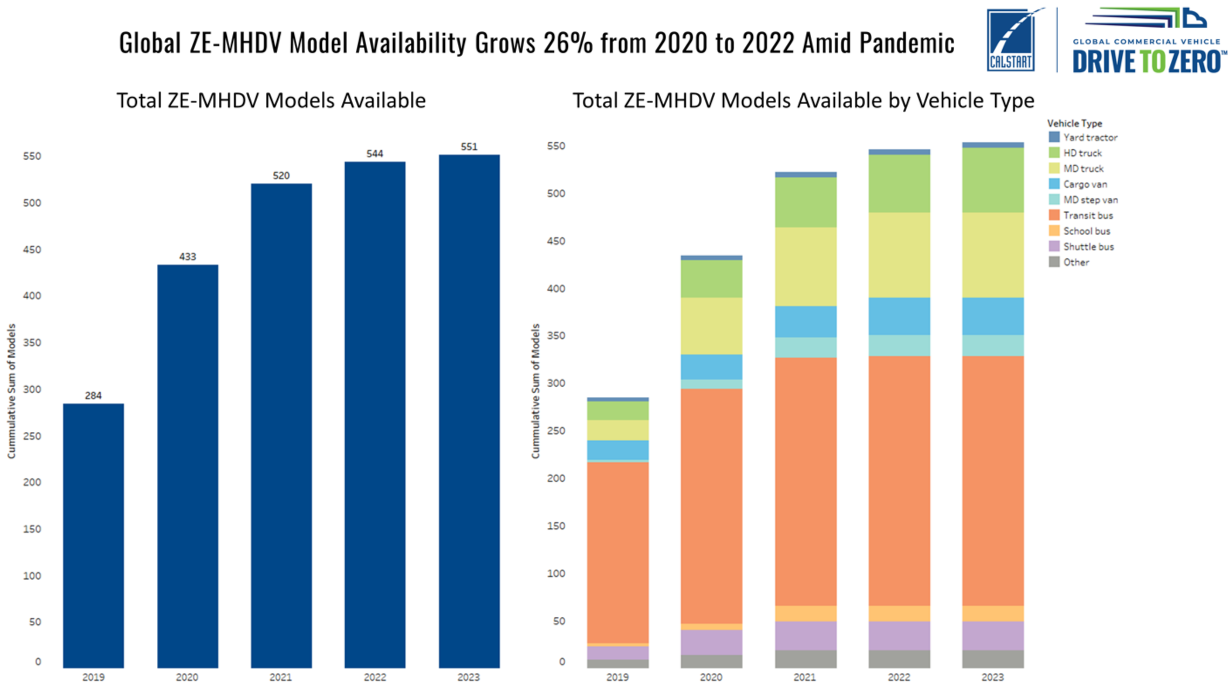


Figure 9. Medium- and Heavy-Duty Zero-Emission Vehicle Model Availability by Type, 2019 -2023

Source: Middlebrooks (2022).

2.2.1 Vehicle Design and Performance

In 2017, a majority of commercially available MHD-ZEVs had ranges between 50-200 miles (Moultak et al., 2017a), see Figure 10. By the end of 2022 (

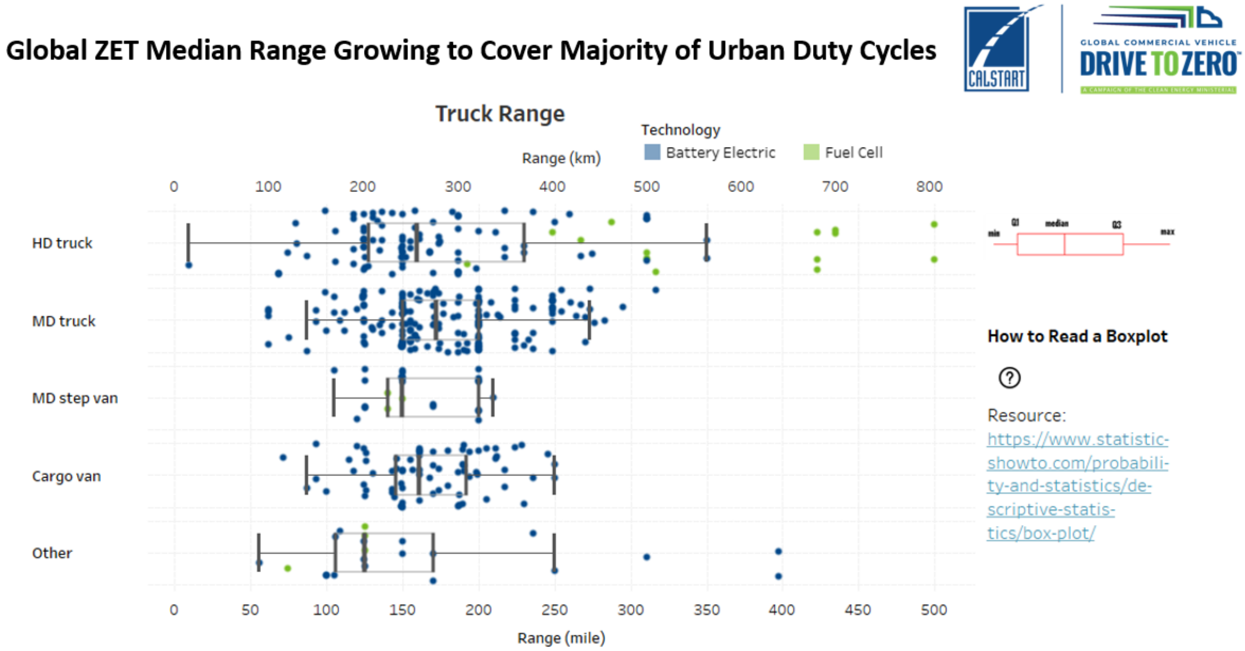


Figure 11) not only had the number of available HD truck models increased significantly but more were available that demonstrated a range of 250 miles (400km) or more.

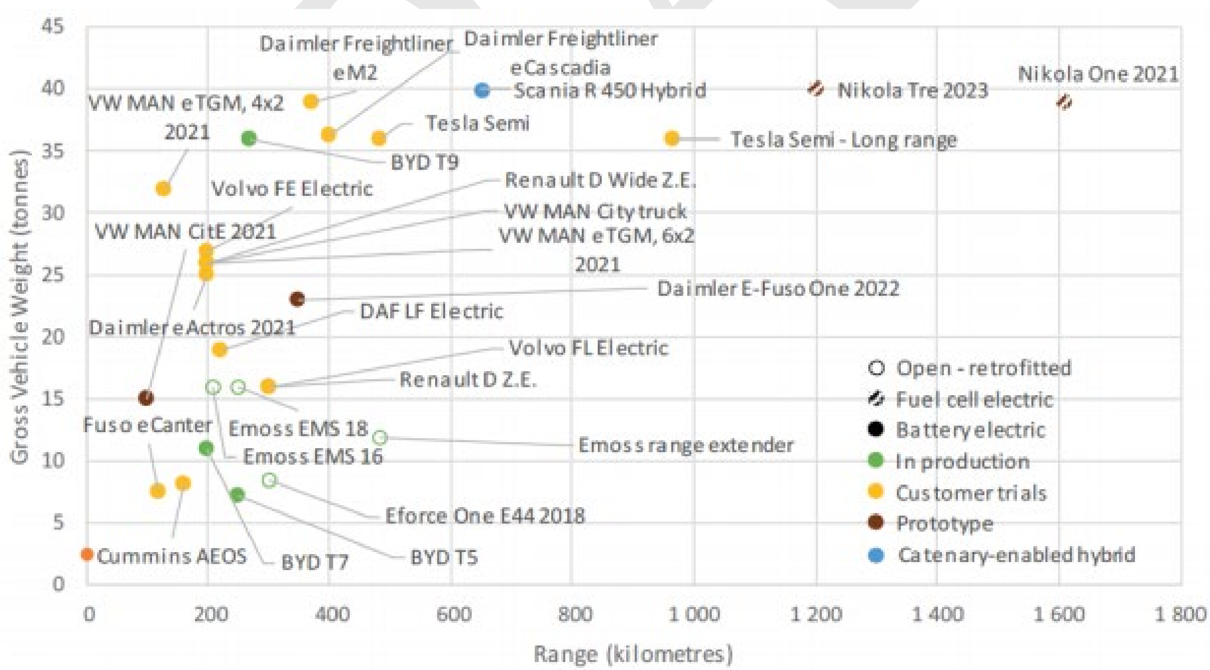


Figure 10. Medium- and Heavy-Duty Zero-Emission Vehicle Model Gross Weight versus Range in 2017

Source: International Council on Clean Transportation (Moultak et al., 2017a)

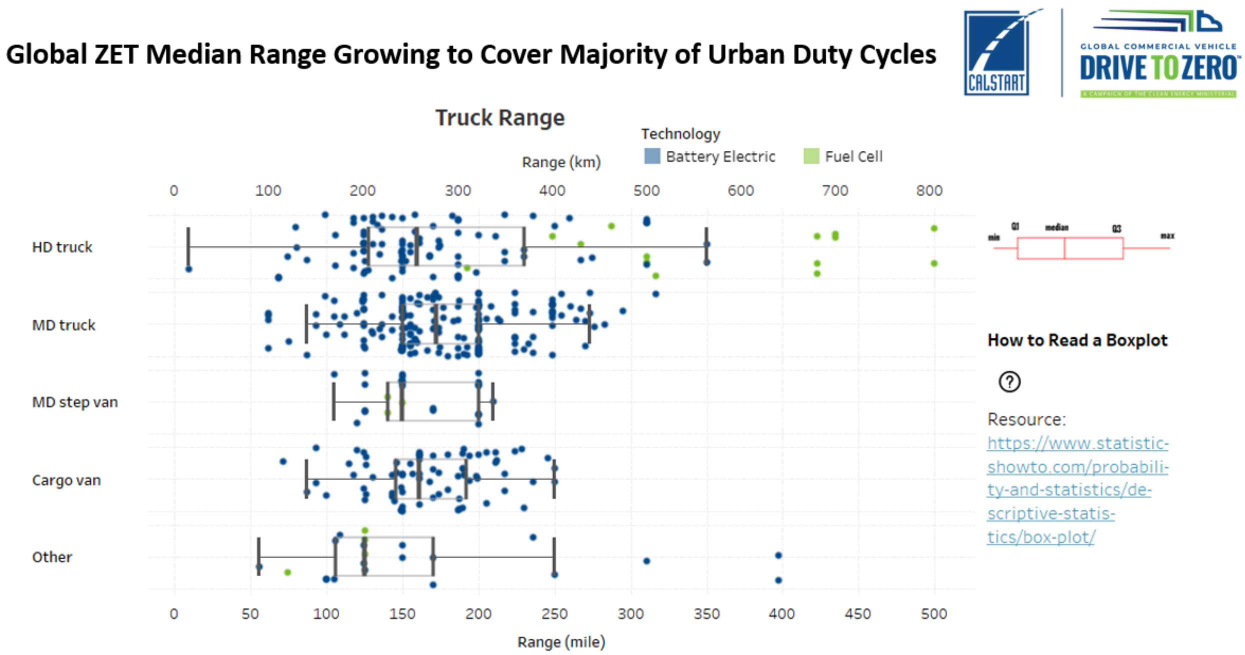


Figure 11. Medium and heavy-duty zero-emission vehicle class versus range in 2022

Source: (Calstart, 2022)

Table 15 presents examples of current MHD-ZEV models and their technical specifications (Forrest et al., 2020). A more complete list of current medium- and heavy-duty zero-emission vehicle models can be found in the NREL database (NREL, 2019).

Table 15. Examples of Heavy-Duty Zero-Emission vehicles and Technical Specifications

Vehicle Make & Model	ZEV type	Vehicle type	Class	Battery size (kWh) H_2 capacity (kg)	Estimated fuel efficiency (kWh/mi or mi/kg)	Range (miles)
BYD	BEV	Bus	7, 8	324,500	2.08, 1.96	156, 255
BYD	BEV	Day Cab	8	435	2.60-3.51	124 (full-load) 167 (half-load)
BYD	BEV	Cab chassis / step van	6	221	1.78	124 (full-load)
Cummins*	BEV	Truck	7	140	1.40	100-300
Daimler / Mercedes*	BEV	Truck	7	240	2.0	≤124
Einride*	BEV	Autonomous truck	8	200	1.61	124
Hyundai	FCEV	Day Cab	6-7	72 kWh, 31 kg	Not available	248
Lightning Systems	BEV	Van	2B-3	43, 86	0.72	60, 120
Navistar eStar**	BEV	Van	3	80	0.74 (reported)	99.4

Vehicle Make & Model	ZEV type	Vehicle type	Class	Battery size (kWh) H_2 capacity (kg)	Estimated fuel efficiency (kWh/mi or mi/kg)	Range (miles)
Smith Newton**	BEV	Truck	6	80, 120	1.34 (reported)	60, ≤150
Smith Newton**	BEV	Van	6	80	1.41 (reported)	99.4
Tesla*	BEV	Truck	8	800 (est.)	<2	300, 500
Zenith Motors	BEV	Van	2B-3	51.8-74.5	0.55-0.65	80-135
Proterra	BEV	Bus	7-8	220, 440	1.88-2.37	93-234
Phoenix Motorcars	BEV	Flatbed	4	105	>1.0	100
Nikola / Bosch*	FCEV	Truck	8	240 kWh, 9 kg	Not available	500-750
Toyota / Kenworth	FCEV	Truck	8	12 kWh, 40 kg	6 mi/kg	200, 300 (Gen 2)
Van Hool / UTC Power**	FCEV	Bus	8	53 kWh, 50 kg	4.79 mi/kg (reported)	240 (est.)
US Hybrid	FCEV	Step van	3	28 kWh, 9.78 kg	1.18-1.47 kWh/mi, 12.8 mi/kg	125
New Flyer (Xcelsior Charge)	BEV	Bus (35ft & 40ft) – Rapid charge	7	160, 213, 267	2.1 – 2.3	75, 100, 115
New Flyer (Xcelsior Charge)	BEV	Bus (35ft & 40ft) – Long range	7	311, 388, 466	1.9 – 2.1	160, 195, 225

Notes: (1) Estimated fuel efficiency assumes 100% discharge of rated battery capacity to meet reported range. Actual fuel efficiency may differ depending on on-road performance. (2) *, ** denote respectively announced and on-road tested vehicles

Parameters to consider for vehicle suitability for a given application include range, fuel efficiency, access to EVSE/refueling stations, energy to weight ratio, energy to volume ratio, power to weight, battery lifetime, and charging time (Birky, Laughlin, Tartaglia, Price, & Lin, 2017; Boer et al., 2013; L. Zhang et al., 2013). The range for some of these parameters are presented in Table 16, though the market continues to evolve with new capabilities at a rapid pace. Of these parameters, average fuel efficiency is often not reported due to limited on-road testing of real-world drive cycles under varying conditions (e.g. cargo capacity, traffic, etc.). Fuel efficiency and the resulting vehicle range are significantly dependent on payload and drive cycle.

Table 16. Information on Zero-Emission Vehicle Model Specifications

Weight Class	Technology	Number of Vehicle Models	Low Battery Capacity (kWh)	High Battery Capacity (kWh)	Low Peak EM Power (kW)	High Peak EM Power (kW)	Low Fuel Converter Power (kW)	High Fuel Converter Power (kW)
3	BEV	7	48.5	99.0	70.0	160.0		
3	PHEV	1	14.0	14.0	92.0	92.0	138.0	138.0
4	BEV	10	61.0	136.0	20.0	188.0		
4	HEV	3	1.8	60.0	44.0	100.0	156.6	190.2
4	FCEV	1	28.0	28.0	120.0	120.0	30.0	30.0
4	ICE	1					149.1	149.1
5	BEV	12	62.0	135.0	91.0	200.0		
5	HEV	3	99.0	99.0	36.0	200.0	120.0	156.6
5	EREV	2	60.0	60.0	200.0	343.0	25.0	50.0
5	ICE	1					149.1	149.1
6	BEV	10	99.0	200.0	134.0	250.0		
6	HEV	6	1.8	28.0	36.0	120.0	80.0	231.2
6	FCEV	2	28.4	28.4	200.0	200.0	30.0	0.0
6	PHEV	1	74.0	74.0	200.0	200.0	179.5	179.5
6	ICE	2					205.1	223.0
7	BEV	10	120.0	352.0	103.0	260.0		
7	HEV	4	1.8	28.0	44.0	71.0	186.4	242.4
7	ICE	1					238.6	238.6
8	BEV	45	88.0	1000.0	103.0	770.0		
8	HEV	8	1.8	28.0	44.0	265.0	149.1	227.4
8	FCEV	7	12.0	700.0	85.0	746.0	29.8	100.0
8	PHEV	5	80.0	175.0	168.0	300.0	29.8	238.6
8	ICE	3					208.8	452.9
ORUV	BEV	19	10.8	209.0	3.0	180.0		
ORUV	HEV	2	N/A	N/A	171.0	198.0	167.8	201.3
ORUV	FCEV	1	22.0	22.0	240.0	240.0	30.0	30.0

Notes: Source is National Renewable Energy Laboratory (2019). ORUV = Off-road utility vehicles.

Not all vocational drive cycles can be satisfied given the current technical capabilities of MHD-ZEV options. Targeting suitable vocations based on current technology constraints can build a market for MHD-ZEV while contributing to technology advancements and improved learning which are needed to enable new markets. Selection criteria for early markets include duty cycle, fuel consumption, criteria pollutant emissions, market size, and location of operation (e.g. within a disadvantaged community) (Birky, Laughlin, Tartaglia, Price, & Lin, 2017). Current MHD-

ZEV models are well suited for short-distance travel where the vehicle can routinely return to a central location to charge or refuel.

2.2.2 Infrastructure

Stations for medium- and heavy-duty battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs) must be designed to support a) an individual fleet without public access, b) a group of fleets with an agreement to share access, c) public access for all medium- and heavy-duty vehicles, or d) public access for multiple vehicle types. Electric charging and hydrogen fueling equipment may be co-located if a fleet or collection of fleets have both types of ZEVs operating in the same vicinity. Fleet-specific infrastructure is more likely to be located at depot facilities to ensure ready access during breaks and end-of-shift dwell periods. Fully public stations will undoubtedly be equipped with both charging and fueling equipment and located along commonly traveled roadways such as major freight corridors to maximize access. So far, MHD-ZEV station construction has tended to be on a fleet-by-fleet basis due to low MHD-ZEV volumes and high capital cost. However, as BEV and FCEV adoption grows in the medium- and heavy-duty sectors, other station business models are likely to become prevalent.

Charging and hydrogen fueling technologies are commercially available; however, California faces the challenge of scaling the infrastructure to meet MHD-ZEV demands given the fast deployment timeline. Charging and refueling infrastructure deployment is challenging due to the high capital costs, long, and sometimes uncertain, lead times, and ambiguity surrounding the process, such permitting and how to appropriately plan for both current and future ZEV needs. In addition, while over 40 hydrogen refueling stations and over 9,000 DC fast chargers are currently deployed across the state (CEC, 2020a), most of these stations were built with light-duty vehicles (LDVs) in mind. Generally, several constraints may limit MHD vehicle use of light-duty-based infrastructure such as: MHD vehicles may have too large an electricity or hydrogen demand for a LDV station, MHD-ZEVs may have different fueling/charging protocols compared to light-duty vehicles (SAE International, 2014, 2020), and/or MHD-ZEVs may not be able to navigate the station due to station location, vehicle size, or turning radius.

Several steps have been taken by the State to reduce uncertainty and cost associated with fleet-based charging and hydrogen fueling infrastructure development. The California Energy Commission continues to provide grant opportunities to fund charging and hydrogen infrastructure projects. Also, the California Public Utility Commission directed the investor-owned utilities to implement charging infrastructure programs (CPUC, 2020). These programs, such as Southern California Edison's Charge Ready Transport program and the others summarized previously in Section 1.2.2, help fleets design, install, and maintain charging infrastructure, including transformer upgrades, as well as covers some of the costs (Southern California Edison, 2020).

There are additional technical and management challenges that need to be considered during medium- and heavy-duty station planning. For charging stations, high power demands require managing on-site loads to stay within transformer limits. High charging rates also increase the need for thermal management systems so that components do not overheat at the station or in the vehicle (Smith et al., 2019).

Furthermore, the number and power rating of chargers will impact how many vehicles can charge at a given station. Long dwell times means lower throughput and more downtime per vehicle. High charging rates may reduce the total number of chargers needed per vehicles and/or how long vehicles need to dwell, but may introduce management challenges, such as vehicle rotation. Charging rate may also be limited by the capability of the battery system. While these issues can be addressed, this level of planning adds complexity to deploying MHD-ZEVs effectively.

Some issues are common between station types, including station downtime and interoperability across stations and vehicle models. Station downtime can be driven by several factors, such as software issues and equipment failure.

2.3 Alternative Fuel and Technology Cost Projections

The focus on this section is to investigate the availability and feasibility of low-carbon fuels for application in the HDV and ORE sectors to map the fuels within low carbon fuel standard (LCFS) to the optimal vocations and use these findings to project the costs of alternative fuels for future-year scenarios. The research team based this work on the Transportation Rollout Affecting Cost and Emissions (TRACE) model produced by CARB 16RD011 (Mac Kinnon et al., 2020). TRACE includes a detailed and thorough assessment of the current and future costs, and resource potential, for renewable natural gas technologies, including biomethane, hydrogen gas, and climate-neutral synthetic natural gas. As part of its optimization, TRACE also projects HDV vehicle costs and efficiencies, which are critical to estimating TCO. Before discussing the specifics of the TRACE model, we provide an overview of LCFS as a background.

2.3.1 Background

California’s LCFS program requires a 20% reduction in carbon intensity by 2030 and all subsequent years. All pathways used to produce fuel are given a regulatory carbon intensity (CI) value (grams of GHG per megajoule of fuel, or gCO2e/MJ) that can incentivize lower carbon fuels based upon their expected emission reductions relative to a baseline carbon intensity for fuels that declines each year (Yeh & Sperling, 2013). The term carbon intensity can be defined as the total life cycle GHG emissions per unit of delivered fuel energy (Arons et al., 2007).

LCFS is targeted to achieve a reduction in the overall CI of California fuels by allowing carbon credit trading between the producers and importers of high carbon fuels and low carbon fuels. In the California LCFS model, two compliance strategies are available, which includes producing or importing low-GHG fuels (i.e., natural gas, biofuels, electricity, and hydrogen) to replace conventional fuels; and purchasing or banking (holding) credits (Yeh et al., 2012). Gasoline and diesel fuel producers can choose among multiple methods within the above compliance strategies to meet LCFS targets such as: reduce CI of gasoline and diesel, increase blending of lower-CI alternative fuels in gasoline and diesel, sell more alternative fuels, and purchase credits from other regulated parties or use credits banked in previous years (Rubin & Leiby, 2013).

2.3.1.1 LCFS credits and deficits

LCFS credits and deficits are generated based on emissions below or above the standard. The credits can be traded or banked over time. Any firm that produces fuel with a CI above the standard generates a "deficit" (Brandt et al., 2007). Firms must account for any accrued deficits over a compliance period by purchasing credits generated by firms producing fuels with CI's below the standard. Thus, the policy influences production of low-carbon fuels while simultaneously discouraging production of high-carbon fuels (Lade & Lin Lawell, 2015).

To enhance flexibility and stimulate innovation, the LCFS allows for trading and banking of emission credits. The combination of regulatory and market mechanisms makes LCFS not only a regulatory but also a market approach (2010).

Trading and banking of credits: Cost-effectiveness of the LCFS depends on the ability of regulated firms to trade and bank (hold) credits. Trading and banking of credits should be limitless with no discount or other adjustment (borrowing). According to Yeh et al. (2013) net credits generated is the number of credits or deficits generated in each period while banked credits after compliance is the number of excess credits banked from the current or previous compliance years.

Life-cycle assessment (LCA) characterizes the environmental impacts of a product or service throughout its full life cycle, from the extraction of raw materials through manufacturing, use, and disposal. It is used to measure the carbon intensity of transportation fuels, but there is no widely-agreed upon LCA methodology for measuring all of the important global warming impacts of transportation fuels (Arons et al., 2007).

Land use change: Massive consumption of biofuels leads to expansion of farmlands at the expense of other crops, forests, and grasslands resulting in a large amount of carbon emission (carbon debt). Searchinger et al. (2008) in their study raised concerns about large biofuel mandates and emphasized using waste products (municipal waste, crop waste, and fall grass harvests from reserve lands) to avoid land use change.

2.3.1.2 Other strategies

The **renewable fuel standard** (Yeh & Sperling, 2013) requires that 36 billion gallons of biofuels be sold annually by 2022, of which 21 billion gallons must be "advanced" biofuels and the other 15 billion gallons can be corn ethanol. The advanced biofuels are required to achieve at least 50% reduction from baseline lifecycle GHG emissions, with a sub- category required to meet a

60% reduction target. These reduction targets are based on lifecycle emissions, including emissions from indirect land use.

Carbon tax: Taxing energy sources according to the amount of carbon dioxide (CO2) they emit.

Carbon cap and trade policy involves placing a cap on the CO2 emissions of large industrial sources and granting or selling emission allowances to individual companies for use in meeting their capped requirements. Emission allowances, once awarded, can be bought and sold. The refineries would be able to trade credits among themselves and with others.

According to Yeh & Sperling (2010), LCFS is considered a second best approach by economists due to its inefficiency compared to the other two strategies: carbon tax and cap-and-trade program. But direct forcing mechanisms like LCFS are the most practical way at present to introduce and popularize alternative fuels due to the unavailability of alternative fuel options (advanced biofuels and electric and hydrogen vehicles) and the limited impact of increased taxes and prices on transportation fuel demand.

With this LCFS background, we now turn to how we are modeling low-carbon transportation fuel costs in this project.

2.3.2 TRACE Model

The Transportation Rollout Affecting Cost and Emissions (TRACE) model is a vehicle fuel and powertrain adoption optimization model that projects fuel and vehicle use from 2020 through 2050 based on minimum cost while complying with various environmental and technological constraints. Though we provide a broad overview of the model here, further details on TRACE can be found in the final report of CARB’s 16RD011 project (Mac Kinnon et al., 2020). TRACE is a supply-side optimization model that assumes fixed demand for transportation fuel in the form assumed fleet VMT. The TRACE model diagram is depicted in Figure 12.

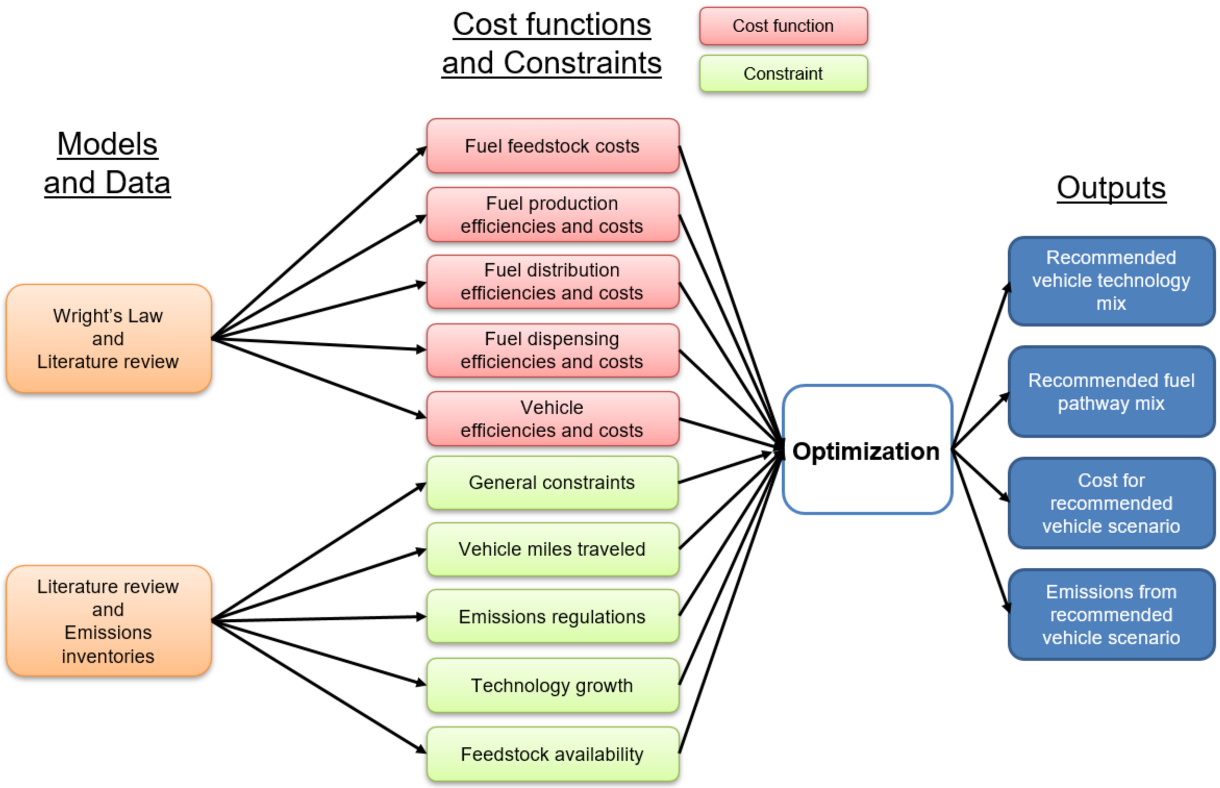


Figure 12. TRACE model diagram

Fuel pathways are detailed from fuel feedstock (electricity and various biomass categories) to fuel dispensing infrastructure. Vehicles are analyzed by primary powertrain components and the glider. Wright's law is used to project the cost of fuel production equipment and vehicle components based on the adoption rate of each of the technologies. Efficiency for the fuel pathways and vehicles themselves are projected based on the literature. Emissions from both fuel pathway and vehicle tailpipe, as appropriate, are sourced from the literature.

Constraints are added to model the problem more accurately, including VMT constraints, fuel feedstock availability, powertrain availability, and both GHG and criteria air pollutant (CAP) emissions (NO_X , and PM_{10}) goals/legislation. Following Mac Kinnon et al. (2020), "VMT constraints use EMFAC data for vehicles of model year 2020 and beyond. Fleet turnover rates are determined by EMFAC projections of vehicle use. These EMFAC data project VMT by vehicle year for each of the vehicle classes included in the present work. Gathering data every five years from 2020 to 2050 shows how the VMT from vehicles of prior years' decreases as time goes on." Germane to the present work are the VMT from vehicles made prior to 2020, as vehicles made in 2020 and beyond to 2050 will be dictated by the optimization. All prior vehicles are assumed to continue as EMFAC projects to 2050. These cost functions and constraints are added to a linear optimization algorithm to determine the lowest-cost method of meeting the constraints.

Modeled fuels include electricity, hydrogen (electrolytic and bio-derived), natural gas (electrolytic and bio-derived), renewable gasoline, and renewable diesel. Several pathways of producing each fuel are included. Modeled vehicle types are LDVs and four HDV vocations: linehaul (in-state long-haul/regional haul), drayage, refuse, and construction. Primary outputs of TRACE include the following: cost of fuels; cost of vehicles; fuel, feedstock, fuel production technology, and vehicle powertrain use for the various vocations; and resulting GHG and CAP emissions.

2.3.3 Fuel Availability Projections

Fuel availability depends on the availability of fuel feedstock, production technology, distribution equipment, and dispensing equipment. Of these four, availability of fuel feedstock and production technology have been determined to be the primary limitations on fuel availability. The present work focuses on fuel feedstock availability as the most stringent constraint on fuel availability.

Generally, there are two mostly independent constraints on fuel availability: (1) electricity feedstock availability and (2) biomass feedstock availability. These are shown in Figure 13, with biomass availability depicted on the left axis and electricity availability on the right axis[37]. Note the difference in magnitude of availability indicating the significantly higher availability of energy in the form of electricity for vehicle fuels and fuel feedstocks.

[37] Note that throughout this section, electricity production is measured in GJ/yr as opposed to gWh as it is an easier unit to compare across all fuels.

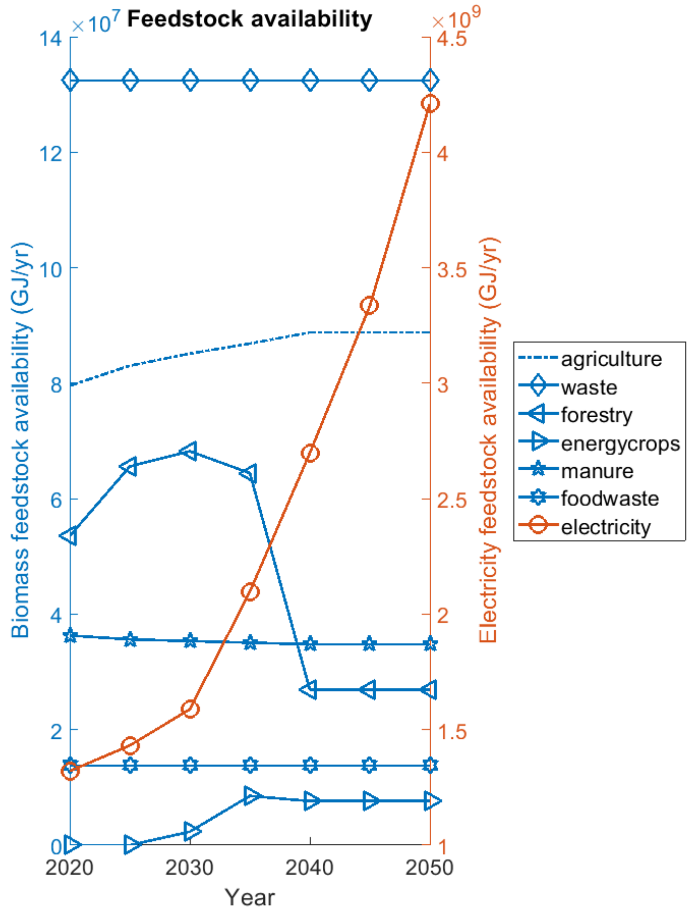


Figure 13. Electricity and biomass feedstock availabilities

Source: data from E3 (Energy and Environmental Economics, 2016) and U.S. DOE (Langholtz et al., 2016)

For electricity availability, it is assumed that approximately 40% of the total electricity capacity projected in E3's PATHWAYS model is available as a vehicle fuel or fuel feedstock. The 40% assumption is higher than what is assumed by E3 (Energy and Environmental Economics, 2016), but it allows for a more aggressive expansion of the electric grid should that expansion be recommended by TRACE. The more aggressive expansion is also accounted for in the modeled cost of electricity distribution. Biomass feedstock availability is sourced from U.S. DOE's Billion Ton Report (Langholtz et al., 2016), which projects out to 2040, and assumes constant availability from 2040 to 2050.

Note the lack of biogas from places such as landfills and wastewater treatment plants. The sources of biogas are much more limited than the biomass sources presented, and the rights to those sources are generally already allocated, hence the focus on biomass rather than biogas (Reed et al., 2020).

Each fuel is further limited by pathway efficiency. The resulting fuel availability shown in Figure 14 uses the average of production pathways should more than one be available to produce a fuel (e.g. renewable diesel can be produced from several technologies and many overlapping biomass categories, so the sum of biomass available that can be used in a given set of renewable diesel technologies is multiplied by the average efficiency of the different production technologies). Projections from EMFAC for the total amount of fuel energy used by the baseline HDV sector is also included demonstrating that quantities of renewable fuel are sufficient to meet projected baseline demands (CARB, 2019e).

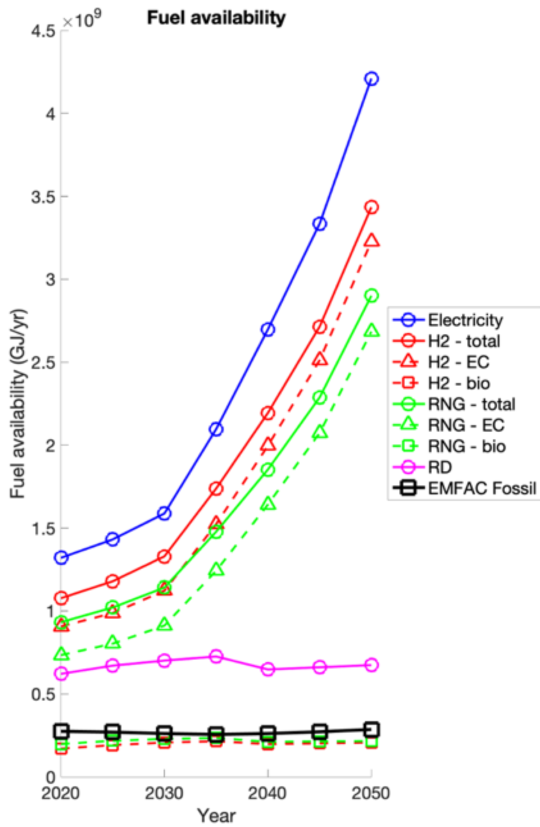


Figure 14. Heavy-duty vehicle fuel availability

Note that these fuel availabilities shown in Figure 14 assume all biomass is potentially available for heavy duty vehicle fuels. In reality, this will likely not be how California decides to allocate its biomass resources, but no specific plans for allocation are available. Further consideration must be given to what sectors of the economy these biomass feedstocks should be apportioned to. It may later be determined that only a fraction of the California-available biomass and electricity should be available to make fuel for heavy duty vehicles, which would yield lower fuel availabilities.

Assuming significant portions of California's projected biomass supply is available for HDV fuel production, biomass-derived hydrogen and RNG are the most affected by biomass availability. HDVs that use these two fuels are currently limited in quantity, so the biomass feedstock constraint is not likely to be felt for some time; by the time enough such vehicles are in use, efficiency improvements or alternative pathways (e.g. electrolytic fuels) could alleviate any challenges in meeting demand. Renewable diesel could also be impacted by feedstock availability, but California's push to ZEVs makes this concern less significant over time as diesel HDVs are retired.

There is a difficult-to-quantify benefit of having a surplus of availability, but both electricity and electrolytic fuels share that benefit due to much greater availability than biomass. Fuel costs can be expected to be less volatile (and especially fewer spikes of increased price) when a surplus of feedstock exists, also enhancing energy independence of the state.

Another benefit of electricity as a fuel or fuel feedstock is the addition of dispatchable loads to the electric grid. As California adds renewables to the electric grid, variance in the generation (caused by variance in solar power, wind power, etc.) will increase the challenge of grid management. Electricity and electrolytic fuels can provide variable and dispatchable electric loads. For electricity as a fuel, this would require smart charging, which times and varies power of charging plug-in electric vehicles based on grid characteristics. For electrolytic fuels, this dispatchability is simpler as the fuels produced (hydrogen and RNG) can be easily stored for later use.

2.3.4 Cost Projection through Wright's Law

The preliminary cost projections for alternative fuels have been set using Wright's Law and data from the literature. Wright's Law projects future capital cost based on cumulative production; the more a specific technology is produced over time, the lower the per-unit cost of that technology. Wright's Law was found to have greater prediction accuracy than Moore's law, which projects cost decline by time elapsed (Nagy et al., 2012). Wright's Law is applied to fuel production, distribution, and dispensing technologies. Fuel feedstock costs, including electricity and biomass, are projected using values from the literature.

Two primary factors affect the cost decline projected by Wright's Law: cumulative production and learning rate. Learning rate relates the fraction of cost decline expected for a given increase in cumulative production. Figure 15 depicts the impact of these factors in two example scenarios. Note the blue lines represent relative cost and the grey lines represent relative cumulative production. Two technology-specific examples following Wright's Law are presented in Figure 16 for solar photovoltaics (PV) and Figure 17 for batteries. Note that both technologies demonstrate similar trends of cost decrease as technology adoption increases over the years. For batteries, the rate of cost decline is decreasing and there are signs the technology is maturing and further substantial cost decline may not be realized as material availability is decreasing (Keen, 2020; Leyland, 2020).

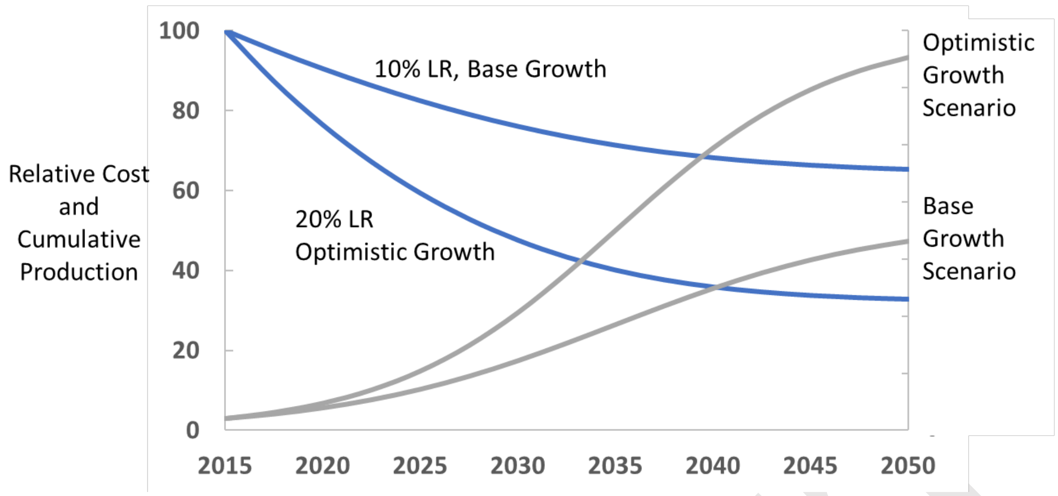


Figure 15. Representative cost decline from Wright's Law

Source: Lane et al. (Lane et al., 2021)

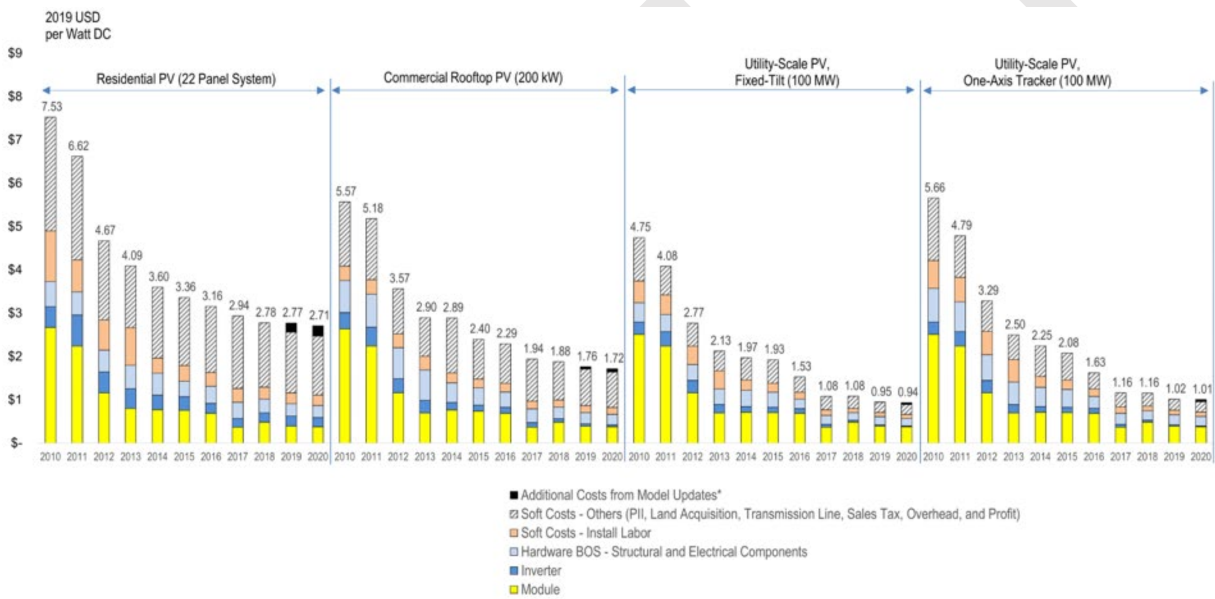


Figure 16. Wright's Law displayed in solar PV cost decline

Source: Feldman et al. (2021)

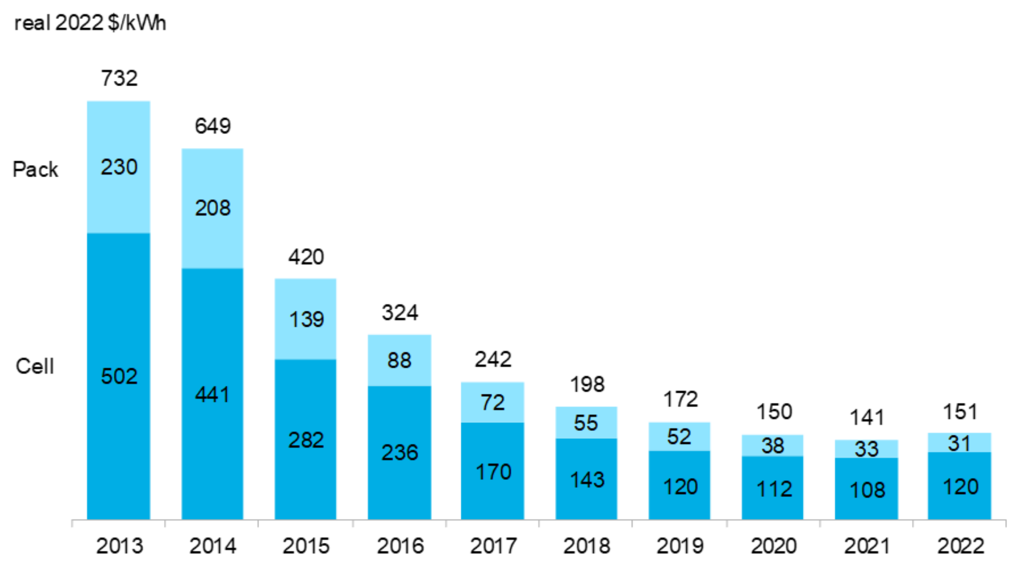


Figure 17. Wright's Law displayed in battery cost decline

Source: Figure from BloombergNEF (Henze, 2022), shows battery in real 2022 dollars per kilowatt.

2.3.5 Fuel Cost Projections Summary

The following summary fuel cost projections provides a band of expected values for each of the four alternative fuels considered (electricity, hydrogen, renewable natural gas (RNG), and renewable diesel (RD)) with the "mid" case presenting the projection with the highest expected probability of occurring. The range in values is due to a range of technology cumulative production. Figure 18 depicts the non-incentivized cost of fuel while Figure 19 depicts the incentivized cost of fuel which incorporates revenue from the LCFS and RFS (Renewable Fuel Standard) programs. For LCFS, all projections presented assume a constant $200 credit price and a linear continuation of the 2020 to 2030 carbon intensity standard reduction through 2050 at which point the standard reaches 55.16 gCO2e/MJ. Note that the addition of incentives consideration can increase cost, which happens when a fuel pathway has a corresponding carbon intensity greater than the LCFS carbon intensity standard. Greater detail on each fuel is provided in Figure 21 through Figure 25 and the accompanying text.

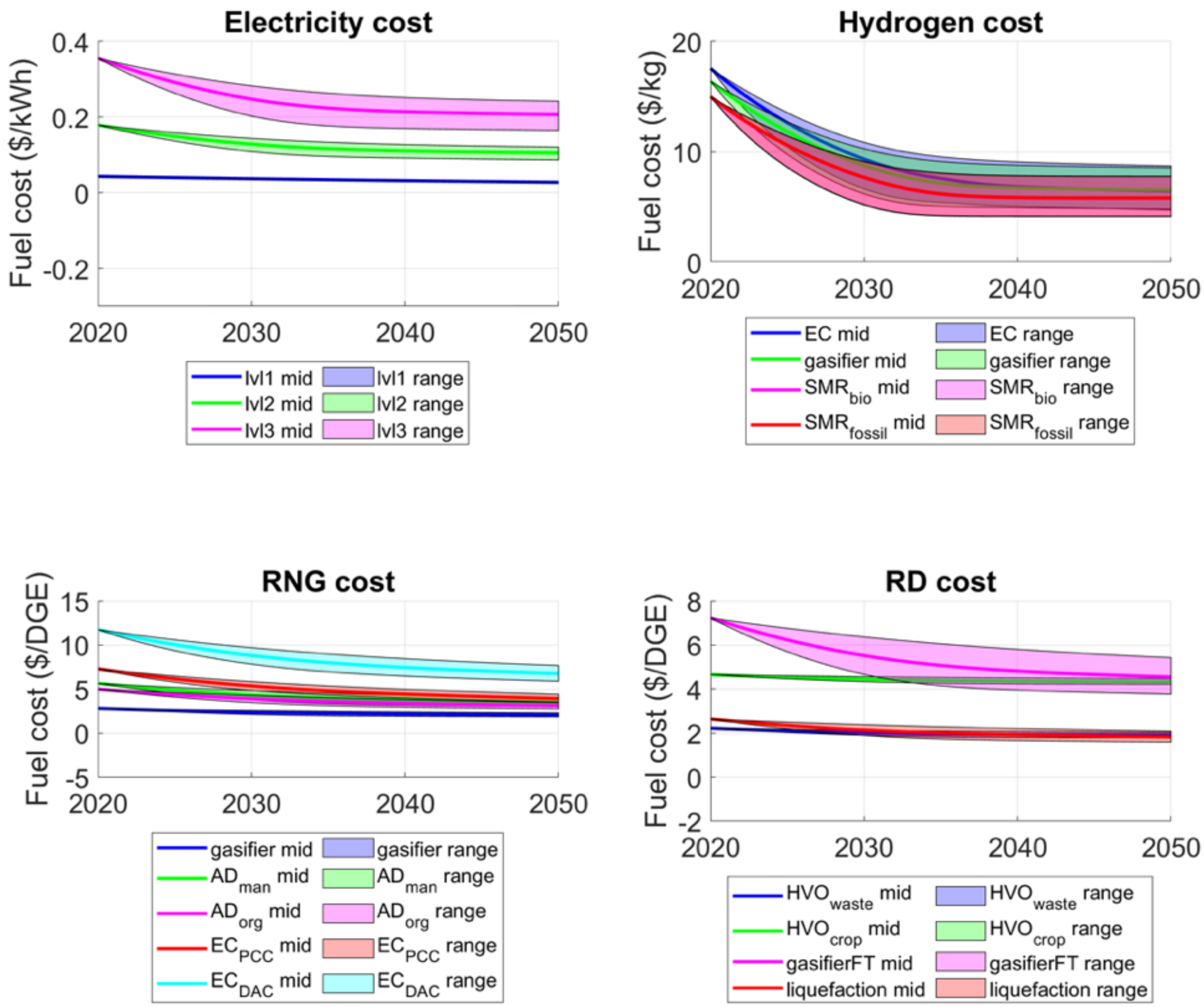


Figure 18. Summary of non-incentivized fuel cost projections

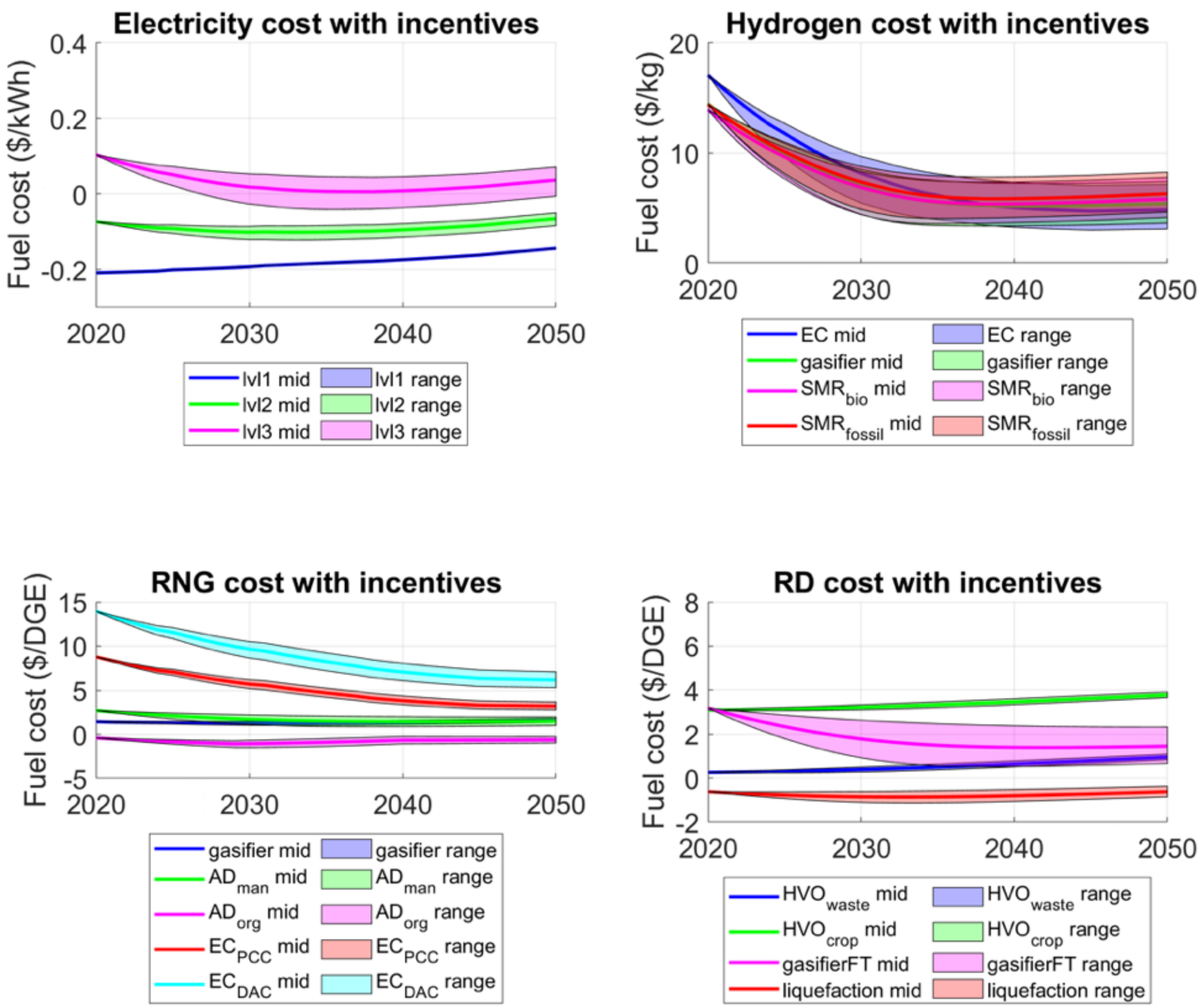


Figure 19. Summary of incentivized fuel cost projections

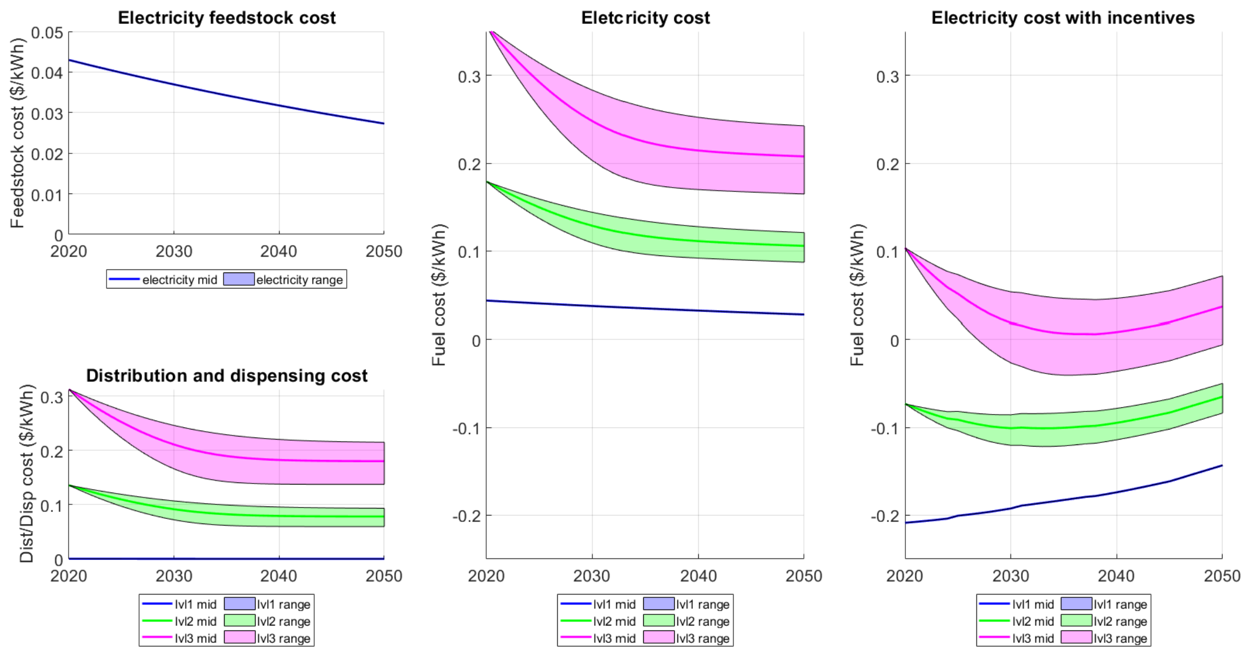


Figure 20. Electricity fuel cost breakdown

2.3.5.1 Hydrogen Cost Projections

A detailed breakdown of hydrogen delivered fuel cost showing each component included in the analysis along with total non-incentivized and incentivized cost is presented in Figure 21. It is evident that for hydrogen, as was the case for electricity, the distribution and dispensing cost is the major cost contributor. The inclusion of incentives makes electrolytic hydrogen the lowest cost option, whereas otherwise gasifiers and steam methane reformation (SMR) are the lower cost options. All hydrogen production methods have overlapping cost bands, which suggests that without further regulation, all technologies can be expected to have some market share of renewable hydrogen.

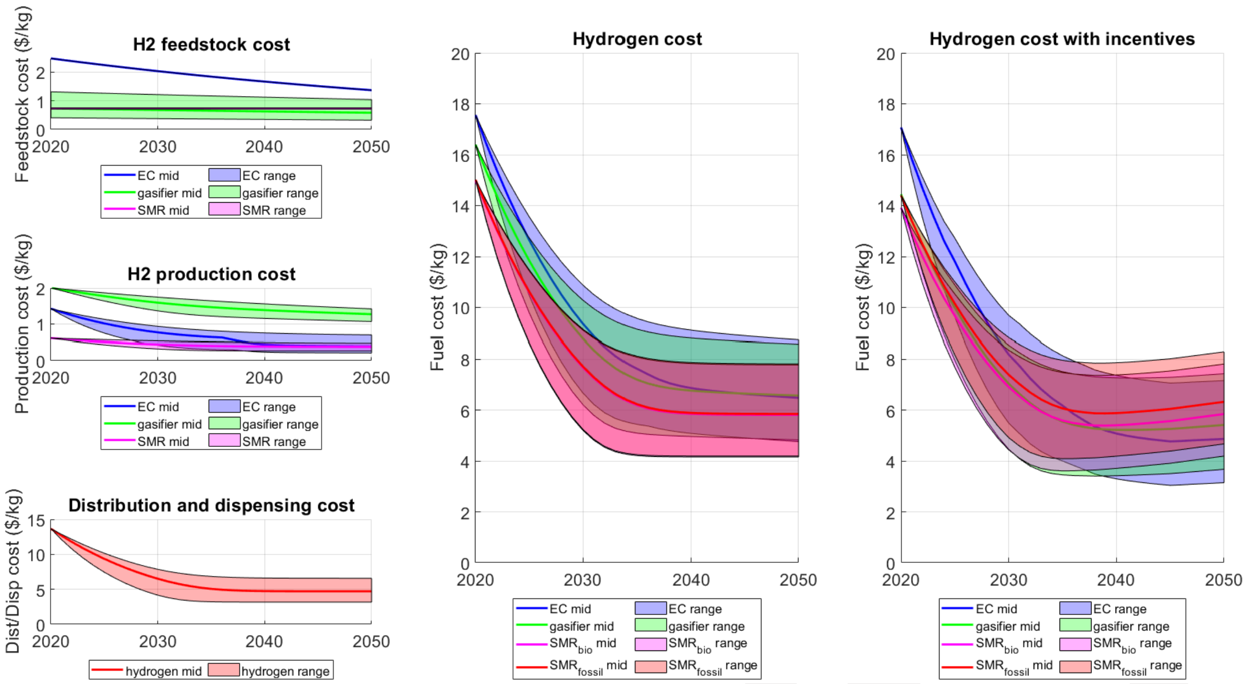


Figure 21. Hydrogen fuel cost breakdown

The hydrogen cost without the distribution and dispensing infrastructure, also known as plant gate cost, is an important metric to consider for hydrogen as it allows comparison between categories of hydrogen production such as electrolyzers and different biomass conversion technologies. Plant gate cost considers only the feedstock and production technology costs. The plant gate cost for hydrogen without and with incentives is presented in Figure 22. It is evident that electrolytic hydrogen experiences the greatest reduction in cost over the analysis period.

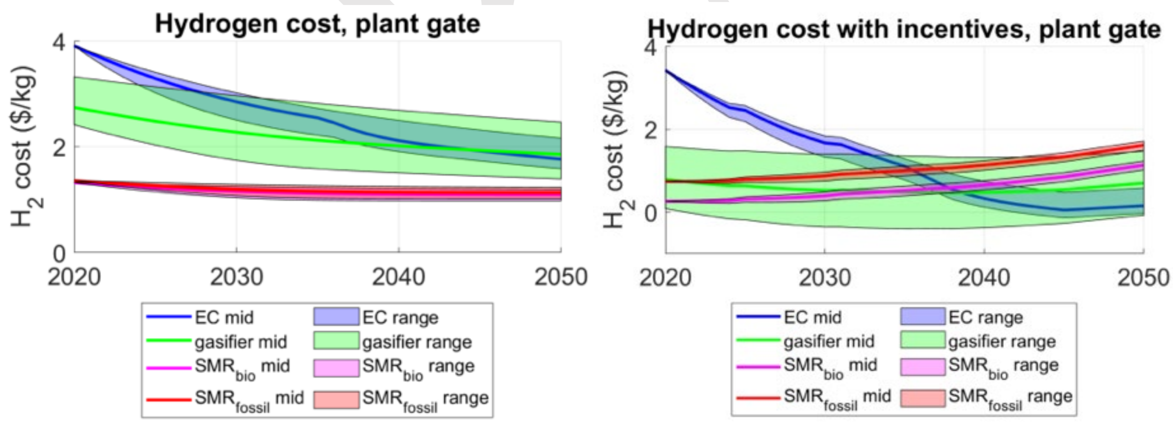


Figure 22. Hydrogen plant gate cost

2.3.5.2 Renewable Natural Gas Cost Projections

A detailed breakdown of RNG delivered fuel cost showing each component included in the analysis along with total non-incentivized and incentivized cost is presented in Figure 23. While electrolytic hydrogen experiences the greatest reduction in cost, these production methods are not expected to have a large market share due the much lower costs of competing gasifier and anaerobic digestion (AD) technologies. Further, electrolytic hydrogen with carbon from post-combustion capture (PCC) technology faces further constraints with the need to be co-located with a fossil fuel power plant, bio-refinery, or similar plant with a carbon-rich exhaust stream. While direct air capture (DAC) technology does not have this constraint, it is a much higher cost technology than PCC.

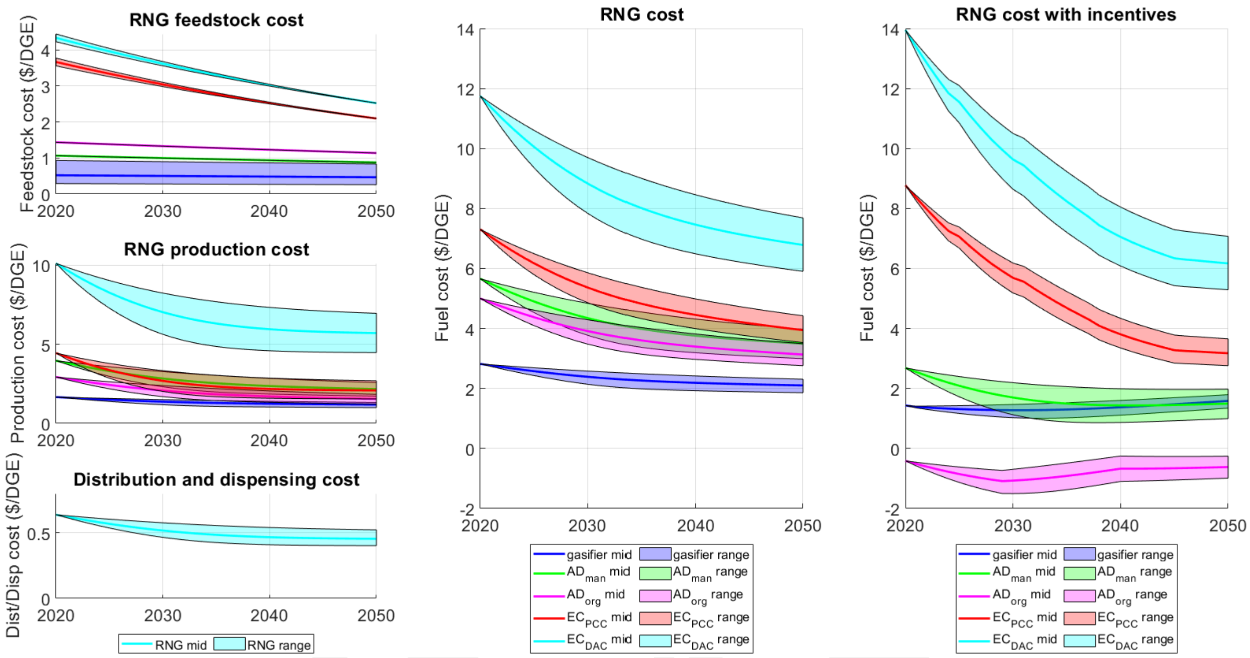


Figure 23. Renewable natural gas fuel cost breakdown

2.3.5.3 Renewable Diesel Cost Projections

A detailed breakdown of renewable diesel delivered fuel cost showing each component included in the analysis along with total non-incentivized and incentivized cost is presented in Figure 24. Hydrotreatment of vegetable oil (HVO) and liquefaction are the two lowest cost renewable diesel production technologies. These two technologies are similar, but HVO starts with a bio-derived oil while liquefaction converts a biomass into oil which is then processed similar to HVO. HVO is a more mature technology and could be expected to be deployed at large scale more quickly.

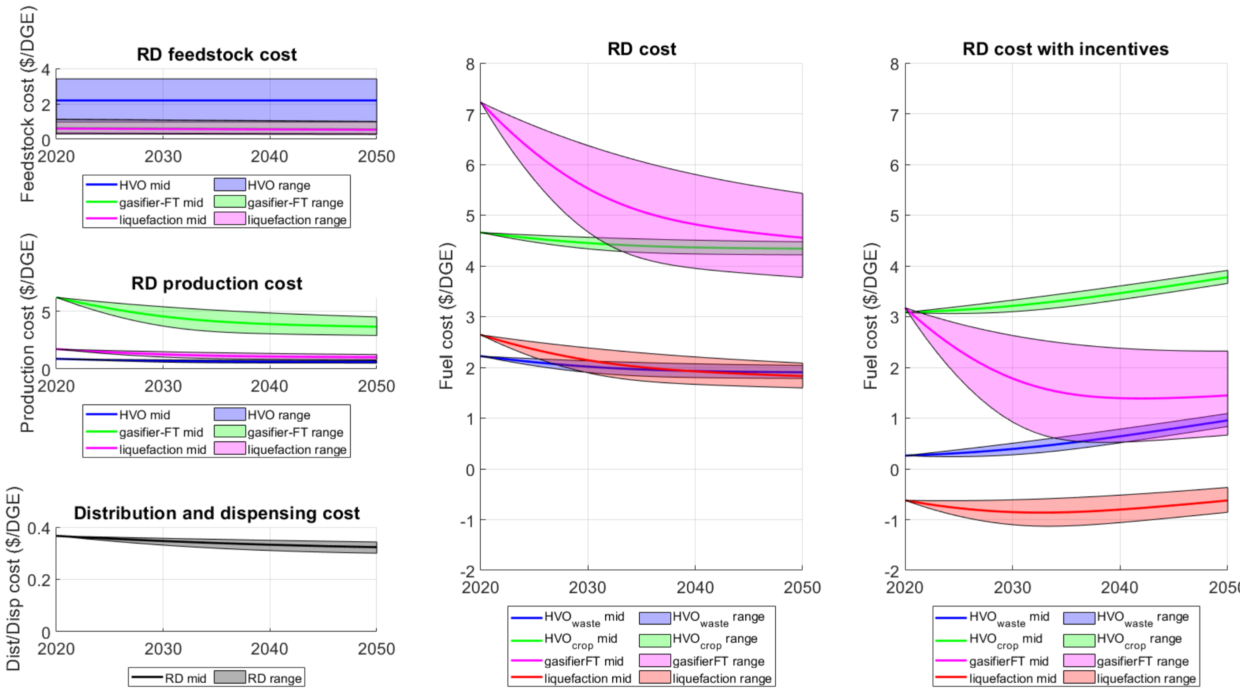


Figure 24. Renewable diesel fuel cost breakdown

2.3.5.4 Impact of LCFS Carbon Intensity Standard

To compare to (1) the non-incentivized cost and (2) the incentivized cost using a continued carbon intensity standard decline as from 2020 to 2030 with $200 LCFS credit, a third option is analyzed. This third option considers LCFS with the carbon intensity standard decreasing to zero in 2050 and assuming a constant $200 credit price. Thus, the difference between options (2) and (3) are the rate of decline for the carbon intensity standard between 2030 and 2050. A summary of the fuel cost projections is provided in Figure 25 which can be compared to Figure 18 and Figure 19 to see the impact of different incentive scenarios on projected fuel cost. The incentivized cost is higher than the non-incentivized cost for some pathways of hydrogen, RNG, and renewable diesel due to the pathway carbon intensity being greater than the hypothetical standard.

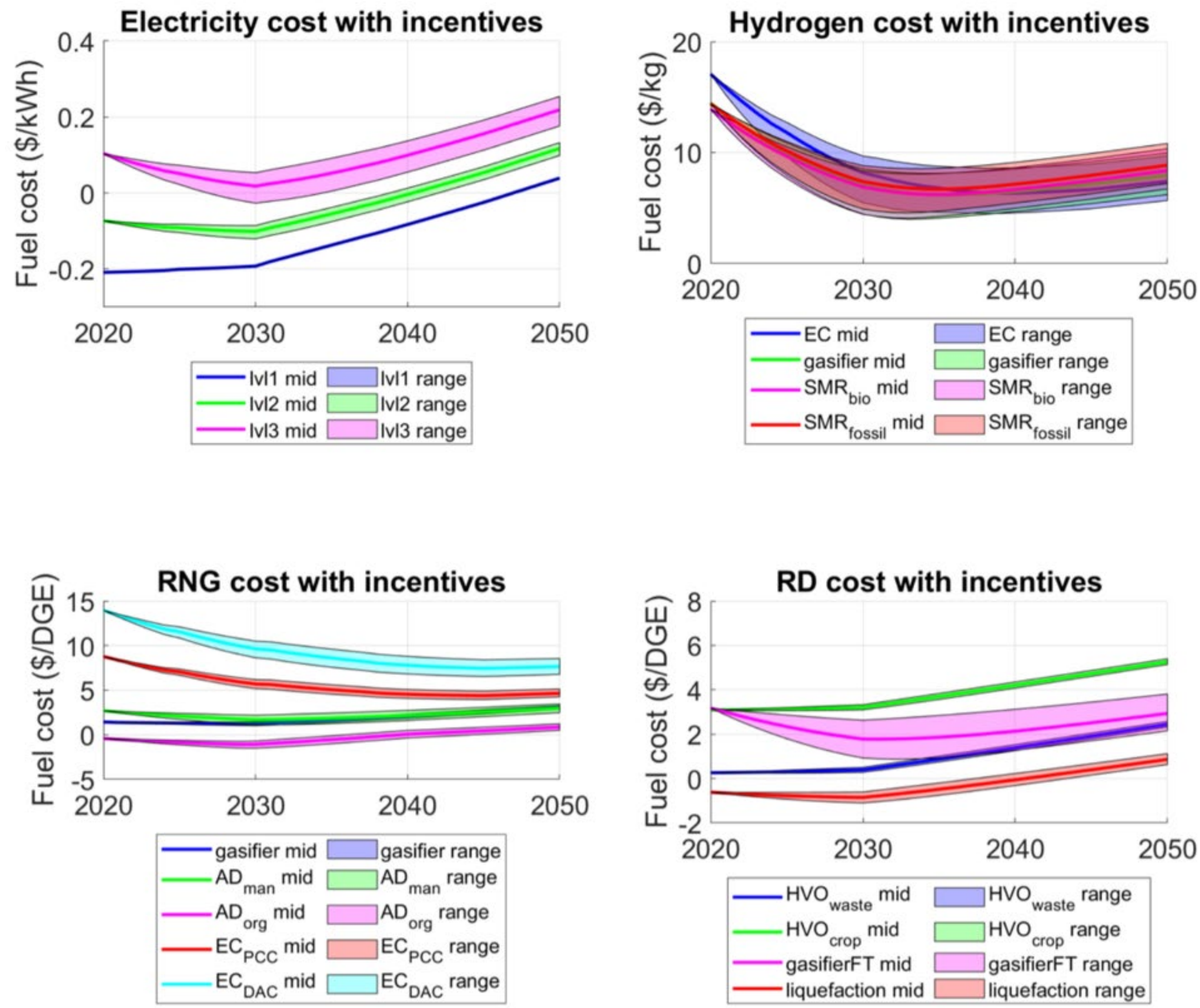


Figure 25. Summary of incentivized fuel cost projections with 2050 carbon intensity standard of zero

2.3.6 Monte Carlo Simulation of Hydrogen Costs

An additional capability being developed for use with TRACE incorporates uncertainty in fuel production costs in a Monte Carlo simulation (MCS) while still using the same Wright's law equation conventionally used in TRACE. Hydrogen cost projections particularly benefit from MCS due to their two feedstock categories and resulting pathways of production: (1) electrolysis and (2) biomass.

Biomass available for fuel production is relatively scarce compared to potential electricity feedstock (e.g. solar, wind) and the quantity of biomass harvested affects the marginal cost of biomass (Langholtz et al., 2016). Given competing sectors of the economy that could use biomass for energy (e.g. heating, agriculture, etc.), adding uncertainty to the cost of biomass. This is in contrast to electrolytic hydrogen production for which electricity is less limited and affected by quantity used. Both electrolysis and biomass conversion are expected to produce hydrogen at costs competitive with each other, hence the MCS methodology can provide insight into how these competing methods may lead to evolving costs.

It is assumed that this methodology is not as critical for other fuel production projections considered by TRACE because production pathways are generally more similar, so focus is placed on applying this methodology to hydrogen production pathways. For renewable diesel, all considered pathways use biomass feedstock and many use production technologies that have overlapping processes. For RNG, previous work found that electrolytic RNG is significantly more expensive than biomass-derived RNG due to the high cost of captured carbon (Mac Kinnon et al., 2020); therefore, electrolytic RNG is not expected to compete in general unless a much lower cost source of carbon is developed or specific projects require that particular production method for individual reasons.

The primary addition of this methodology is accounting for uncertainty in (1) projected total renewable hydrogen demand from 2020 to 2050, (2) the learning rate of hydrogen production technologies which determine cost reduction per a given increase in cumulative production, and (3) final production plant cost accounting for factors that affect plant-specific project costs (e.g. locational cost differences, factory loading for components, competitive discounting).

Preliminary hydrogen cost projections using the MCS that incorporates uncertainty in feedstock and technology costs are presented in Figure 26. Note the total hydrogen cost does not include distribution and dispensing, which is $4.50 per kg of hydrogen dispensed (U.S. Department of Energy, n.d.).

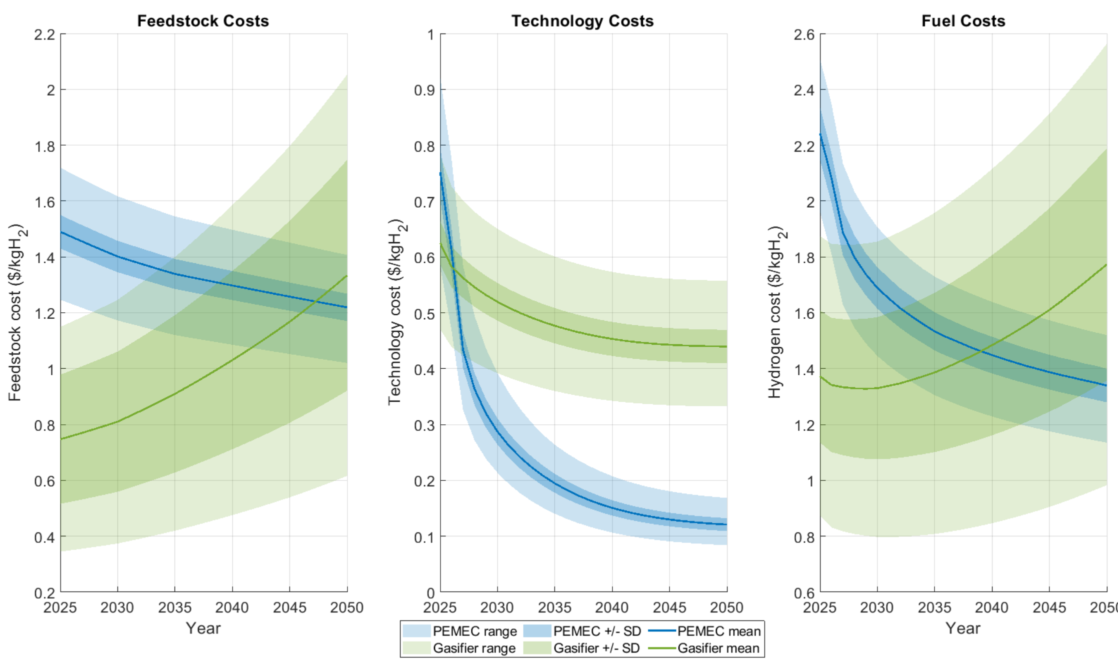


Figure 26. Hydrogen costs from Monte Carlo simulation

2.3.7 Data Handoff to the Fleet TCO Model

The above-presented techno-economic projections serve as inputs to the development of a TCO model for HDV and ORE. This was achieved by exporting a set of results for business-as-usual (BAU) scenario with relatively low ZEV adoption compared to both the GHG and ZEV scenarios previously introduced. This BAU scenario is based on the VISION ZEV expanded scenario (CARB, 2017b). The handoff provides TRACE results to the TCO module including:

- Fuel costs both with and without LCFS and RFS incentive revenue affecting the final cost.
- Vehicle costs and efficiencies (see Section 2.4).

Some coordination was necessary to maintain consistency while also respecting the difference in approach between the TRACE deployment optimization framework and the TCO model in the PET. There are two primary examples for the difference in approach: (1) TRACE's use of cost compared to the PET's use of purchase price and (2) TRACE's statewide scale compared to the PET's local approach from the perspective of a single fleet.

2.4 HDV vocations and technologies for the PET

2.4.1 Selection of HDV vocations to model

Determining which technologies to focus on for the development of the incentive program performance evaluation tool (Section 3.5) and our subsequent strategy analysis and recommendations (Section 5) involved a range of factors, driven both by the policy needs and by the availability of the necessary data to develop a meaningful model. On the policy side, we were informed by the CARB's beachhead strategy in which early successes, or *beachheads,* "are built around applications that can best make early use of one of the pathway technologies based on duty cycle, business case, industrial capacity, and performance" (CARB, 2021c, p. D-23). CARB's zero-emission beachhead Figure 27 that guides its funding plan on clean transportation incentives elucidates a clear strategy that is useful here (also see Welch, 2020, for a discussion in the context of CALSTART's Drive to Zero program).

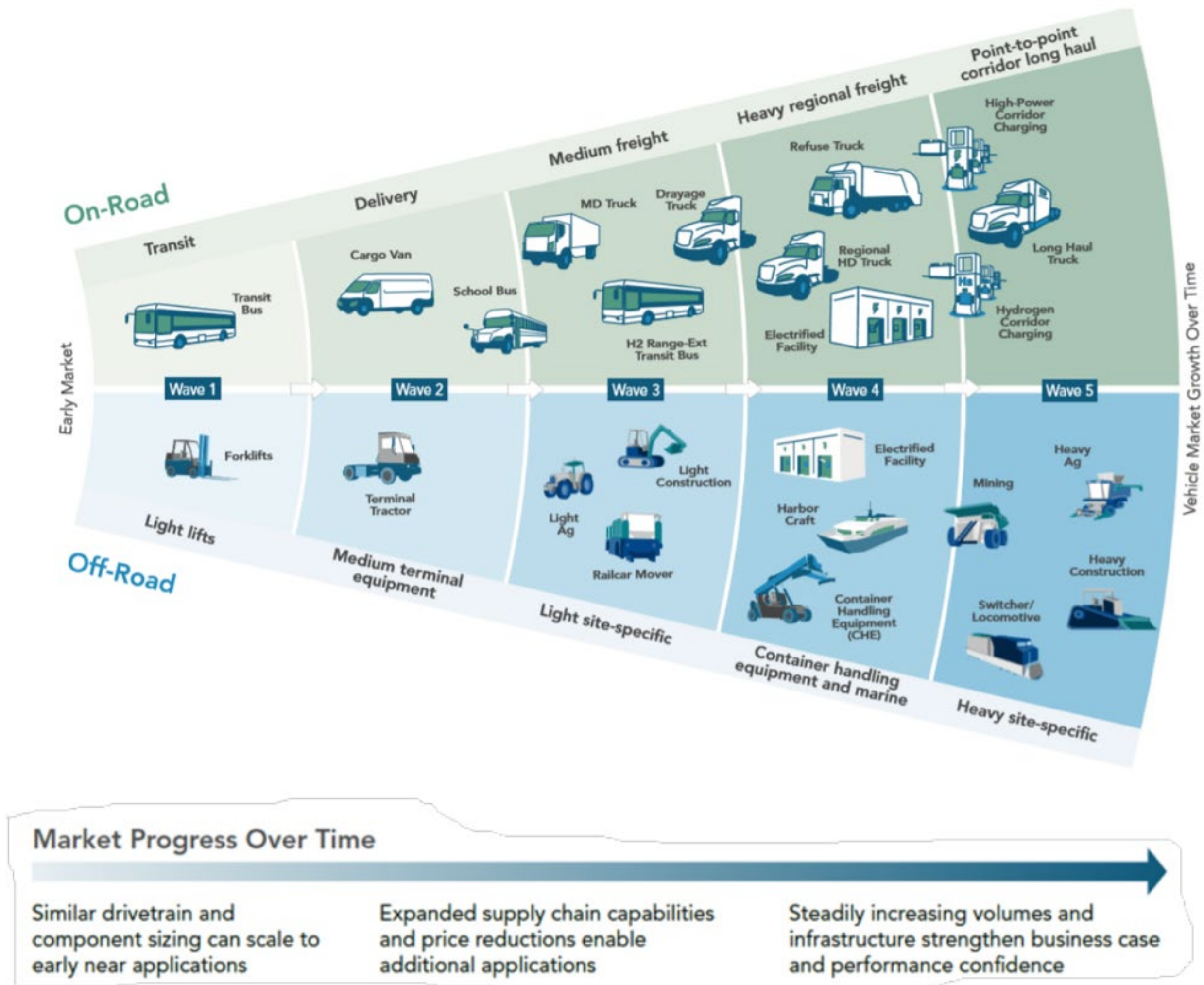


Figure 27. CARB's zero-emission pathway beachhead strategy

Source: Proposed Fiscal Year 2021-22 Funding Plan on Clean Transportation Incentives – Appendix D: Heavy-Duty Investment Strategy (CARB, 2021c)

While it is desirable to represent as many vocations as possible, focus is needed to construct a viable model. This project's focus on policies related to heavy-duty on-road vehicles and off-road equipment best aligns with Wave 4 of the zero-emission pathway beachhead strategy. As such, our focus was drawn to specific vocations in these waves that have the potential to build from early successes with transit buses and light construction and agricultural equipment. The notable follow-on applications that are entering TRL 7-9 and are suggested in CARB's strategy include:

(a) Battery electric shuttle and school buses;

(b) Battery electric delivery vehicles;

(c) Battery electric off-road work trucks designed for site-specific functions (in agricultural, construction, rail, and mining operations);

(d) Battery electric refuse trucks;

(e) Battery electric, fuel cell electric, and plug-in hybrid (sometimes operating as range extender systems) drayage trucks; and

(f) Battery electric, fuel cell electric, and plug-in hybrid (and range extender) regional heavy-haul trucks.

Considering the list above, (a) transit and school buses are more of a Wave 3 application and have already seen significant ZEV deployment in the State. In their recent report for CalEPA, Brown et al. (2021) concurred, concluding that "most buses will be electric by 2045 if current policies are continued because the duty cycle of transit buses is well adapted to ZE technologies" (p 202). Similarly, (b) delivery vehicles tend to be on the lighter side of the heavy-duty vehicle spectrum, and the delivery application is well on its way to a full ZEV transition[38]. As such, the transit and delivery applications are not considered in this work.

Beyond the policy and technology requirements, the secondary question remains of whether there is sufficient data available to construct a useful model. The data needs for our incentive performance evaluation tool are extensive, requiring sufficient information for each vocation to compute the capital expenses (including vehicle and infrastructure purchase costs, associated fees and installation costs, and residual values), operating expenses (fuel, maintenance, and insurance), and incentives and credits (HVIP, LCFS, utility, etc.). As such, practical considerations led us to limit our model on the on-road HDV side to three vocations.

Here, our starting point was to consider the vocations modeled in the recent CARB project 16RD011 *Pathways Towards a Near-Zero Heavy Duty Sector* (Mac Kinnon et al., 2020), which selected vocations based upon on total number of miles traveled in California and the relative impact they have on air quality through CAP emissions. The on-road vocations considered conveniently correspond to the Wave 4 beachhead (we include the EMFAC classes for each vocation):

- **construction** (T7 Single Concrete/Transit Class 8, T7 Single Dump Class 8), which move construction material on-road or assist in construction of buildings and other built structures, aligns in part with the site-specific support in (c) as well as the regional-haul of materials in (f) above,

- **refuse** (T7 SWCV), transporting residential and commercial waste to transfer stations and landfills, aligns with (d) above,

- **drayage** (T7 POAK Class 8, T7 POLA Class 8, T7 Other Port Class 8), which transport goods from ports to distribution centers, aligns with (e) above, and

[38] See, for example, https://about.ups.com/us/en/social-impact/environment/sustainable-services/electric-vehicles---about-ups.html and https://newsroom.fedex.com/newsroom/global/fedex-continues-advancing-fleet-electrification-goals-with-latest-150-electric-vehicle-delivery-from-brightdrop.

- **linehaul** (T7 Tractor Class 8), which transport goods long distances (in state) and align with the regional heavy-haul trucks in (f) above.

To prioritize, we analyzed the different vocations likely to make a substantial difference in greenhouse gas (GHG) and CAP emissions in California by 2035. We first downloaded emissions data from the EMFAC2021 model (v1.0.2) and plotted emissions of four pollutants by sector vocational type (Figure 28). Here we see that drayage and particularly linehaul trucking are among the largest contributors to air pollution and greenhouse gas emissions in California and are obvious choices for inclusion in our study on the emissions basis. Refuse and construction are expected to contribute roughly the same levels of emissions going forward, which are significant, but at a slightly lower scale. To choose between them, we were interested in the vocation that offered the most distinct and challenging application for a ZEV transition. By this standard, the relatively regular depot-based patterns of behavior that are typical of the refuse truck vocation shares similarities with the depot-based drayage vocation, whereas the construction vocation involves more variable and intensive activity often occurring in and around urban areas, making it a more interesting vocation to consider for our purposes. Furthermore, the refuse vocation is often shaped by additional policies stemming from its nature as a service to the public. This creates a more complex decision environment that may be difficult to represent in a general-purpose choice model.

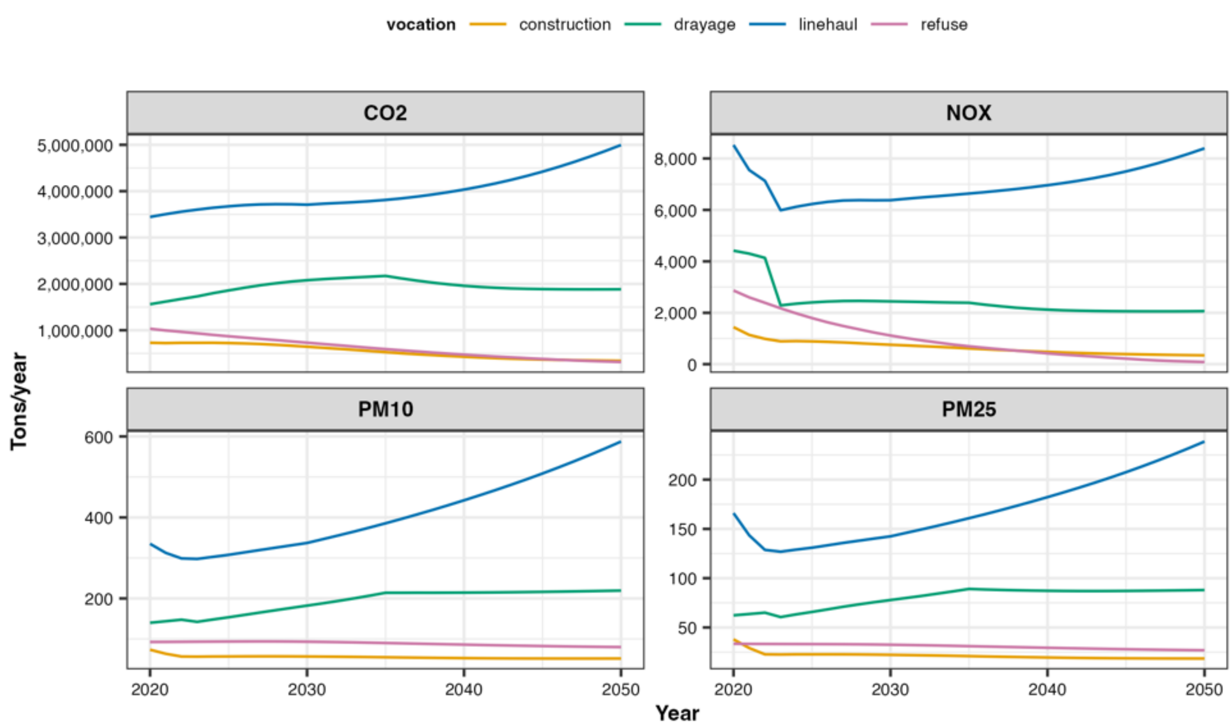


Figure 28. EMFAC2021 projected emissions from four major on-road HDV vocations

Source: EMFAC2021 web database (CARB, 2021a)

For these reasons, we selected **linehaul, drayage, and construction** as the three on-road HDV vocations to focus on in this work. They are all characterized by high mileage and heavy-duty applications, which makes the transition to zero-emission vehicles more challenging and requires specialized technologies and infrastructure, but each represents specific characteristics that, if overcome, will advance the transition by removing barriers to related applications. By focusing on these specific vocations, this work can provide a more targeted approach to identifying and addressing the economic challenges to deploying zero-emission trucks in these sectors through effective incentive policy design.

2.4.2 HDV equipment costs

Because our three selected vocations (linehaul, drayage, and construction) are already part of the TRACE model we followed the vehicle configurations developed for that model to determine the costs. The vehicle configurations for each vocation are summarized in Table 17 through Table 19.

Table 17. Linehaul vehicle specifications

Component	ICEV, diesel	ICEV, CNG	BEV	FCEV
Glider, HDV (ea.)	1	1	1	1
ICE, diesel (kW)	324			
ICE, RNG (kW)		324		
Fuel cell (kW)				363
Traction battery (kwh)			500	2.28
Electric motor and inverter (kW)			400	400
Liquid fuel tank (GJ)	12.61			
RNG tank (GJ)		15.86		
Hydrogen tank (GJ)				10.91
Hybrid cost, HDV				1

Source: TRACE model (Lane et al., 2022)

Table 18. Drayage vehicle specification

Component	ICEV, diesel	ICEV, CNG	BEV	FCEV
Glider, HDV (ea.)	1	1	1	1
ICE, diesel (kW)	232.09			
ICE, CNG (kW)		232.09		
Fuel cell (kW)				247
Traction battery (kwh)			443.26	4.61
Electric motor and inverter (kW)			286.53	286.53
Liquid fuel tank (GJ)	11.2			
RNG tank (GJ)		14.09		
Hydrogen tank (GJ)				9.69
Hybrid cost, HDV				1

Source: TRACE model (Lane et al., 2022)

Table 19. Construction vehicle specification

Component	ICEV, diesel	ICEV, CNG	BEV	FCEV
Glider, HDV (ea.)	1	1	1	1
ICE, diesel (kW)	172.68			
ICE, CNG (kW)		172.68		
Fuel cell (kW)				139
Traction battery (kwh)			299.2	2.76
Electric motor and inverter (kW)			213.18	213.18
Liquid fuel tank (GJ)	5.01			
CNG tank (GJ)		6.3		
Hydrogen tank (GJ)				3.68
Hybrid cost, HDV				1

Source: TRACE model (Lane et al., 2022)

Recall that TRACE is a full optimization model that determines the optimal shares of HDV technology pathways for on-road heavy-duty technology over time subject to supply-side constraints around various fuel pathways with a demand-side constraint to meet projected vocational HDV VMT. These pathways include both the fuel pathways *and* the on-road technology being used across four vocations. These on-road technologies include internal combustion engine (ICE) vehicles running on diesel, renewable diesel (RD), compressed natural gas (CNG), and renewable natural gas (RNG), as well as fuel-cell electric (using hydrogen) and battery electric trucks that require grid electricity charging to add energy to their batteries. The upshot is that because TRACE models on-road technologies as part of its optimization, it produces three outputs that are necessary for total cost of ownership: the fuel costs discussed in Section 2.3.5 as well as the vehicle component costs and vehicle efficiencies.

TRACE forecasts component costs based upon market penetration. These are then used with the above vehicle configurations to estimate capital production costs. Base year (2020) component costs for the scenarios are shown in Table 20. Component costs for future years are forecast by applying Wright's Law using the learning rates associated with the baseline, conservative, and optimistic scenarios from TRACE. Further details of how TRACE estimates vehicle costs are provided in the 16RD011 report (Mac Kinnon et al., 2020) and published work by (Lane et al., 2022).

Table 20. Base year HDV component costs

Component	Cost
Glider, HDV ($/ea)	$95,539
ICE, diesel ($/kW)	$28
ICE, CNG ($/kW)	$31
Fuel cell ($/kW)	$290
Traction battery ($/kWh)	$370
Electric motor and inverter ($/kW)	$50
Liquid fuel tank ($/GJ)	$79
CNG task ($/GJ)	$2,207
Hydrogen tank ($/GJ)	$4,167
HDV hybrid cost ($/ea)	$5,000

The forecast component costs are combined with the configurations from Table 17 through Table 19 to estimate vehicle production costs for each vocation, scenario, and fuel combination as shown in Figure 29.

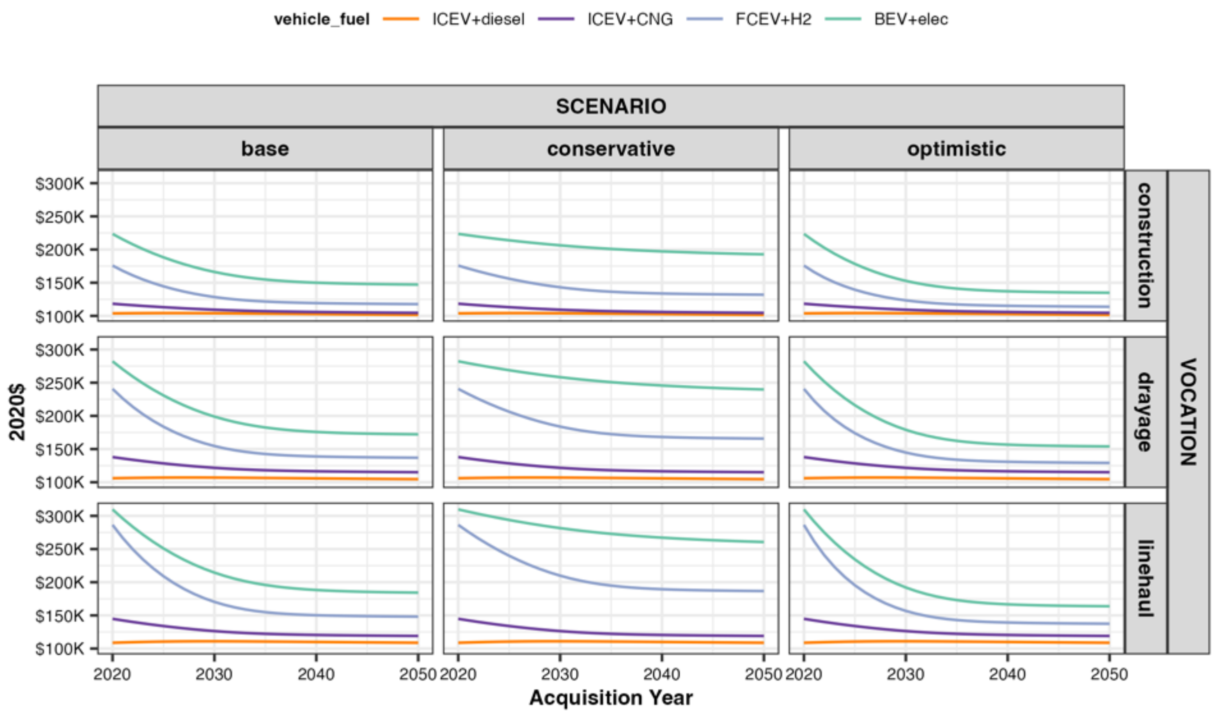
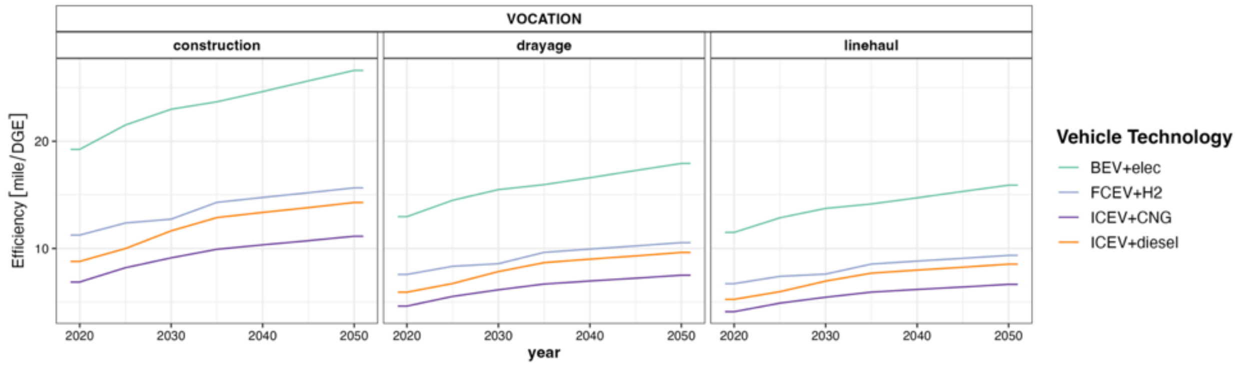
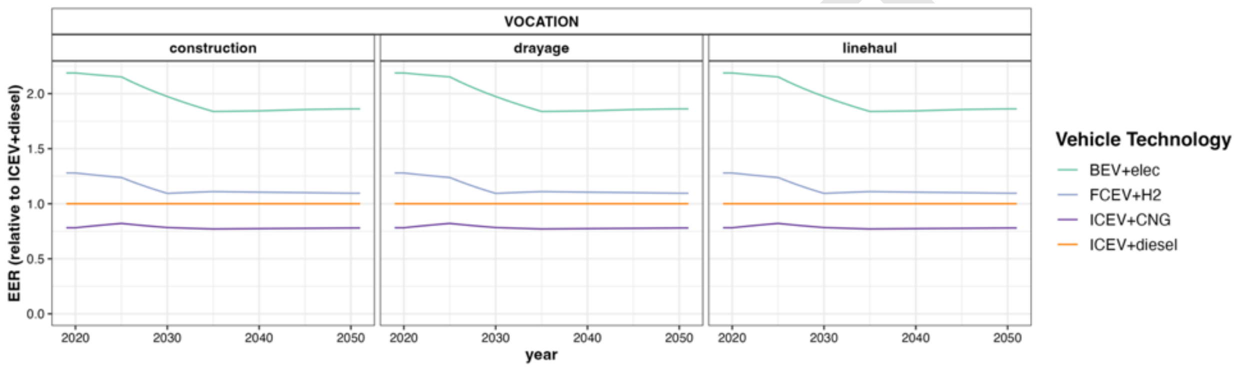


Figure 29. Wholesale vehicle price projections for three scenarios from the TRACE model.

Next, the TCO of a HDV will depend on fuel usage. Although our work will be using data from EMFAC2021, which includes fuel consumption estimates, those estimates are based upon specific fuel splits embedded in EMFAC's results. Because our modeling will predict alternative shares based upon TCO, we need to be able to estimate the fuel consumption for a given technology based upon VMT usage. Converting VMT to fuel usage requires vehicle efficiencies associated with the drivetrain of the specific technologies being modeled. Figure 30 shows the vehicle efficiencies produced by TRACE for the three vocations to be modeled.



(a) Fuel economy in miles per diesel gallon equivalent (DGE)



(b) Energy economy ratio (relative to ICEV+diesel)

Figure 30. Projected vehicle fuel economy and energy economy ratios, 2020-2050.

These two outputs along with the fuel price forecasts represent the necessary data to compute vehicle-related costs in our TCO formulation in the PET, which is described in Section 3.5.

2.5 ORE equipment and technologies for the PET

2.5.1 Selection of ORE to model in the PET

Equipment types previously determined feasible for battery electrification and/or demonstrated with battery electric technology were selected for the analyses in this work (Boriboonsomsin, Un-Noor, Scora, & Wu, 2022; Carer Forklifts, Inc., 2023; CASECE, Inc., 2023; *Electric Intermodal Port Forklifts*, n.d.; Frederickson et al., 2022; LBLN, 2021; Un-Noor et al., 2021, forthcoming), the types are defined by EMFAC2021 (CARB, 2021a):

- Agricultural Tractor
- Cargo Handling Equipment
    - Port Forklift
    - Port Rubber Tired Gantry Crane
    - Port Truck
    - Port Yard Truck

- Construction and Mining
    - Crawler Tractor
    - Excavator
    - Grader
    - Rubber-Tired Loader
    - Skid Steer Loader
    - Tractor/Loader/Backhoe

2.5.2 Off-road equipment costs

Battery electric equipment cost was calculated by sizing the components, getting component costs, and then combining those. Per-unit component costs over the calendar years were sourced from the TRACE model using values generated from the modeling described in Section 1.6 (Lane et al., 2022; Mac Kinnon et al., 2020). Figure 31 shows estimated costs for diesel engines compared to electric motor and inverters in 2020$ per kW needed from 2020-2050. The starting point for electric motor costs of $50 per kW is comparable to the literature.

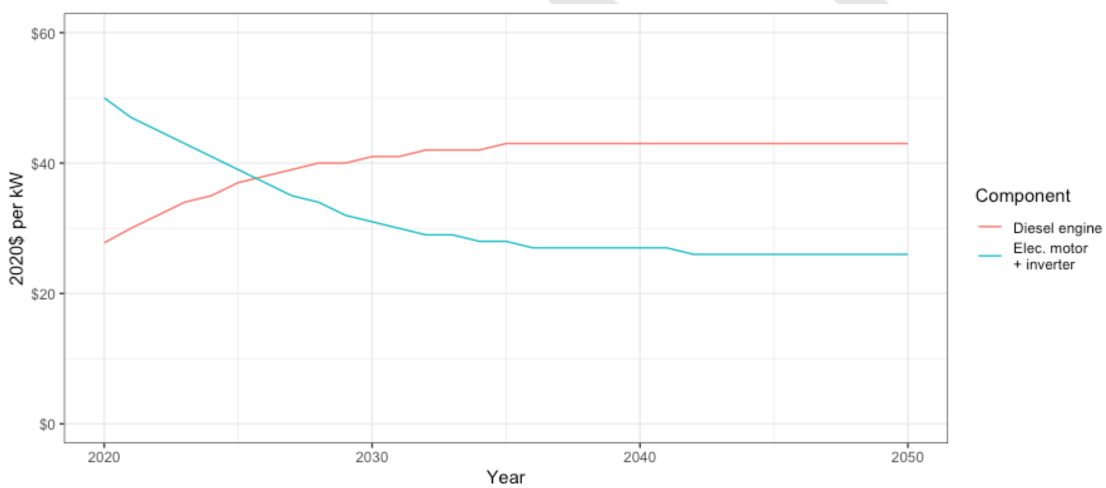


Figure 31. Component costs for diesel engines and electric motors by kW (2020-2050)
Source: TRACE model outputs (Lane et al., 2022), base vehicle production scenario

Figure 32 similarly shows estimated battery costs per kWh from 2020-2050. We note that the 2020 starting point of $370/kWh for battery costs is consistent with the Advanced Clean Fleets workgroup cost estimates that estimate roughly $350/kWh battery costs for heavy-duty vehicles based upon a 5-year delay of light-duty vehicle batteries (CARB, 2019b). However, the learning rate for this baseline case shows that while it tracks a recent study performed for CARB by YUNEV on commercial vehicle battery costs (Beaty, 2021) it tends to be significantly higher than a range of sources identified by the ICCT (Sharpe & Basma, 2022). Still, recent projections by BloombergNEF (Henze, 2022) suggest an uptick in battery costs that may justify the more conservative estimate shown here for TRACE. Furthermore, the aggressive scenario reflects a faster learning rate that is more in-line with estimates in the literature.

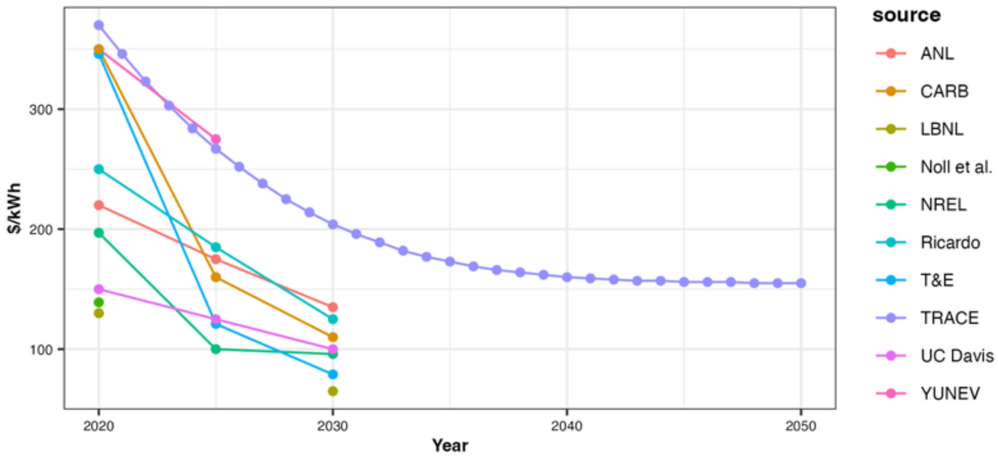


Figure 32. Battery costs per kW (2020-2050)

Source: TRACE model outputs (Lane et al., 2022), base vehicle production scenario compared to various sources: ANL=(Burnham et al., 2021); CARB=(CARB, 2019b); LBNL=(Phadke et al., 2021); Noll et al.=(Noll et al., 2022); NREL=(Hunter et al., 2021); Ricardo=(Kuhn et al., 2021); T&E=(Unterlohner et al., 2021), TRACE=Section 2.3; UC Davis=(Burke & Sinha, 2020); YUNEV=(Beaty, 2021)

Finally, Figure 33 shows unit costs produced by TRACE for both light duty and heavy duty gliders over that time frame.

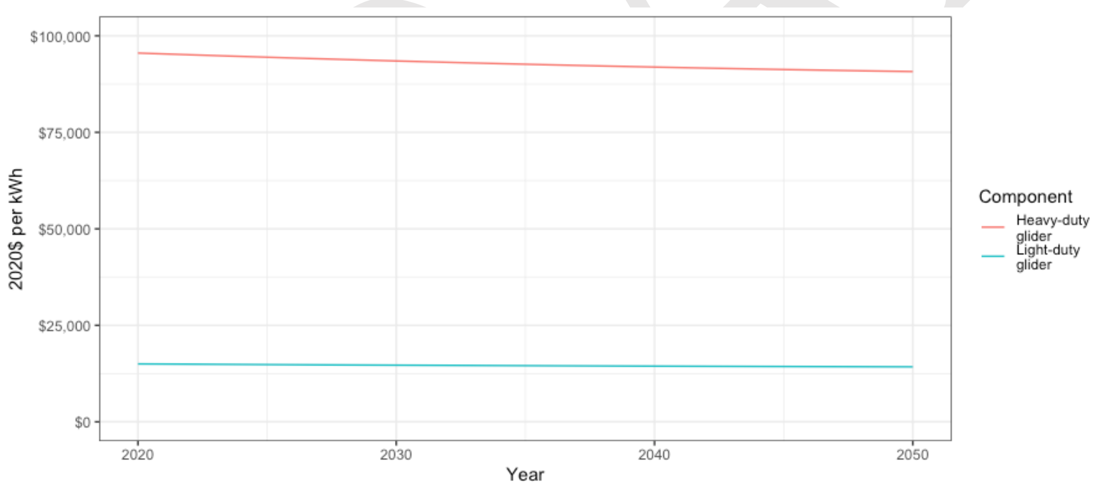


Figure 33. Glider costs (2020-2050)

Source: TRACE model outputs (Lane et al., 2022), base vehicle production scenario

Generally, regulations have been mandated for the off-road sector years after they were put into practice for on-road engines. Thus, this needs to be reflected on the off-road diesel engine price. To address this, comparable particulate matter (PM) limits for on- and off-road regulations were compiled (DieselNet, 2023a, 2023b) as shown in Table 21 and the years when these regulations were introduced were studied. From the regulation timeline, intervals between comparable on-and off-road emission limits were calculated by HP bins. For cases with multiple comparison points (HP bins 300, 600, and 750), average intervals were calculated. The costs for off-road diesel engine were finally taken from the on-road engine cost data according to these average intervals (e.g., if on-road diesel engines in 75 HP bin had a cost of X dollars per kW in year Y, the off-road engine in the same HP bin would cost X dollars per kW in year Y+17).

Table 21. Regulation intervals for on- and off-road diesel engine emission (PM) standards

Engine Power, Off-Road (horsepower)	HP Bin in OFFROAD Database	Regulation Year, Off-Road	Regulation Year, On-Road	Regulated PM, Off-Road (g/bhp-hr)	Regulated PM, On-Road (g/bhp-hr)	Regulation Interval (years)	Average Regulation Interval (years)
25 ≤ hp < 50	50	2008	1991	0.22	0.25	17	17
50 ≤ hp < 75	75	2008	1991	0.22	0.25	17	17
100 ≤ hp < 175	175	2003	1991	0.22	0.25	12	12
175 ≤ hp < 300	300	2003	1994	0.15	0.1	9	7
175 ≤ hp ≤ 750	300	2011	2007	0.015	0.01	4	7
300 ≤ hp < 600	600	2001	1994	0.15	0.1	7	6
175 ≤ hp ≤ 750	600	2011	2007	0.015	0.01	4	6
600 ≤ hp < 750	750	2002	1994	0.15	0.1	8	6
175 ≤ hp ≤ 750	750	2011	2007	0.015	0.01	4	6
hp ≥ 750	9999	2006	1994	0.15	0.1	12	12

Source: (DieselNet, 2023a, 2023b)

With these values in hand, we can describe how we computed equipment costs for electric and diesel applications.

2.5.2.1 Battery-electric off-road equipment costs

Battery size for each type and HP bin was determined based on the assumption that the battery must be able to provide enough energy to be capable of serving the highest anticipated daily activity demand for the equipment to be considered by consumers. Ideally, this would be based on a comprehensive set of daily activity data for each type of equipment where the most energy intensive day could be selected as the design target. However, there is no comprehensive database available that can provide this type of data across a significant number of equipment type categories. As such, an alternative method was employed following recent work for CARB by Boriboonsomsin et al. (2022). In this approach daily energy usage was calculated from the data on diesel fuel usage reported in CARB's OFFROAD database for all years out to 2050 (CARB, 2021a). As fuel usage was provided in the data for whole equipment populations on an annual basis, daily fuel consumption at single-equipment level was calculated first:

$$\text{per-equipment fuel consumption by age (gram/day)} = \frac{\text{aggregate fuel consumption by age (gram/year)}}{\text{population by age} \times \text{number of operating days in a year}} \quad \textbf{Eq. 6}$$

Two additional estimates were used to better approximate maximum daily energy use. First, again following Boriboonsomsin et al. (2022), rather than using a full 365 days as the number of operating days, which would bring the daily fuel consumption estimate down, the number of operating days in a year was estimated to be 186 days. This estimate is based upon the reported fraction of operating days in a year for 105 pieces of equipment—35 internally collected at UC Riverside and 70 from Baker (2008).

Second, the assumed daily usage requirement for each type of equipment was taken as the maximum daily usage computed above from all years during which that equipment category had new equipment sales (equipment with ages -1 or 0).

$$\begin{aligned}&\text{per-equipment fuel consumption (gram/day)}\\ &= \max\left(\text{per-equipment fuel consumption by age (gram/day)}\right)\end{aligned} \quad \textbf{Eq. 7}$$

We then calculated the energy content of the consumed fuel in these maximum consumption scenarios. Using this energy content along with diesel engine efficiency and electric motor efficiency provides the required battery energy content for battery electric equipment with similar level of performance. Energy content of each U.S gallon of diesel fuel was taken as 40.7 kWh[39]; conservative assumptions for diesel engine and electric motor efficiencies (η_{ICE} and η_{Motor}) were assumed at 35% and 72%, respectively (ANL, 2021; Boriboonsomsin, Un-Noor, Scora, Wu, et al., 2022). We assume that adequately specified battery electric equipment can perform the same duty cycle as the diesel equivalent.

$$\begin{aligned}&\text{energy of consumed fuel (kWh)}\\ &= \text{per-equipment fuel consumption (gram/day)} \times 40.7\end{aligned} \quad \textbf{Eq. 8}$$

[39] https://epact.energy.gov/fuel-conversion-factors and https://www.convertunits.com/from/gallon+[U.S.]+of+diesel+oil/to/kilowatt-hour

$$\text{battery size (kWh)} = (\text{energy of consumed fuel (kWh)} \times \text{engine efficiency}) \div \text{motor efficiency} \qquad \textbf{Eq. 9}$$

Using the per-kWh battery cost in each calendar year derived from the TRACE model and shown previously in Figure 32, the battery costs for each equipment type can be calculated as follows using the same per-unit battery costs discussed for HDVs in Section 2.4.2:[40]

$$\text{battery cost (\$)} = \text{battery size (kWh)} \times \text{per-unit battery cost (\$/kWh)} \qquad \textbf{Eq. 10}$$

Motor-inverter rating was taken as the HP bin value converted to kWh (1 kW = 1.341 HP):

$$\text{motor rating (kW)} = \text{HP bin}/1.341 \qquad \textbf{Eq. 11}$$

Using per-kW motor-inverter cost, motor-inverter cost is calculated as follows:

$$motor\_inverter\ cost\ (\$) = motor\_inverter\ rating\ \text{(kW)} \times \text{per\_unit motor\_inverter cost (\$/kW)} \qquad \textbf{Eq. 12}$$

The cost for heavy-duty gliders in each calendar year was taken as the glider cost. Because the component costs used were based on on-road vehicles, additional costs would likely be incurred to make the components suitable for off-road applications and for fitting necessary attachments such as power take-off (PTO). Following Boriboonsomsin et al. (2022), these costs were considered as advanced engineering costs; it was considered as an additional 10% of the total component costs (CARB, 2020b). The price markup for battery electric equipment (MU_{BE}) was assumed to be 40% during 2020-2029; from 2030-2050, it was assumed to be 35% (following Sharpe & Basma's, 2022 estimates for on-road heavy-duty trucks).

Total cost of battery electric equipment for equipment type j and HP bin k in year m is then calculated as:

$$VC_{BE,j,k,m} = (\text{battery cost}_{j,k,m} + \text{motor-inverter cost}_{j,k,m} + \text{glider cost}_{j,k,m}) \times 1.1 \times MU_{BE,j,k,m} \qquad \textbf{Eq. 13}$$

2.5.2.2 Diesel equipment costs

The diesel internal combustion engine (ICE) cost for equipment type j and HP bin k in year m was calculated using the kW rating obtained from HP bin, and the per-KW diesel engine cost:

$$ICE\ rating_k\ \text{(kW)} = HP\ bin_k/1.341 \qquad \textbf{Eq. 14}$$

[40] This estimate does not account for battery degradation over equipment lifetime, but this will be addressed in future work.

$$ICE\ cost_{j,k,m}\ (\$) = \text{ICE rating (kW)} \times per\text{-}unit\ ICE\ cost_{j,k,m}\ (\$/\text{kW}) \qquad \textbf{Eq. 15}$$

Fuel tank size for equipment type j and HP bin k in year m was determined by the energy content of the corresponding maximum fuel consumption in GJ. Then, the fuel tank cost was obtained by using per-GJ fuel tank cost value:

$$fuel\ tank\ cost_{j,k,m}\ (\$) = (per\text{-}equipment\ fuel\ consumption\ (gpd)_{j,k,m} \times 0.14652)\ (\text{GJ}) \times \text{per-unit fuel tank cost}_{j,k,m}\ (\$/GJ) \qquad \textbf{Eq. 16}$$

Price markup for diesel equipment (MU_{ICE}) was assumed to be 35%. No advanced engineering costs were applied in the diesel case.

Total cost of diesel equipment for equipment type j and HP bin k in year m is then calculated as:

$$VC_{ICE,j,k,m} = (ICE\ cost_{j,k,m} + \text{fuel tank cost}_{j,k,m} + \text{glider cost}_{j,k,m}) \times MU_{ICE,j,k,m} \qquad \textbf{Eq. 17}$$

The results costs are discussed later in Section 4.4.

3 Technical and behavioral factors in the transition to LCT

In the prior sections we have established the policy landscape under which California's LCT transition is occurring and reviewed the status of LCT technology including HDV, ORE, and low-carbon fuels and generate cost projection scenarios to support modeling. Next, we turn to identifying the technical and behavioral factors that will govern this transition from the perspective of the fleets. Section 3.1 reviews the literature that describes both the current understanding of LCT adoption behavior in the HDV and ORE sectors. Section 3.2 discusses barriers to adoption of LCT by fleets to provide a set of questions the PET can be used to address. Section 3.3 describes how we conceptualize the adoption problem for heavy-duty and off-road fleets based upon prior related work. Finally, Section 4 describes the findings of fleet interviews conducted to fill gaps in knowledge based upon work in the prior sections.

3.1 Literature Review

This section comprises the relevant studies regarding the current adoption of LCT and the incentive plans available both in the HDV and ORE sectors.

3.1.1 LCT adoption in HDV Sectors

Some recent studies in Europe conducted research to analyze the barriers to adopting alternative fuel adoption in heavy-duty sectors. To gauge fleet operator preferences for hydrogen-powered sweepers, Walter et al. (2012) performed a choice experiment in Switzerland and Germany. They discovered that the two financial factors, the vehicle purchase price, and operating costs, had the most impact on the decision to purchase. In another study in Germany, Seitz et al. (2015) find that corporate social responsibility with environmental attitudes can play a profound influence in choosing CO2 – saving powertrain technologies. For the three vehicle markets in China, Europe, and the US, Moultak et al. (2017a) analyze the zero-emission heavy-duty vehicle technologies to aid the freight sector's decarbonization. Meeting the numerous freight vehicle standards for daily trip range, starting vehicle cost, charging time, and sustaining vehicle cargo weight and volume capacity are found to be the main obstacles for plug-in battery electric vehicles. The study also indicates battery-swapping technologies, although currently only used in a few isolated applications, it has the potential to largely address the charging time issue. By employing a Delphi study, Anderhofstadt and Spinler (2019) attempt to determine the factors affecting the adoption of alternative fuel-powered HDVs in Germany. By combining the effects of cost variables, socioeconomic concerns, environmental standards, operational aspects, and political considerations, the study finds that the availability of fueling or charging infrastructure, the ability to enter low-emission zones, as well as current and projected fuel costs, are crucial considerations while purchasing and operating an alternative fuel-powered HDV. Moreover, battery electric, fuel cell electric, compressed natural gas, and liquefied natural gas are identified as viable technologies to reduce emissions from HDVs.

According to Burke and Miller (2020), CARB has had extensive experience with mandates and incentives for light-duty ZEVs, and they are apparently planning to follow a similar path for MHD trucks. In this respect, several monetary incentives for electric vehicle fleets, many in the form of vouchers are available in medium and heavy-duty truck sectors Jin et al. (2014). For example, the California Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) offers $7,500 to $120,000 vouchers (based on Gross Vehicle Weight Rating) for new medium- and heavy-duty electric vehicle fleets (CARB, 2022b).

However, the heavy-duty truck sector is complex and very heterogeneous as it is related to many stakeholders' making decisions having different rational choices (Winebrake et al., 2012). For example, some short-haul trucks serve ports primarily, while others might convey items from distribution centers. Port trucks must adhere to all port requirements and typically spend more time idling or traveling at a slow speed. However, due to various drive cycles, rules, and other potential circumstances, the mileage and fuel efficiency of short hauls may differ from the long hauls (Fulton & Miller, 2015). Owner-operators (people who own one or a small number of trucks) and businesses with a large fleet of trucks can both buy short-haul or long-haul trucks. The purchasing preferences of these proprietors can vary greatly. Therefore, it will be challenging to create a standard or set of mandates for MHD vehicles that the trucking sector can implement and accept. The best course of action would appear to be to create separate regulations for various kinds of vehicles that share usage patterns, size and cost features, and ownership/business models.

By conducting a series of in-depth qualitative interviews, Bae et al., (2022) detect 38 motivators or barriers related to the adoption of alternative fuel vehicles (AFV) by the HDV sectors in California. The study finds the functional suitability, monetary costs, fuel infrastructures, and reliability/safety of the vehicles and engines as the driving factors towards the AFV adoption decisions. On the other hand, unsuitable functionality, reliability/safety issues, unacceptable financial costs, or increased operational complexity due to insufficient refueling/charging infrastructures are found to be responsible for the non-adoption decisions. Bae et al. (2022) also summarize more general behavioral factors influencing attitudes towards alternative-fueled vehicles, specifically noting whether organizations:

- use a TCO approach toward purchase decisions,
- operate vehicles on fixed and therefore predictable routes,
- seek a "first-mover" advantage, or
- prioritize minimizing environmental impacts in their business decisions as a form of Corporate Social Responsibility (CSR).

3.1.2 LCT adoptions in Off-road sectors

As part of the global effort to address greenhouse gas emissions, governments are actively working towards reducing emissions from the transportation sector. However, the task of controlling emissions from off-road equipment sectors presents a unique set of challenges compared to on-road vehicle emissions.

Most governments are dedicated to lowering emissions from the transportation sector as part of their plans to limit greenhouse gas emissions. However, Hall et al. (2018) indicate a variety of reasons behind a greater challenge to control emissions from off-road equipment sectors than on-road vehicle emissions. Due to the cross-boundary nature of aviation, maritime, and rail as well as the widespread use of off-road construction and agricultural equipment, calculating the precise emission consequences is more challenging. Moreover, Hall et al. (2018) also indicate that government regulation of off-road land vehicles is uneven because of the wide variety of vehicles in the sector, slow vehicle turnover, and operating models that frequently include leases and rentals.

Nevertheless, McCullough et al. (2021) point out that California has been at the forefront of agricultural regulations, which is unique in providing millions of dollars in incentives to encourage growers to prepare for possible mandatory air quality implementation plans.

As we mentioned earlier, CARB introduced a $135 million allocation to Funding Agricultural Replacement Measures for Emission Reductions (FARMER) program in September 2017 as a primary initiative. Since then, the state legislature has so far authorized a total of $685.6M from multiple funding sources for this program. These acts allotted money for the replacement of tractors, trucks, pumps, and other heavy-duty agricultural equipment with reduced-emission models. The program was designed with California Air Resources Board (CARB) personnel and local air districts and agricultural groups to ensure that the projects funded would fulfill the emissions reduction goals. However, a clear understanding is needed to analyze the awareness, perception, and importance of incentives in adopting LCT in off-equipment sectors.

3.2 Barriers to adoption of LCT by HDV and ORE

The deployment of low carbon and zero-emission HDV and ORE has notable barriers. The sections below summarize the barriers to adoption identified during our work.

3.2.1 Barriers for On-Road HDV Adoption of LCT

Our starting point for identifying barriers to LCT adoption for on-road HDV was informed by the results from the recently completed report for CARB's 16RD011 contract titled "Pathways Towards a Near-Zero Heavy Duty Sector" (Mac Kinnon et al., 2020), which involved several members of this project's research team. This report summarized barriers in broad categories as follows:

- **Vehicles**: The team identified the lack of available vehicle models as a notable barrier to broad adoption, with vocational applications generally limited to class 8 drayage, buses, and delivery trucks, though projected improvements in vehicle and drivetrain performance are expected to broaden model availability. Generally, the tradeoffs between range and powertrain weight is a critical factor to be addressed through technology improvements, as negative impacts on fuel efficiency and maximum payload make the technologies less attractive in terms of both functional- and cost-based criteria.
- **Infrastructure**: The primary ZEV technologies employing either battery-electric or fuel-cell electric (FCEV) powertrains are dependent on the existence of the necessary refueling infrastructure for successful deployment. This includes both whether the geographical distribution of refueling locations is suitable to support particular fleet operations as well as the nature of the refueling activities themselves, which differ from conventional fuels in terms of refueling time and other factors, and can require changes in a fleet's operational strategies to accommodate longer refueling times and limited refueling locations. The build-out of refueling infrastructure itself adds additional complexity. The production and distribution of hydrogen lacks the maturity of the century plus of industry support conventional fuels enjoy, leading to higher costs and technical challenges that are still being resolved. The charging infrastructure for BEV needs the support of the state's broader electrical grid, which is still evolving to meet the needs of the light-duty transportation sector. The added demands of the high-rate level 3 charging necessary to support HDV operations exacerbates this problem and it is yet to be determined who will bear the costs of expanding this infrastructure. The result of these barriers are reflected in the vocational distribution of ZEV HDV deployments discussed above, which are concentrated in large fleets (drayage, transit, delivery) whose operations are amenable to centralized refueling and whose size can justify targeted investment in alternative fuels.
- **Grid Services and Battery Degradation**: Some scenarios for successful BEV deployment in the HDV sector rely on vehicle-to-grid discharging. However, these scenarios have increased concerns about battery degradation resulting from a range of associated factors including energy throughput, cycling patterns, (dis)charging rates, depth of discharge, and temperature. Depending on specific HDV duty-cycles, degradation levels could reduce effective lifetime of HDV batteries by years, in some cases amounting to 40-50% reduction. If vehicle-to-grid approaches are expected to be used for supporting BEV deployment and maintaining a healthy grid, utilities will need to create revenue streams for fleets participating in grid services in order for fleets to earn revenue from modifying their charging patterns that can offset the associated costs of degradation.

They also highlighted a number of factors influencing alternative-fuel adoption by fleets on the basis of interviews with fleets. Several of the identified factors highlighted fleet perceptions of barriers to general LCT adoption:

- Regulations requiring AFV purchases combined with a limited technology availability have created a constrained choice set for fleets, with CNG being the most common choice to meet regulation. ZEV regulations will create similar constraints toward an even smaller set of alternatives. Policy to increase the viability of multiple powertrain solutions will likely create a more robust market with increased competition accelerating technological improvements and lowering costs.
- The availability of governmental financial incentives for offsetting initial capital costs were a driver to adoption. That cost is a barrier to adoption is not a surprising finding, but rather that the presence of incentives can impact the timing of purchase decisions. This has relevance for the development of the fleet turnover model described in Section 3.5.
- Technical capabilities, including unsuitable functionality and reliability/safety issues, were a deciding factor resulting in non-adoption decisions. Here, some fleets emphasized that available alt-fuels were broadly insufficient or infeasible for their operations. To achieve a broad transition to LCT, a focus on developing vehicles that can satisfy the complete set of vocational applications is critical.

Supplemental work by Bae et al. (2023) explored barriers identified by fleets related to infrastructure that highlighted insufficient refueling infrastructures are another major barrier to heavy duty alt-fuel adoption: most of the organizations interviewed do not want to solely rely on off-site stations. Again, this insight is confirming information already identified in the literature. However, concerns about off-site refueling costs include both for the fuel itself and for the time associated with offsite refueling at stations that are geographically dispersed. The associated labor costs of refueling trips were noted as an added cost that was significant.

Muratori et al. (2023) emphasized the challenges of BEV operations for certain longer-haul applications where effective operations will likely require charging at the megawatt scale. Still, they note that there is unlikely to be a one-size-fits-all solution for commercial MHDV operations, and instead suggest that charging solutions will be more tailored to specific operations rather than the status quo we see with diesel refueling. Hydrogen, they note, will likely resemble today’s operational behaviors, but suffers from the high costs associated with producing clean hydrogen. They add that the lack of infrastructure is both a cause and effect of slow MHD uptake, with the minimal market for infrastructure delaying deployment, but the lack of infrastructure being a primary impediment to increasing the vehicle market. They conclude that grants and rebates are critical for seeding the market to lower these barriers and facilitate market growth.

Finally, Brito (2022) provides a recent review of barriers to zero-emission trucks that emphasized the unique problems of smaller fleets, who make up about 44% of the trucks on the road nationwide. After interviewing around 40 drivers Brito noted the differences between the barriers emphasized by small versus large fleets. Smaller fleets were most concerned with cost factors including TCO, insufficient government support, and upfront cost while larger fleets agreed on the lack of government support but noted lack of zero-emission trucks and fuel or other infrastructure as the most important obstacles.

3.2.2 Barriers for Off-Road Equipment Electrification

The drawbacks of using zero-emission technologies in ORE vary with the application area, which is even more diverse than the on-road sector. Specific applications include long charging time and short range (Un-Noor et al., 2017). These can cause shortened operating time and increased downtime for construction and agricultural equipment. Also, as the off-road equipment have far superior and dynamic power requirements, sizing of motor and energy storage systems considering design constraints (e.g. weight) become major design concerns (Wagh & Sane, 2015; Wang et al., 2017). Charging off-road equipment can also present unique challenges. For construction equipment, jobsites can be temporary and often are constructing the very infrastructure that would be needed to set up a temporary grid link to support on-site charging. For agricultural equipment, wide operating areas can demand strategic placement of charging stations. The high price of EVs, and strong competition from conventional ICE-driven equipment can also be considered as probable barriers for electrification in the off-road segment (Singh, 2014). Beyond these shortcomings inherent to the early stages of EV adoption, the lack of research for multiple equipment types can be considered as a major impediment for electrifying this sector.

In recent work for CARB, Saphores et al. (2023) surveyed the literature and interviewed industry stakeholders to summarize the major challenges for ZE equipment in a number of vocational areas. The major challenges to agricultural equipment electrification include the following:

- Technical barriers, including the lack of widely accepted duty cycles for agricultural tractors, long charging times, and the need to upgrade the distribution grid infrastructure for larger equipment.
- Lack of a repair network for ZEV equipment and operator familiarity with new technologies.
- Extreme weather conditions, such as hot temperatures, dusty conditions, dirt, moisture, and cold temperatures, which can affect the performance and battery life of equipment.

- Economic barriers, including higher upfront costs and a lack of availability and choice, especially for smaller operations.
- Concerns about increased costs, both for the equipment and for the electricity to run the equipment.

Challenges to electrifying construction and mining equipment are similar in many ways to that faced by agriculture. Some additional concerns for this sector include:

- Energy storage is a major challenge for the electrification of heavy-duty construction equipment, with large and energy-dense batteries being necessary.
- Site design for providing energy infrastructure, especially in remote locations, is critical for success.

Additional challenges to electrifying industrial equipment, such as those used at ports and warehouses, include:

- Heavy-duty operations: Industrial equipment used in ports and warehouses often need to lift and move heavy loads, which requires significant power and energy. This can make the transition to zero-emission electric power particularly challenging.
- Long duty cycles: The duty cycles for industrial equipment can be longer and more varied than those for other types of equipment. The fluctuation in power demand can place a strain on the battery and energy storage system, which may not be able to meet the energy requirements.
- Limited range and charging infrastructure: Electric industrial equipment may have limited range, which can limit their usability. Furthermore, charging infrastructure may not be available in all locations, leading to potential downtime for charging.
- Safety concerns: Safety concerns may arise with the use of high-voltage batteries and charging systems in industrial equipment. Proper training and safety protocols must be implemented to prevent accidents and ensure safe operation.

In many cases, fuel-cell solutions can mitigate some of the challenges to electrifying ORE, particularly as they relate to recharging infrastructure. However, fuel cells have their own challenges to overcome, including:

- Higher equipment costs, in part due to low volumes as fuel cell drivetrains are not built at the same volume as batteries to achieve economies of scale. This would be mitigated with higher market penetration, but it remains an issue for now.
- Fuel cells require cooling in a way that is challenging in dirty environments as they are very sensitive to dust and dirt.

A final low-carbon, but not zero emission alternative is the use of hydrogen combustion, which overcomes some of the challenges of fuel cells with the potential for carbon-free ORE energy depending on the hydrogen fuel pathway used. Hydrogen combustion does produce emissions, though recent progress on reducing NO_X and other CAP has been reported (PIN Online, 2023).

3.3 Characterizing the low-carbon transportation adoption process for HDV and ORE

Bae et al. (2022) developed a theoretical framework for heavy-duty alternative fuel vehicle (AFV) fleet adoption decisions in California based upon the Diffusion of Innovations theory (Rogers, 1983), the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990), and a two-level framework for organizational innovation adoption proposed by (Frambach & Schillewaert, 2002). Though Bae et al.'s work focused on AFVs that include alternatives such as natural gas trucks, it is generally applicable to broader low-carbon transportation alternatives, that are by definition alternative fuel vehicles. Using interviews with adopters of natural gas vehicles, they identified 38 factors related to AFV adoption and their relationships with each other that they merged into a theoretical framework, shown in Figure 34. Here, the decision to purchase vehicles "are assumed to happen at fleet-specific time intervals and involve the evaluation of potential alternatives by a decision-making unit (DMU) of one or multiple people in the organization." This DMU concept represents the complexity of organizational decision-making that may be influenced by organizational structure that is both informed by and constraints the behavior of individuals. The acceptance of specific technologies by individuals in the organization evolves from a complex web of interactions involving that organizational structure, the characteristics and performance of specific technologies, and external influences that includes manufacturer marketing and education, governmental policies, and sector-specific shared experience.

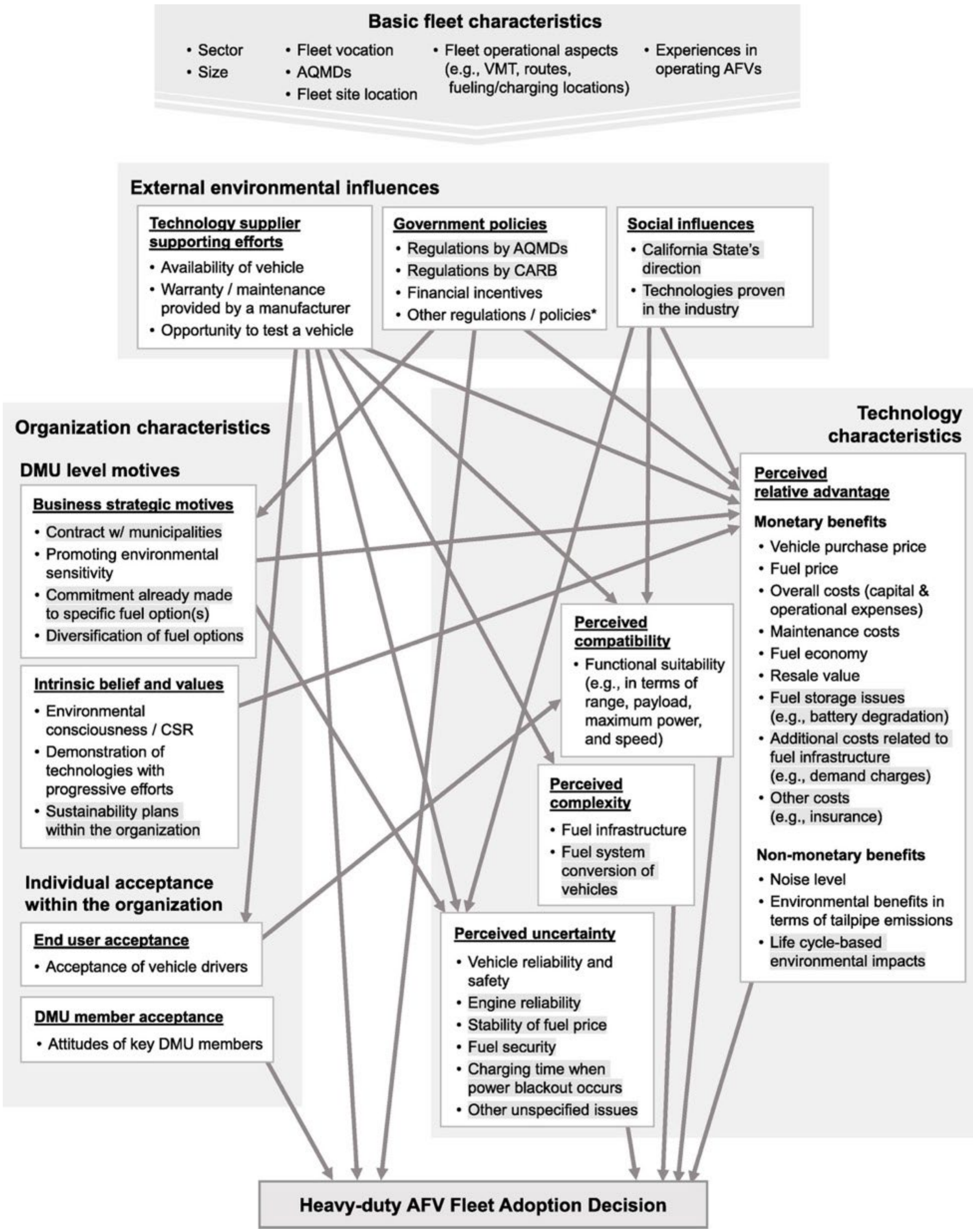


Figure 34. A framework for heavy-duty fleet adoption

Source: Factors influencing alternative fuel adoption decisions in heavy-duty vehicle fleets (Bae, Mitra, et al., 2022). The grayed items were not previously identified by the authors in their literature review and were considered novel.

This framework remains a hypothetical construct that has been developed through qualitative interviews. Generally, the qualitative interviews suggest that the basic characteristics of fleets, such as size, sector (public versus private), vocation, location, and experience with AFVs, will all impact the strength of the relationships between the identified factors and the adoption decision. The most common influential factors include:

- Fleets tended to evaluate the perceived technology characteristics of heavy-duty AFVs, including their functional suitability, monetary costs, fuel infrastructures, and reliability/safety of the vehicles and engines, in a comprehensive manner when making adoption decisions.

- Fleets may overcome major perceived barriers to AFV adoption, whether cost related or functional, if they are motivated by corporate social responsibility and environmental consciousness, especially if they align with strategic business motives.

- Government regulations mandating the purchase of alternative fuel vehicles or zero-emission vehicles, coupled with a limited selection of AFV models, have led some heavy-duty vehicle fleets to face restricted vehicle energy technology choices (e.g., diesel, natural gas, battery-electric, fuel-cell electric), but fleets note that financial incentives have offset the impacts of these more limited choices by lowering the costs of vehicle purchases and supporting the construction of EVSE or on-site refueling facilities.

- Policymakers should continue to support the evolution of the ZEV HDV market to ensure that heavy-duty AFVs meet all criteria including functionality, reliability/safety, financial feasibility, and adequate refueling/charging infrastructure to increase adoption rates. This is particularly true when regulations mandate the purchase of zero-emission vehicles when the market still only provides a limited selection of AFV models at higher costs. In these situations, fleets note that financial incentives have offset the impacts of these more limited choices by lowering the costs of vehicle purchases and supporting the construction of EVSE or on-site refueling facilities.

- If an organization has already committed to a specific fuel option, typically with a large investment in fueling/charging facilities, they may reject any other alternative fuel options – except for a few large fleets which desire to diversify fuel options.

- It is important to encourage HDV fleet operators to remain open to considering alternative fuel options, even if they have already invested in a particular fueling or charging infrastructure. Policymakers could provide financial incentives or other support to help fleets transition to different alternative fuel options, or to diversify their fuel portfolios. Additionally, policymakers could encourage collaboration between fleets to share experiences and best practices for adopting and operating different types of alternative fuel vehicles.

- To encourage the adoption of ZEVs for specific HDV vocations, such as electric refuse trucks and hydrogen hauling trucks, policymakers should consider implementing measures that address the limited availability of these vehicles. One potential solution is to offer incentives and increase investment in research and development to encourage manufacturers to expand their offerings in these areas. By doing so, policymakers can help to alleviate concerns about the commercial availability of AFVs and promote their adoption in the HDV sector.

Translating these findings into a quantitative model remains difficult. Fleet operators—particularly small fleets—are a particularly challenging population from which to collect data on a scale necessary to develop fully quantitative and validated models of behavior. As such, the research reviewed above may not fully explain the low-carbon transportation fleet adoption as well as developing effective incentive strategies in heavy-duty, which justifies the need for further research on the barriers to adopting low-carbon technologies by HDV fleet operators concerning fleet (small vs large) and hauling (short haul vs long haul) types.

3.4 Fleet Interviews

To fill knowledge gaps in understanding low-carbon transportation adoption in Heavy-Duty Vehicles (HDV) and Off-Road Equipment (ORE) sectors we conducted a series of interviews with fleets focusing on the awareness, impression, and factors influencing the acquisition and impression of low-carbon vehicles and incentives. These semi-structured interviews were conducted over the phone to collect data from a) on-road heavy-duty vehicle fleets, and (b) off-road equipment operators to better understand the fleet turnover and business decision-making processes. Section 3.4.1 describes the data collection and sampling techniques we employed for our structured interviews. The interview methodology adopted for this study follows in 3.4.2. Section 3.4.3 provides a detailed synthesis of what we learned from the interviews. Section 3.5 summarizes the findings for use in this project.

3.4.1 Data Collection and Sampling

3.4.1.1 Indexing

Companies operating Heavy-Duty vehicles and off-road equipment were recruited for over-the-phone interviews from a list prepared by indexing all potential companies that operate in California. Most of the companies in our index were identified from Dun & Bradstreet's online website, [41] which contains a free directory of businesses across the world that can be filtered by sector and location. The profile given for each company provides a brief description, business analytics, and contact information. We also cross-referenced on-road trucking companies with

[41] Dun & Bradstreet (https://www.dnb.com/) is a data analytics company that provides commercial data and data services for other businesses.

the FMCSA Company Snapshot,[42] another online directory that provides business and contact information for freight companies registered with USDOT. The FMCSA dataset was used to estimate the size of each company's heavy-duty fleet. Using these resources, we identified 74 on-road companies and 56 off-road companies. On-road companies added to the index were primarily general freight trucking, with some public transit and waste collection fleets being added as well. Off-road companies were based in the industries of construction and demolition, farming, and landscaping.

3.4.1.2 Recruitment

After completing the indexing, we obtained Institutional Review Board (IRB) approval for the research protocol and began contacting companies through email and phone calls. While all companies had a phone number to contact, it's worth noting that not all companies had an email address. We conducted five rounds of emails and telephone outreach to recruit participants. Only companies that lacked email addresses were contacted during the first round of calls and if they agreed to participate then their e-mails were collected. Throughout the contact phase, around 400 calls were made to the indexed HDV and ORE companies. A total of 12 companies—8 on-road companies, and 4 off-road—agreed to participate in the interview. The interview time was fixed based on the availability of the participants. Before each interview, a consent letter describing the objective of the study along with the questionnaire of the survey were sent to the participants via e-mail addresses. Each of the participants was offered a $200 amazon gift card as compensation for their time.

3.4.2 Methodology

3.4.2.1 Semi-structured Interviews

Research team members conducted the semi-structured interviews over the phone. Based on the literature review and proposed questions by members of the research team, we prepared two sets of questions for the on-road and off-road vocations respectively. The surveys asked participants to give their name, job title, and affiliation. All data were be kept confidential to the extent allowed by the University of Arkansas and the State of Arkansas. Participation in this study was voluntary. If participants wanted, they could choose to skip questions by notifying the research team immediately. The interviewees were free to express their opinions. The interviews lasted between 25 minutes and one hour.

3.4.2.2 Content Analysis

Content analysis was used in this study to analyze the qualitative data from the semi-structured interviews. Content analysis seeks to analyze data within a specific context by taking into account the meaning that is attributed to the data under consideration (Krippendorff, 1989).

[42] See https://safer.fmcsa.dot.gov/CompanySnapshot.aspx

3.4.2.2.1 Coding Framework

In content analysis, a coding framework is used to structure the material for the analysis (Schreier, 2012). In this study, the coding framework had 11 main categories with multiple subcategories (reaching down to one or more levels) under each main battery cost category. The framework was developed using a mix of concept-driven and data-driven strategies (Figure 35). The main categories, also known as dimensions, were concept-driven. At first, a set of research questions were fixed, and the main categories were directly translated from the research questions. For example, if a research question was "What are the barriers to LCT adoption in the heavy-duty vehicle sector?", then a main category named "barriers to LCT adoption" was created. The subcategories, on the other hand, were data-driven as they were extracted from the transcribed interviews using a "subsumption" process (Schreier, 2012). We first highlighted the segments of the interviews relevant to the previously selected main categories. Then, we read through the highlighted material to add subcategories under each main category. If a highlighted segment discussed a new concept that was pertinent to a main category, then a subcategory with an appropriate name (describing that concept) was added under that main category. Highlighted segments that discussed concepts that were already captured by a previously added subcategory were passed over or mentally "subsumed".

A pilot coding phase was conducted to adjust the initial coding framework. The final framework fulfilled four conditions namely, one-dimensionality, mutual exclusiveness, saturation, and exhaustiveness (Schreier, 2012). In a one-dimensional coding framework, a dimension/main category captures only one aspect of the material. Mutual exclusiveness pertains to the subcategories under one main category, and it dictates that a coding unit/relevant statement can only be assigned to one subcategory under a main category. Saturation and exhaustiveness dictate that no subcategory should be empty, and all coding units should be assigned to one sub-category or another.

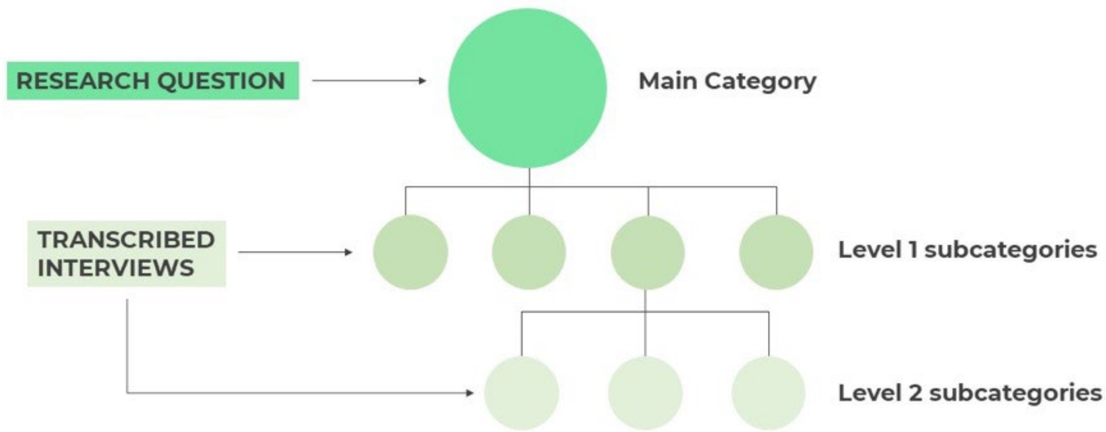


Figure 35. Mixed approach (concept-driven and data-driven) to build the coding framework

3.4.2.2.2 Segmentation

Before coding the material, it was segmented into units of analysis, context units, and coding units using ATLAS.ti. The interviews were selected as the units of analysis in the study. They were further segmented into context units and coding units. The coding units are those segments of the units of analysis that can be meaningfully interpreted with respect to the selected main categories (Schreier, 2012). In this study, they were defined by breaking down the texts and examining underlying assumptions (Stemler, 2001). Since the interviews were semi-structured, the interviewees sometimes made a point using only a word, and sometimes, they made a point using several sentences. Hence a fixed boundary for coding units would not be conducive to the objectives of this study. Hence, changes in topics signaled the end of one coding unit and the beginning of another (Schreier, 2012). The larger segment of the material around the coding units which helped the characterization and assignment of the coding units were the context units (Prasad, 2008).

3.4.2.2.3 Coding and Analysis

After the development of the coding framework and the segmentation of the material, the coding units were assigned to one or more lowest-level sub-categories using ATLAS.ti. Besides examining the presence of the concepts captured by the subcategories, the researchers also looked at the emphasis or importance placed on the concepts by an interviewee. The statements associated with all the subcategories were independently assessed by two raters and a data abstraction sheet was filled out with importance ratings for each subcategory. The raters placed a rating for each of the lowest-level subcategories (for each interviewee) by reading all the statements from the interviewee associated with a particular subcategory. Ratings from individual raters were compared and disagreements were settled through a follow-up discussion (Schreier, 2012). The inter-rater agreeability was assessed using Kohen's Kappa (Cohen, 1960), which was 0.48. Hence, the agreement between the two raters was moderate (Stemler, 2001). Since the interviews were semi-structured, the assessment of importance (placed on a topic) from the interviewees' statements was open to interpretation. This may explain the moderate level of agreement that was achieved between the two readers (Neuendorf et al., 2017).

3.4.3 Results and Discussion

The qualitative data from 12 interviews were analyzed using content analysis. Given the qualitative nature of this study, collecting a statistically representative sample was not the intention. However, a sample size large enough to produce data saturation was collected, and studies have shown that a sample size of 12 is large enough to produce data saturation (Boddy, 2016). Despite the small sample size, the recruited organizations exhibited as much variability as possible in terms of adoption behavior, vocation, and fleet size. The results from the content analysis were aggregated and compared based on the adoption behavior of organizations (3 adopting organizations vs 9 non-adopting organizations), the vocation of the organizations (8 on-road organizations vs 4 off-road organizations & 3 long-haul organizations vs 3 short-haul organizations vs 2 mixed-haul organizations), and fleet size (8 small fleet organizations vs 4 large fleet organizations) (Table 22). We used a scale of 0 to 3 (0 = no awareness, 1 = low awareness, 2 moderate awareness, and 3 = high awareness) to rate awareness levels. Impression ratings used a scale of -2 to +2 (-2 = highly negative, -1 = somewhat negative, 0 = neutral, +1 = somewhat positive, and +2 = highly positive) (Murdoch et al., 2019). The importance/emphasis placed on all other subcategories used a scale of 0 to 3 (0 = not stated, 1 = implied, 2 = explicitly stated, and 3 = emphasized) (Carley, 1993).

Table 22. Adoption behavior, vocation, and fleet size of the organizations interviewed

Interviewee/organization	Adoption behavior	Vocation	Fleet size
1	Non-adopter	On-road (long-haul)	Small (<25)
2	Non-adopter	On-road (long-haul)	Small (<25)
3	Non-adopter	On-road (mixed-haul)	Small (<25)
4	Non-adopter	On-road (mixed-haul)	Small (<25)
5	Non-adopter	On-road (short-haul)	Small (<25)
6	Non-adopter	On-road (long-haul)	Large (>25)
7	Non-adopter	On-road (short-haul)	Small (<25)
8	Non-adopter	On-road (short-haul)	Small (<25)
9	Adopter	Off-road	Large (>25)
10	Non-adopter	Off-road	Large (>25)
11	Adopter	Off-road	Small (<25)
12	Adopter	Off-road	Large (>25)

3.4.3.1 Awareness and Impression of LCT

On a scale of 0 to 3, the average awareness of low-carbon vehicles among all the interviewees in the study was 2.5 (Figure 36). On the other hand, the interviewees demonstrated a negative impression of low-carbon vehicles. With a rating of -1.17, the overall impression was somewhat negative to highly negative (Figure 36). The following sub-sections present a comparison of awareness and impression among the different categories of organizations interviewed.

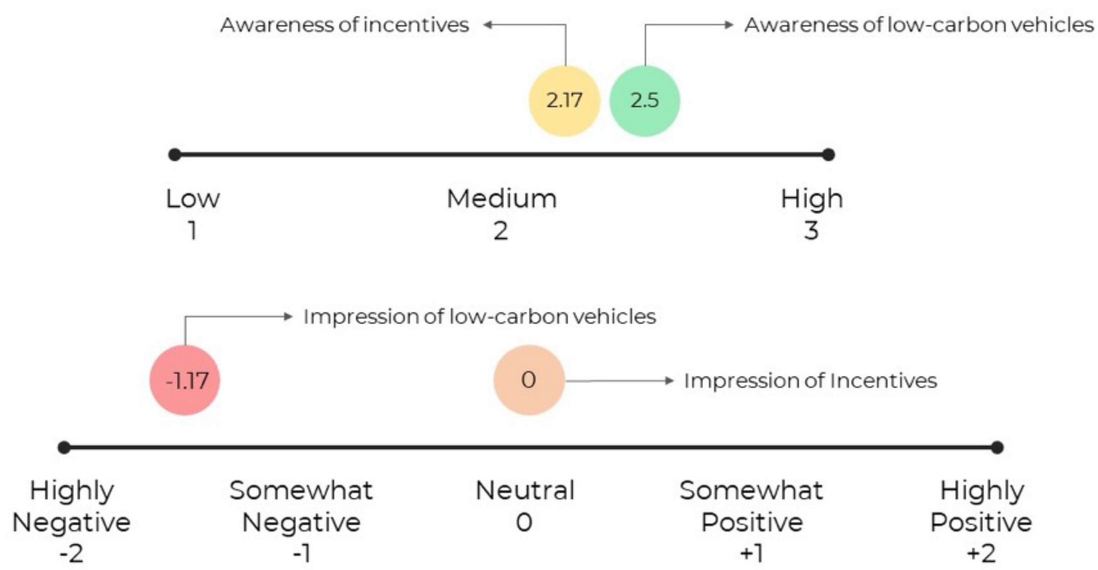


Figure 36. Awareness and impression of low-carbon vehicles and incentives

3.4.3.1.1 Adopters vs non-adopters

Among the 15 organizations interviewed, there were 9 non-adopters and 3 adopters. On average the adopters demonstrated a higher awareness (3 on a scale of 0 to 3) of low-carbon vehicles compared to the non-adopters (2.33 on a scale of 0 to 3). This makes sense as adopting organizations have a more hands-on experience with the technology while the non-adopters are more likely to know about these technologies indirectly. They also had a better impression of the technology (-1 on a scale of -2 to +2) compared to the non-adopters (-1.22 on a scale of -2 to +2).

3.4.3.1.2 On-road fleets vs off-road fleets

Among the 12 organizations interviewed, 8 operated on-road fleets, and 4 operated off-road fleets. The off-road fleets in the study had a higher awareness (3 on a scale of 0 to 3) compared to the on-road fleets (2.25 on a scale of 0 to 3). Although both groups of interviewees had a negative impression of low-carbon vehicles, the off-road fleet interviewees had a better impression (-0.75 on a scale of -2 to +2) of the vehicles compared to the on-road interviewees (-1.38 on a scale of -2 to +2).

3.4.3.1.3 Long-haul vs short-haul vs mixed-haul

Among the 12 organizations interviewed, there were 8 who had on-road fleets. Among them, 3 operated short-haul fleets, 3 operated long-haul fleets, and 2 operated mixed-haul (combination of long- and short-haul) fleets. The interviewees from mixed-haul organizations had the highest awareness of low-carbon vehicles (3 on a scale of 0 to 3), followed by the long-haul (2.33 on a scale of 0 to 3) and short-haul organizations (1.67 on a scale of 0 to 3). The mixed-haul organizations have different types of vocations and use a wide range of vehicles within their fleet, which may be responsible for their higher level of awareness about available technologies. The impressions of long-haul, short-haul, and mixed-haul organizations were -1.33, -1.33, and -1.5 respectively on a scale of -2 to +2.

3.4.3.1.4 Small fleets vs large fleets

According to Stodolsky et al. (2000), Small fleets are those with fewer than 25 heavy-duty trucks, hence companies with more than 25 heavy-duty trucks fall under the large fleet category. Among the 12 organizations interviewed, 4 had large fleets and 8 had small fleets. The awareness level of large fleet organizations was higher (3 on a scale of 0 to 3) than that of small fleet organizations (2.25 on a scale of 0 to 3). And the impression of large fleet organizations on low-carbon vehicles was better (-1 on a scale of -2 to +2) than the small fleet organizations (-1.25 on a scale of -2 to +2).

3.4.3.2 Factors influencing LCT adoption

3.4.3.2.1 Facilitators

The different reasons/facilitators for adoption that came up during the interviews can be subdivided into 4 categories namely, environmental, financial, repair and maintenance, and technical. Among them, the environmental reasons/facilitators received the highest emphasis (1.1 on a scale of 0 to 3) in the interviews followed by repair and maintenance (0.25 on a scale of 0 to 3), financial (0.25 on a scale of 0 to 3) and technical facilitators (0.25 on a scale of 0 to 3). The reasons for adoption were ranked according to their importance ratings (Table). The three most important reasons for LCT adoption were environmental regulations (1.67 on a scale of 0 to 3), environmental friendliness of the vehicles (1.17 on a scale of 0 to 3), and green public relations (0.5 on a scale of 0 to 3).

The researchers compared the importance of different reasons between adopting organizations and non-adopting organizations using their average importance ratings. Among the adopters, environmental regulations, the requirement for less frequent maintenance, and the tendency of low-carbon vehicles to produce less noise were the most important reasons for adoption. Like the adopters, the non-adopters also found the presence of environmental regulations to be the most important reason for adopting low-carbon vehicles. However, two other facilitators were the environmental friendliness of the vehicles and the potential to form green public relations by adopting LCT.

Similarly, the importance of different facilitators to on-road and off-road organizations was compared. For the on-road interviewees, the presence of environmental regulations was the most important reason for adopting LCT. Some of the off-road interviewees believed that low-carbon vehicles are good within a small boundary, and they collectively considered this to be the most important reason for LCT adoption. Two other important facilitators for both on-road and off-road interviewees were environmental friendliness and the potential to form green public relations.

Both long-haul and short-haul interviewees considered the presence of environmental regulations as the most important reason for adopting low-carbon vehicles. This was followed by environmental friendliness and green public relations for both groups of interviewees. The only facilitator that came up from mixed-haul interviewees was the environmental friendliness of the vehicles.

The large fleet organizations mentioned environmental friendliness, green public relations, and environmental regulations as the three most important facilitators for LCT adoption. And the small fleet organizations also mentioned environmental regulations and environmental friendliness as important facilitators. Interestingly, one of the small fleet organizations also mentioned that low-carbon vehicles required less frequent maintenance, which was the third most important facilitator for small fleet organizations. The interviewee from a small fleet organization stated, “They’re relatively maintenance-free, so I don’t have to worry about checking the oil on them every time I start it up, I don’t have to worry about air filters clogging up”.

3.4.3.2.2 Barriers

The barriers to LCT adoption that came up during the interviews can be subdivided into four categories namely, financial barriers, repair and maintenance barriers, technical barriers, and other barriers. Among them, the technical barriers (0.96 on a scale of 0 to 3) received the highest emphasis in the interviews followed by financial barriers (0.65 on a scale of 0 to 3), repair and maintenance barriers (0.39 on a scale of 0 to 3) and other barriers (0.39 on a scale of 0 to 3). These findings are consistent with the findings on reasons for LCT adoption. The technical features of low-carbon vehicles received the least importance as reasons for adoption, but they received the highest importance as barriers. This highlights the need to improve the technical capabilities of these vehicles to meet fleet operators’ expectations. Among all the barriers stated, lack of refueling/recharging facilities (1.92 on a scale of 0 to 3), high purchase cost (1.5 on a scale of 0 to 3) and low range (1.42 on a scale of 0 to 3) were the three most important.

The importance of barriers to LCT adoption was compared among the adopting and non-adopting organizations. It was found that the non-adopters considered the high purchase cost of low-carbon vehicles to be the biggest barrier followed by a lack of refueling/recharging stations and low range. On the other hand, purchase cost was not among the top 3 barriers to adoption for the adopting organizations. This adds up because adopting organizations have already overcome the financial barrier to purchasing these vehicles. Therefore, they are more likely to be concerned with the technical shortcomings of the vehicles after purchase. Hence, lack of refueling/recharging stations, low operational/load carrying capacity, and low range were the three most important barriers mentioned by the representatives of adopting organizations.

Similarly, the importance of barriers to LCT adoption was compared among the on-road and off-road organizations. For the on-road interviewees, the high purchase cost, lack of refueling/recharging facilities, and low range were the three biggest barriers to adoption. For the off-road interviewees' lack of refueling/recharging facilities, low operational/load carrying capacity and low range were the top three barriers to adoption. Low range was one of the most important barriers for both sets of interviewees.

The importance of these barriers to long-haul, short-haul, and mixed-haul organizations were compared. For all three of them, low range, high purchase cost, and lack of refueling/recharging facilities were the three biggest barriers. However, the order of importance differed. To long-haul organizations, low range received the highest importance. This is understandable given that their vehicles are expected to cover the longest distances. For short-haul organizations, the lack of refueling/recharging stations received the highest importance. And for mixed-haul organizations, the high purchase cost of low-carbon vehicles was the biggest barrier to adoption.

The emphasis placed on different types of barriers by large fleet organizations and small fleet organizations were assessed. For large fleet organizations, the three biggest barriers to adoption were low range, lack of refueling/recharging facilities, and low operational/load-carrying capacity. For small fleet organizations, they were the lack of refueling/recharging facilities, high purchase cost, and low range. As expected, the high purchase cost of low-carbon vehicles was found to be a bigger barrier for smaller organizations compared to the larger ones.

3.4.3.2.3 General Considerations for vehicle purchase

Apart from facilitators and barriers to LCT adoption, the interviews featured some statements about general considerations that organizations have when purchasing vehicles. There were three types of general considerations that were brought up. Financial considerations (0.96 on a scale of 0 to 3) received the highest importance followed by technical (0.43 on a scale of 0 to 3) and repair/maintenance considerations (0.29 on a scale of 0 to 3). Among all the considerations, the top three considerations were operating cost (1.92 on a scale of 0 to 3), purchase cost (1.58 on a scale of 0 to 3), and presence of incentives (1.33 on a scale of 0 to 3), which were all financial. The presence of incentives in the top three considerations shows that they play an important role in the decision-making process of these organizations. However, the importance rating (1.33 on a scale of 0 to 3) tells us that incentives alone cannot persuade organizations to purchase low-carbon vehicles. A statement from one of the interviewees partly explains why this is the case. He/she mentioned, "The incentives don't make up for the short-range on the electric vehicles. You know the incentives don't overcome the problems they just offer you a little cash to deal with the problems indefinitely". The validity of this statement can be further explained by considering where electric vehicles stand in terms of technical feasibility. Since technical attributes rank second among vehicle purchase considerations, the technical barriers to adoption (ranking first among barriers discussed previously) need to be minimized for BEVs to achieve feasibility. The skepticism about the technical feasibility of battery electric vehicles/equipment was highlighted in a quote from one of the interviewees- "If we used electric excavators, how would you charge them? It's a brand-new site. There's no utilities there. So, basically you're defeating the purpose of having an electric out there because you would have to bring a generator out there that runs on diesel to charge your equipment". While talking about excavators, another interviewee mentioned- "Unless they make something larger and they figure out a way to swap out the cells, there's really no advantage for us at this point in time". These statements indicate that even in the presence of incentives, technological improvements need to be made in order to make BEVs a feasible alternative.

A comparative assessment of considerations made by adopting and non-adopting organizations was made. It was found that the top three considerations for non-adopters were all financial namely, operating cost, purchase cost, repair, and maintenance cost. However, for adopters, the top three considerations were the presence of incentives, load-carrying capacity, and refueling/recharging time. Two out of the three most important general considerations made by adopters are technical and those made by non-adopting organizations were all financial. This further highlights the finding from the earlier discussion of barriers in Section 3.2; adopting organizations were more concerned about the technical capabilities of the vehicles while the non-adopting organizations were more concerned about the financial considerations.

The general considerations were compared between on-road and off-road interviewees. Operating cost, purchase cost, and repair & maintenance cost were three of the most important considerations that the eight on-road interviewees made during a vehicle purchase. For the four off-road interviewees, refueling/recharging time, the presence of incentives, and load-carrying capacity were the three most important considerations. From these findings, it can be observed that the on-road and off-road interviewees placed importance on different categories of considerations for vehicle purchase. While the on-road interviewees put a higher emphasis on financial considerations (3 out of the most important considerations were financial), the off-road interviewees were more interested in the technical aspects of the vehicles they purchase (2 out of 3 most important considerations were technical).

A comparative assessment of considerations made by the three groups of on-road interviewees (long-haul, short-haul, and mixed-haul) was also performed. From the assessment, it was found that the operating cost (3 on a scale of 0 to 3), repair/maintenance cost (2.67 on a scale of 0 to 3) and purchase cost (2 on a scale of 0 to 3) were the three most important considerations for long-haul interviewees. For the short-haul interviewees, they were purchase cost (2 on a scale of 0 to 3), operating cost (1.67 on a scale of 0 to 3), and repair & maintenance cost (1.33 on a scale of 0 to 3). And for the mixed-haul interviews they were operating cost (3 on a scale of 0 to 3), purchase cost (2 on a scale of 0 to 3), and the availability of refueling/recharging facilities (2 on a scale of 0 to 3). The importance ratings tell us that long-haul organizations place more importance on operating costs and repair/maintenance costs compared to the other groups. The vehicles of long-haul organizations cover the longest distances and are likely to need more frequent refueling/recharging and maintenance. Hence, it is expected that they would be more concerned about the costs associated with these activities for the vehicles they purchase.

For organizations with large fleets, the operating cost, purchase cost, and range were the three most important considerations for vehicle purchase. For small fleet organizations, the three most important considerations were operating cost, purchase cost, and incentives, which were all financial. This is consistent with the findings from Section 3.2. Since smaller organizations place high importance on financial considerations while purchasing a vehicle, the high purchase cost of low-carbon vehicles is expected to be a significant barrier to adoption, as discussed in the barriers section.

Table 23. Awareness, impression, and the three most important factors influencing the LCT adoption behavior of different categories of organizations

Category of organization (Number of interviewees from this category)	**Knowledge and perception**		**Factors influencing LCT adoption**		
	Awareness rating on a scale of 0 to 3	Impression rating on a scale of -2 to +2	Facilitator (Importance rating on a scale of 0 to 3)	Barrier (Importance rating on a scale of 0 to 3)	General Consideration (Importance rating on a scale of 0 to 3)
Adopters (3)	3	-1	Environmental regulations (1)	Lack of refueling/recharging facilities (2.67)	Incentives (1.5)
Adopters (3)	3	-1	Less frequent maintenance (1)	Low operational/load-carrying capacity (2)	Load carrying capacity (1.5)
Adopters (3)	3	-1	Produces less noise (1)	Low range (2)	Refueling/recharging time (1.5)
Non-adopters (9)	2.33	-1.22	Environmental regulations (1.89)	High purchase cost (1.67)	Operating cost (2.33)
Non-adopters (9)	2.33	-1.22	Environmentally friendly (1.44)	Lack of refueling/recharging facilities (1.67)	Purchase cost (1.89)
Non-adopters (9)	2.33	-1.22	Green public relations (0.56)	Low range (1.57)	Repair & maintenance cost (1.56)
On-road (8)	2.25	-1.38	Environmental regulations (2.13)	High purchase cost (1.88)	Operating cost (2.5)
On-road (8)	2.25	-1.38	Environmentally friendly (1.25)	Lack of refueling/recharging facilities (1.88)	Purchase cost (2)
On-road (8)	2.25	-1.38	Green public relations (0.25)	Low range (1.38)	Repair & maintenance cost (1.63)
Off-road (4)	3	-0.75	Good within a small boundary (1.25)	Lack of refueling/recharging facilities (2)	Refueling/recharging time (1.5)
Off-road (4)	3	-0.75	Environmentally friendly (1)	Low operational/load-carrying capacity (1.5)	Incentives (1)
Off-road (4)	3	-0.75	Green public relations (1)	Low range (1.5)	Load carrying capacity (0.75)
Long-haul (3)	2.33	-1.33	Environmental regulations (2.67)	Low range (2.33)	Operating cost (3)

Long-haul (3)	2.33	-1.33	Environmentally friendly (2)	High purchase cost (2)	Repair & maintenance cost (2.67)
Long-haul (3)	2.33	-1.33	Green public relations (0.67)	Lack of refueling/recharging facilities (2)	Purchase cost (2)
Short-haul (3)	1.67	-1.33	Environmental regulations (3)	Lack of refueling/recharging facilities (2)	Purchase cost (2)
Short-haul (3)	1.67	-1.33	Environmentally friendly (0.67)	High purchase cost (1.67)	Operating cost (1.67)
Short-haul (3)	1.67	-1.33	Green public relations (0)	Low range (1)	Repair & maintenance cost (1.33)
Mixed-haul (2)	3	-1.5	Environmentally friendly (1)	High purchase cost (2)	Operating cost (3)
Mixed-haul (2)	3	-1.5	Environmental regulations (0)	Lack of refueling/recharging facilities (1.5)	Purchase cost (2)
Mixed-haul (2)	3	-1.5	Green public relations (0)	Low range (1.5)	Availability of refueling/recharging facilities (2)
Small Fleet (8)	2.25	-1.25	Environmental regulations (1.88)	Lack of refueling/recharging facilities (1.88)	Operating cost (2.13)
Small Fleet (8)	2.25	-1.25	Environmentally friendly (0.88)	High purchase cost (1.5)	Purchase cost (1.75)
Small Fleet (8)	2.25	-1.25	Less frequent maintenance (0.38)	Low range (1.33)	Incentives (1.5)
Large Fleet (4)	3	-1	Environmentally friendly (1.75)	Low range (2.25)	Operating cost (1.25)
Large Fleet (4)	3	-1	Green public relations (1.5)	Lack of refueling/recharging facilities (2)	Purchase cost (1.25)
Large Fleet (4)	3	-1	Environmental regulations (1.25)	Low operational/load-carrying capacity (1.5)	Range (1.25)

3.4.3.3 Awareness and Impression of Incentives

The interviewees' awareness of incentives was rated on a scale of 0 to 3. The rating for an interviewee was 1 if his/her statements didn't include any general or specific information about incentives, 2 if his/her statements demonstrated only a general awareness of incentives, and 3 if he/she could state specific information about the existing incentive programs. The ratings for all the interviewees were averaged to find the overall awareness of the interviewees. On a scale of 0 to 3, the overall awareness of the interviewees was 2.17 which was between moderate (2) to high (3). This was lower than the awareness that they demonstrated of low-carbon vehicles.

On a scale of -2 (highly negative) to +2 (highly positive), the overall impression of incentives that they had on incentives was 0.08. In contrast to the somewhat negative (-1.17) impression that they had of low-carbon vehicles, the overall impression of incentives was between neutral

(0) to somewhat positive (+1) (Figure 36). Since high purchase cost was found to be one of the biggest barriers to adoption, the incentives could make these vehicles a more cost-effective option (Breetz & Salon, 2018).

3.4.3.3.1 Adopters vs non-adopters

A comparative assessment of adopting and non-adopting organizations shows us that the adopters have higher awareness (2.67 on a scale of 0 to 3) of incentive programs compared to the non-adopters (2 on a scale of 0 to 3). Moreover, Figure 37 (parts a and b) shows that interviewees who demonstrated a higher awareness of incentive programs are more likely to be current adopters or potential adopters of low-carbon vehicles. A positive association between awareness of incentives and the adoption of low-carbon vehicles is expected since incentives are designed to make low-carbon vehicles a more favorable option.

(54) (b)

Figure 37. Awareness of incentives

Note: Panel (a) shows awareness of incentives and presence of low-carbon fleet. Panel (b) shows awareness of incentives and potential to adopt low-carbon fleet.

3.4.3.3.2 On-road fleets vs off-road fleets

The overall awareness of incentives among off-road interviewees was higher (2.25 on a scale of 0 to 3) than that of the on-road interviewees (2.13 on a scale of 0 to 3). But the higher awareness did not come with a better impression. The off-road interviewees demonstrated a neutral impression (0 on a scale of -2 to +2) of incentives, whereas the on-road interviewees had a slightly positive impression (0.13 on a scale of -2 to +2).

3.4.3.3.3 Long-haul vs short-haul vs mixed-haul

Among long-haul, short-haul, and mixed-haul organizations, mixed-haul interviewees demonstrated the highest awareness of incentives (2.5 on a scale of 0 to 3), followed by long-haul interviewees (2.33 on a scale of 0 to 3), and short-haul interviewees (1.67 on a scale of 0 to 3).

3.4.3.3.4 Small fleets vs large fleets

The large fleet organizations had a greater awareness of incentives (2.25 on a scale of 0 to 3) compared to the small fleet organizations (2.13 on a scale of 0 to 3). However, the greater awareness did not come with a better impression. The smaller organizations had a better impression (0.125 on a scale of -2 to +2) of the incentives compared to the larger ones (0 on a scale of -2 to +2).

3.4.3.4 Factors influencing impression of incentives

The interviewees talked about the factors that influence their impression of incentives. The purchase cost reduction of low-carbon vehicles (1.09 on a scale of 0 to 3) was the only factor that positively influenced the interviewees' impression of incentives. However, they stated 5 reasons that negatively influence the impression they have of incentive programs namely, condition/restriction, cost ineffectiveness, difficulty to acquire, paperwork, and waiting period. Among the factors, conditions/restrictions had the highest importance rating (0.67 on a scale of 0 to 3) among all the interviewees. One of the interviewees stated, "The grants are scheduled for, like, five years, you got to be monitored for five years, you've got to turn in mileage for five years". Another interviewee stated that applying for incentives would mean that a huge chunk of his operations would be restricted within California only and it would be detrimental to his/her business. The other factors can be ranked in the following order: difficulty to acquire (0.58), cost ineffectiveness (0.50), paperwork (0.25), and waiting period (0.25).

Among factors mentioned by the non-adopting organizations, conditions/restrictions, cost ineffectiveness and waiting period were the top three causes of negative impressions. For adopting organizations, difficulty to acquire, conditions/restrictions, and cost ineffectiveness were the three most influential factors.

For on-road organizations, the three most important reasons that affected the impression of incentives were conditions/restrictions, cost ineffectiveness, and waiting period. For off-road interviewees, the difficulty to acquire, conditions/restrictions, and cost ineffectiveness were three of the most important reasons that resulted in a negative impression.

For long-haul, short-haul, and mixed-haul interviewees, the most important reasons for the negative impression of incentives were conditions/restrictions, waiting period, and cost ineffectiveness, respectively.

For large fleet organizations, the most important reasons behind the negative impression of incentives were difficulty to acquire, conditions/restrictions, and cost ineffectiveness. And for the small fleet organizations, they were conditions/restrictions, cost ineffectiveness, and waiting period.

3.4.3.5 Expected Government Support

The interviewees were also asked about the type of support that they would like to see from the government. Among the various types of support that were expected, the ones with the highest importance ratings were charging infrastructure support (1.75 on a scale of 0 to 3), more monetary incentives (0.92 on a scale of 0 to 3), and collaboration with manufacturers (0.5 on a scale of 0 to 3). This is consistent with the findings from Section 3.2. Since the lack of charging/refueling infrastructure came up as the most important barrier, it is expected that the interviewees would be looking forward to charging infrastructure support. Some of the interviewees suggested that the government should collaborate with the manufacturers to improve the technology. Some interviewees also suggested ideas (e.g., swappable batteries and solar chargers) that can help resolve issues with range and lack of infrastructure.

Like the other sections, the expected government support received varying importance among adopting and non-adopting interviewees and on-road and off-road interviewees. For non-adopting interviewees, the three most important forms of support were charging infrastructure, more monetary incentives, and indirect/concealed government support. For the on-road interviewees, the top three expected support and their ranks were the same. For adopters, less restrictive environmental regulations, charging infrastructure support, and collaboration with manufacturers were the three most important forms of expected support. The off-road interviewees placed the highest emphasis on these three expected supports in the same order. Charging infrastructure support was among the top three for all four groups of interviewees, which highlights the urgency of government intervention in this area.

The importance of different forms of government support was also compared between long-haul, short-haul, and mixed-haul interviewees. For long-haul representatives, charging infrastructure support, more monetary incentives, and educational/marketing campaigns for the new technology were the top three forms of expected support. For the short haul, they were more monetary incentives, charging infrastructure support, and indirect/concealed government involvement. And for mixed-haul interviewees, charging infrastructure support, collaboration with manufacturers, and indirect/concealed government involvement were the most important expected supports, but they placed the same level of importance on all three. This suggests that some of the organizations may be more open to support that does not come directly from the government. They may be more open to support that comes from the manufacturers instead. As one of the mixed-haul interviewees mentioned, "And to tell you the truth, I think the greatest success would be through manufacturers as opposed to directly with end users". Like previous sections, charging infrastructure was one of the most important forms of expected support for all three groups of interviewees.

For large fleet organizations, the three most important forms of expected support were charging infrastructure support, less restrictive environmental regulations, and collaboration with manufacturers. On the other hand, the smaller organizations expected charging infrastructure support, more monetary incentives, and indirect/concealed government involvement. Like findings in the previous sections, one of the top three forms of support for smaller organizations is financial (more monetary incentives).

Table 24. Awareness, impression, and the three most important reasons negatively influencing the impression of incentives and expected government support for different categories of organizations

Category of interviewees	Knowledge and perception		The reason behind negative impression (Importance rating on a scale of 0 to 3)	Expected government support (Importance rating on a scale of 0 to 3)
	Awareness rating on a scale of 0 to 3	Impression rating on a scale of -2 to +2		
Adopters (3)	2.67	0.33	Conditions/restrictions (0.56)	Less restrictive environmental regulations (1)
			Cost ineffective (0.33)	Charging infrastructure support (0.67)
			Waiting period (0.33)	Collaboration with manufacturers (0.67)
Non-adopters (9)	2	0	Difficult to acquire (1.67)	Charging infrastructure support (2.11)
			Conditions/restrictions (1)	More monetary incentives (1.22)
			Cost ineffective (1)	Indirect/concealed government involvement (0.56)
On-road (8)	2.13	0.13	Conditions/restrictions (0.63)	Charging infrastructure support (2)
			Cost ineffective (0.38)	More monetary incentives (1.38)
			Waiting period (0.38)	Indirect/concealed government involvement (0.63)
Off-road (4)	2.25	0	Difficult to acquire (1.25)	Less restrictive environmental regulations (1.5)
			Conditions/restrictions (0.75)	Charging infrastructure support (1.25)
			Cost ineffective (0.75)	Collaboration with manufacturers (0.5)
Long-haul (3)	2.33	0.67	Conditions/restrictions (1)	Charging infrastructure support (2.67)
			Difficult to acquire (0.67)	More monetary incentives (1)
			-	Educational/marketing campaigns for the new technology (0.33)
Short-haul (3)	1.67	0.33	Waiting period (1)	More monetary incentives (2.67)
			-	Charging infrastructure support (1.67)
			-	Indirect/concealed government involvement (0.67)
Mixed-haul (2)	2.5	-1	Cost ineffective (1.5)	Charging infrastructure support (1.5)
			Conditions/restrictions (1)	Collaboration with manufacturers (1.5)
			-	Indirect/concealed government involvement (1.5)

Category of interviewees	Knowledge and perception		The reason behind negative impression (Importance rating on a scale of 0 to 3)	Expected government support (Importance rating on a scale of 0 to 3)
	Awareness rating on a scale of 0 to 3	Impression rating on a scale of -2 to +2		
Small Fleet (8)	2.13	0.13	Conditions/restrictions (0.63)	Charging infrastructure support (1.88)
			Cost ineffective (0.38)	More monetary incentives (1.38)
			Waiting period (0.38)	Indirect/concealed government involvement (0.5)
Large Fleet (4)	2.25	0	Difficult to acquire (1.25)	Charging infrastructure support (1.5)
			Conditions/restrictions (0.75)	Less restrictive environmental regulations (1.5)
			Cost ineffective (0.75)	Collaboration with manufacturers (0.5)

3.5 Conclusion

The interviews conducted in this project aimed to fill a key knowledge gap in Low-Carbon Transportation (LCT) research by understanding the adoption of (LCT) in Heavy-Duty Vehicles (HDV) and Off-Road Equipment (ORE) sectors. We used semi-structured interviews (conducted via phone call) to collect data from a) on-road fleet operators, and (b) off-road equipment operators to better understand the fleet turnover and business decision-making processes.

The findings suggest that environmental regulations are likely to be the most important reason for adopting low-carbon vehicles in the heavy-duty vehicle sector. Many of the organizations also placed importance on the environmental friendliness of low-carbon vehicles and their ability to initiate green public relations. Hence, policymakers can indirectly influence adoption behavior by encouraging (through subsidies or regulations) projects that seek to partner with organizations owning green fleets. As one of the interviewees mentioned, “Well, we’re located right near Silicon Valley in California. So, a lot of the high-tech companies use biodiesel or use low-CARB emission type equipment. We try to cater to them a little bit”.

Although environmental regulations are often cited as the primary driver for the adoption of low-carbon technologies (LCTs), it is worth noting that their presence does not always result in widespread LCT adoption. Non-adopting organizations have instead opted to make their diesel vehicles compliant with California Air Resources Board (CARB) standards by incorporating DEF (diesel exhaust fluid) filters. This demonstrates that while these organizations meet the minimum requirements set by environmental regulations, they are not necessarily motivated to embrace alternative fuel vehicles. This can be attributed, in part, to the technical limitations of low-carbon vehicles, which may include factors such as limited range, reduced load capacity, and insufficient refueling or recharging infrastructure, particularly with battery electric vehicles (BEVs). These technical considerations were identified by interviewees as major barriers and received less importance as facilitators for LCT adoption. Simultaneously, interviewees emphasized the significance of technical feasibility when making vehicle purchasing decisions.

These findings collectively underscore the need for technological advancements to drive long-term diffusion of BEVs. Mere imposition of environmental regulations on heavy-duty fleets is insufficient; it is imperative for the government to actively support the development and enhancement of these vehicles. Some interviewees explicitly mentioned the importance of government collaboration with manufacturers and indirect government support to drive technological improvements in the industry.

Financial barriers, such as high purchase costs, did come up as some of the most important barriers to adoption in the interviews. At the same time, the presence of incentives was one of the top three considerations made by the organizations while purchasing vehicles. These two findings suggest that continued subsidization of low-carbon vehicles can still be an effective way to allow the diffusion of LCT. More importantly, the small fleet organizations placed a higher emphasis on the financial barriers and had a more favorable impression of monetary incentives while expecting further government support in that area. This highlights the need to design incentives that specifically cater to smaller organizations since they are in greater need of subsidization.

The results of the interviews conducted for this research were consistent and coherent, and they can partly inform decision-makers to accelerate the diffusion of LCT. However, the study is limited in terms of its sample size, which may make it hard to generalize the findings on a broader level. Future work can collect larger samples on the individual categories of organizations and focus on more specific adoption behavior of these categories in both heavy-duty, and medium-duty sectors as well as the off-road sector.

4 Incentive and Regulatory Program Performance Evaluation Tool

In the previous sections we discussed our review of incentive programs, described how we forecast fuel and vehicle technology characteristics and costs using the TRACE model (Section 1), explored the state of the market for both heavy-duty ZEV production (Section 2) as well as the stated decision-making process and revealed attitudes of fleet operators toward ZEV alternatives (Section 3). With this background, we can now turn to the development of model to forecast uptake of different ZEV technologies over time.

Figure 38 diagrams the overall design of the incentive and regulatory program evaluation tool (PET), showing how it is structured around a Total Cost of Ownership (TCO) model, a Fleet Turnover Model, and an Emissions Model. These models produce outputs that are processed in the Impact Module to produce desired metrics related to LCT uptake, state program costs, employment impacts, as well as emissions-related reductions. The approach is generally the same whether we are modeling on-road heavy-duty vehicles or off-road equipment, though the approaches for computing component costs may differ, and some costs may only apply to HDVs or ORE.

The input requirements for the PET step from the work described previously. Section 1 describes our efforts to characterize the effect incentives and regulations have via a review of existing regulatory and incentive programs for the HDV and ORE domains. Section 2 explains how we conducted a review of vehicle technology evolution, the LCFS program to assess its impact on fuel costs, and describe our method for estimating the effect of market innovation over time on vehicle costs, vehicle efficiencies, and fuel costs (including LCFS) using the TRACE model from CARB contract 16RD011 (Mac Kinnon et al., 2020).

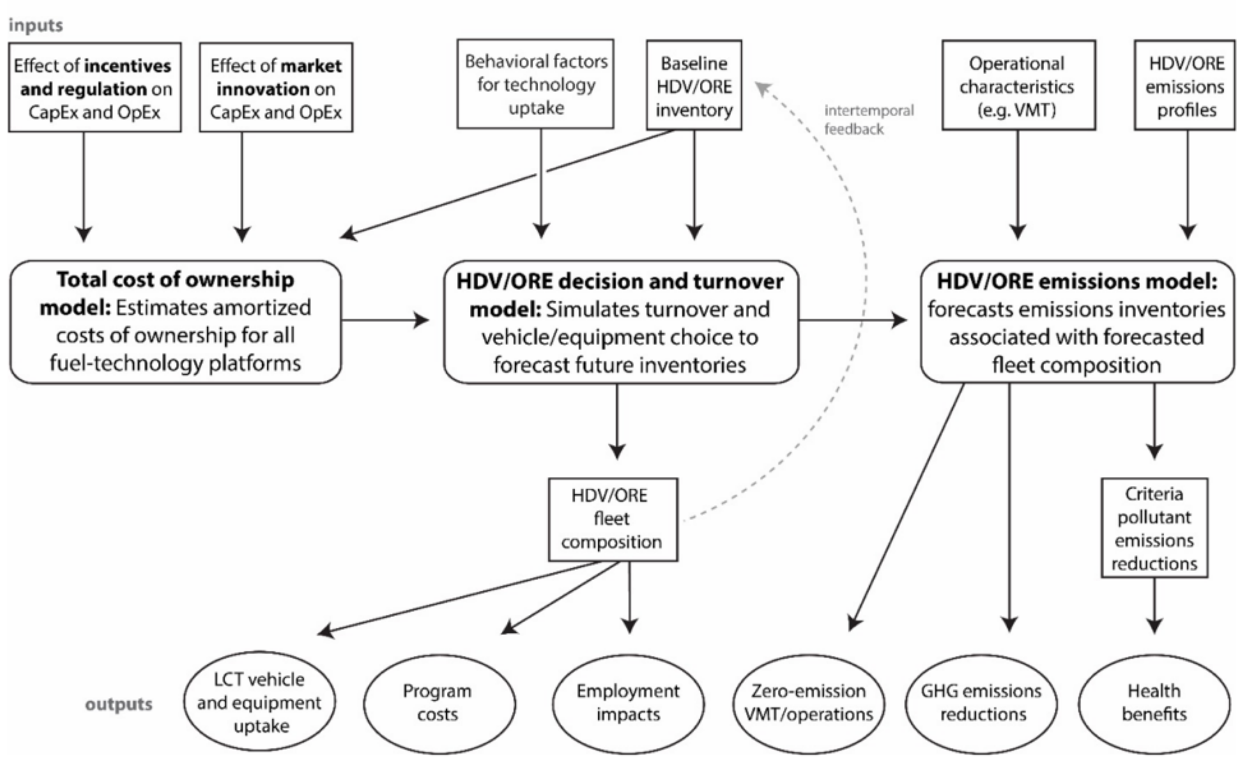


Figure 38. Incentive Program Performance Evaluation Tool (PET) – process flow diagram

The total-cost-of-ownership (TCO) module estimates amortized costs of ownership for a variety of vehicle and fuel technologies. TCO is the method of calculating total expenditure for owning a product over a set period and has used extensively by consumers, policymakers, and manufacturers for evaluation and decision-making purposes (Liu et al., 2021). After its inception in the 1990s, the TCO concept was first applied to EV lifetime cost estimation in 2001 (Liu et al., 2021). EVs tend to have higher purchase prices compared to ICEVs, and thus can appear unfavorable when consumers are making a purchase decision. However, EVs also have lower operating and maintenance costs, which can make them the cheaper option over the ownership period. Dumortier et al. (2015) conducted a survey to investigate consumer preference when five-year fuel cost savings and TCOs are provided considering these factors. They reported that providing the TCO information increased the possibility of consumers favoring some form of EV

(HEV, PHEV, or BEV) over ICEVs in the small/mid-sized car segment. Lebeau et al. (2013) compared TCOs for commercially available ICEVs and EVs (BEV, HEV, PHEV) for three vehicle segments: small city car, medium car, and premium cars. They discovered EVs to be cheaper only in the premium segment. A TCO study conducted by Bubeck et al. (2016) showed that full and mild HEVs appeared as economic options in Germany for many user types and vehicle sizes. They anticipated that BEVs could also become economically viable by 2030 for a wide range of users and vehicles.

Figenbaum (2022) used retrospective TCO analysis to investigate the development of passenger battery electric vehicle (BEV) affordability compared to ICEVs in Norway. This analysis highlighted how BEVs appeared favorable to increasingly larger populations as TCO decreased over the years, aided by incentives. Additionally, it also pointed out that only a competitive TCO was not enough to make BEVs succeed, sufficient supply and meeting customer needs were crucial. As incentives appear crucial to keep BEV TCO lucrative, Figenbaum suggested that they should be remedied by some other income source to keep them cost neutral and sustainable. For Norway's case, the lost revenue from different fee remissions for BEVs were neutralized with earnings from the oil industry.

Van Velzen et al. (2019) looked into developing a comprehensive model for future TCO estimation. They laid out 34 interdependent factors that affect TCO calculations, including production costs, profit margin, resale value, vehicle performance, and discount rate. They highlighted that profit margin assumptions must be realistic as it can have a big impact on TCO calculation. If manufacturers opt to increase their profit margins, manufacturing of scale might not necessarily result in significantly cheaper BEV retail price. Also, effective policymaking for EVs and ICEVs could play a major role in stimulating EV adoption due to their effects on TCOs.

Recent comprehensive TCO analyses have been reported for on-road HDV, including a recent comprehensive study by Argonne National Laboratory (Burnham et al., 2021) that estimated TCO for a wide range of light, medium, and heavy-duty configurations, including class 8 day cabs as shown in Table 25. The Advanced Clean Fleets TCO discussion document (CARB, 2021d), shown in Table 26, provides TCO estimates for a similar day cab configuration from CARB. The day cab configuration used in these reports aligns with the drayage vocation we selected for modeling and therefore provide a good comparison for our results that we will reference frequently below.

Table 25. Estimated TCO from ANL for MY2025 class 8 day cab tractor

Lifetime Costs	ICE-CI	HEV	PHEV125	FCEV	BEV250
Vehicle	$98,661	$102,594	$148,398	$151,759	$189,365
Financing	$12,081	$12,563	$18,171	$18,583	$23,187
Fuel	$215,658	$209,582	$228,365	$446,172	$161,522
Insurance	$49,989	$50,658	$58,443	$59,014	$65,405
M&R	$121,090	$105,348	$101,716	$72,654	$72,654
Tax & Fees	$69,765	$70,817	$83,063	$83,962	$94,017
Payload	$0	$0	$19,562	$0	$0
Labor	$405,871	$405,871	$405,871	$405,871	$405,871
Total	$973,115	$957,433	$1,063,589	$1,238,015	$1,012,021

Source: Comprehensive Total Cost of Ownership Quantification for Vehicles with Different Size Classes and Powertrains (Burnham et al., 2021). ICE-CI=diesel-fueled compression-ignition internal combustion engine, HEV=hybrid electric vehicle, PHEV125= plug-in hybrid diesel/electric vehicle with an all-electric range of 125 miles, FCEV=fuel cell electric vehicle, BEV250=battery electric vehicle with a 250 mile range.

Table 26. Estimated TCO from CARB for MY 2025 day cab

	Diesel	Natural Gas	BEV	FCEV
Total Miles	599280	599280	599280	599280
Operating Year	12	12	12	12
Energy Storage			450 kWh	10 kWh/40 kg H2
Vehicle Power			350 kW	350 kW/175 kWFC
Vehicle Price	$143,862	$195,607	$201,999	$212,353
Taxes	$28,772	$39,121	$40,400	$42,471
Financing Costs	$31,571	$42,927	$44,329	$46,602
Total Vehicle Cost	**$204,205**	**$277,655**	**$286,728**	**$301,426**
Fuel Economy	6.7 mpg	6.5 mpg	0.54 mi/kWh	10.9 mi/kg
Unit Fuel Cost	$4.06/gal	$1.98/gal	$0.21/kWh	$5.48/kg
DEF Consumption	$361,069	$181,399	$234,326	$300,201
LCFS Revenue	$4,975	$0	-$248,902	-$84,907
Total Fuel Cost	**$366,044**	**$181,399**	**-$14,576**	**$215,294**
Maintenace Cost	$118,898	$118,898	$89,174	$89,174
Midlife Costs	$0	$0	$40,545	$29,750
Registration Fee	$35,732	$37,733	$16,860	$17,261
Depreciation	-$43,159	-$58,682	-$60,600	-$63,706
Residual Value	-$33,363	-$45,363	-$46,845	-$49,246
Insurance Costs	$10,078	$13,702	$14,150	$14,876
Total Other Costs	**$88,186**	**$66,288**	**$53,284**	**$38,109**
EVSE Cost	$0	$0	$84,954	$0
Infrastructure Upgrade Cost	$0	$45,309	$99,679	$0
Total Infrastructure Cost	**$0**	**$45,309**	**$184,633**	**$0**
TOTAL	**$658,435**	**$570,651**	**$510,069**	**$554,829**
Payback Period vs Diesel (yr)			8.1	12.1

Source: Advanced Clean Fleets TCO discussion document (CARB, 2021d)

The PET TCO module estimates costs on an annual basis from 2020 to 2050 and considers vehicle costs, infrastructure costs, fuel costs, and incentives (Figure 39). Though this figure focuses on HDV, the approach to modeling ORE is essentially the same.

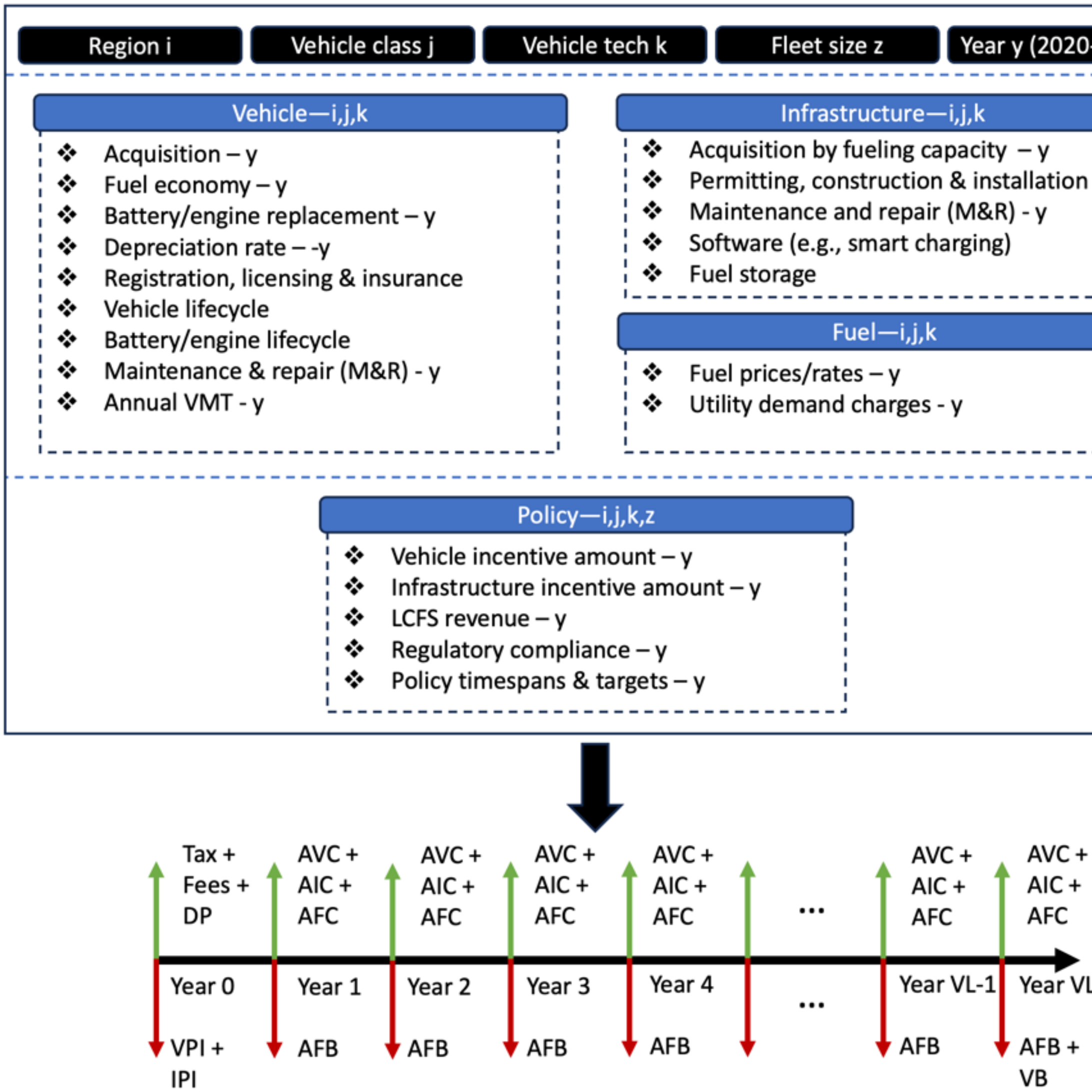


Figure 39. The modeling framework for the TCO module.

Note: AVC – annual vehicle costs; AIC – annual infrastructure costs; AFC – annual fuel costs; VPI – vehicle purchase incentives (for instance, HVIP); IPI – infrastructure purchase incentives (utility, CEC); AFB – annual fuel benefits (for instance, LCFS revenue); VB – vehicle benefits (residual value); DP – downpayments on capital expenses; VL – vehicle life (first owner)

The fleet turnover module models vehicle turnover as a stock and flow system where annual vehicle stock is modeled by tracking the net annual flows of vehicles into and out of active use. Net stock loss of vehicles by age is determined by historical data of net vehicle stock flows in California obtained from the EMFAC model, and all remaining trucks retire when they reach 20 years of age as well as under specific regulatory conditions represented in different scenarios that will be discussed later in Section 4.1.6. Retired trucks and additional truck additions from overall fleet growth are then replaced by new trucks and imported used trucks at the average rate of net increases of new and used trucks in historical inventories. A graphical representation of the turnover module is illustrated in Figure 40.

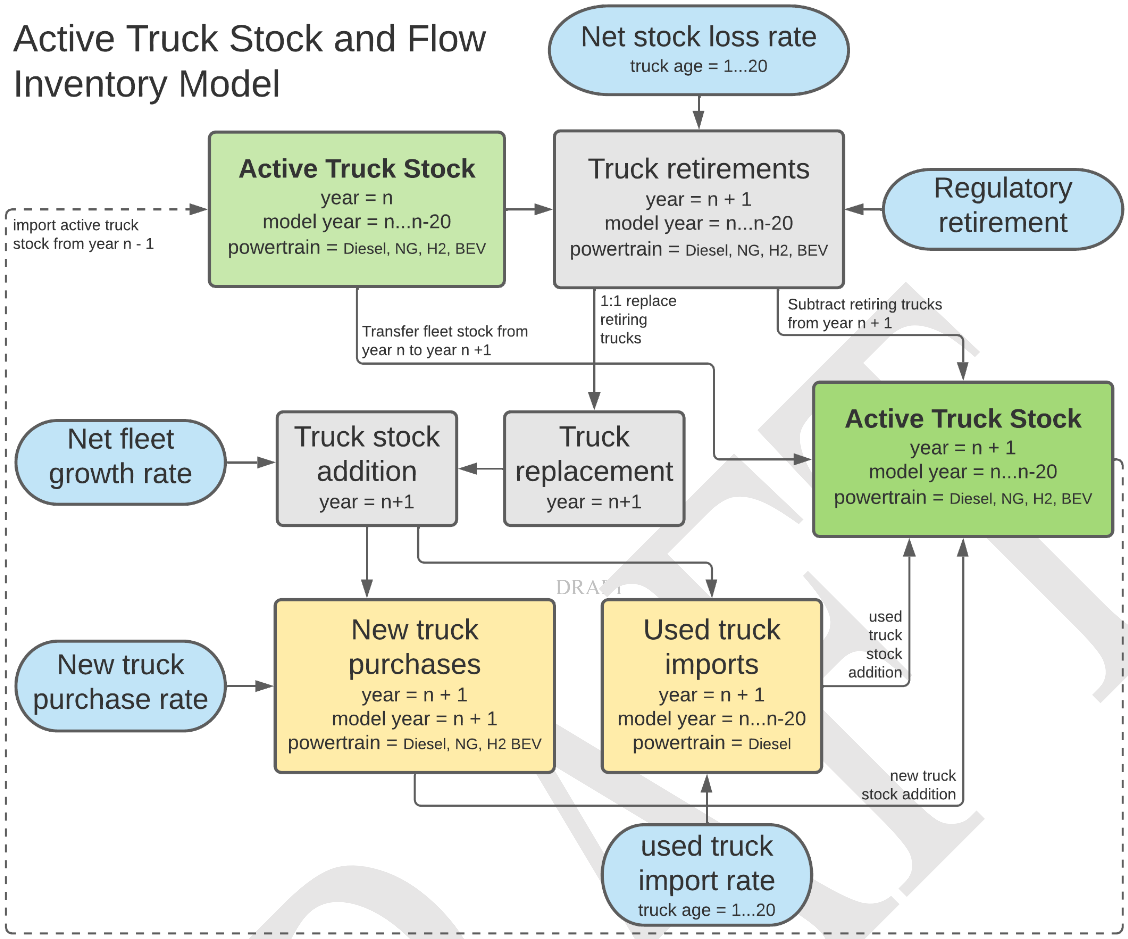


Figure 40. The modeling framework for the truck turnover module.

The state of California is represented as 163 regions in the PET as shown in Figure 41. The regions are defined as a combination of county, air basin, and air district boundaries as well as major utility territories, including Pacific Gas & Electric (PGE), Southern California Edison (SCE), San Diego Gas & Electric (SDGE), Los Angeles Department of Water and Power (LADWP), Sacramento Municipal Utility District (SMUD), Imperial Irrigation District (IID), and a combined area[43] that includes Burbank Water and Power (BWP), Glendale Water and Power (GWP), and Pasadena Water and Power (PWP). Other smaller utilities are aggregated as the rest of the state. As compared to the EMFAC subareas, the PET regions are further disaggregated with utility territories to consider utility-specific rate designs and utility-level incentives.

[43] This combined area is one of the CEC's planning areas.

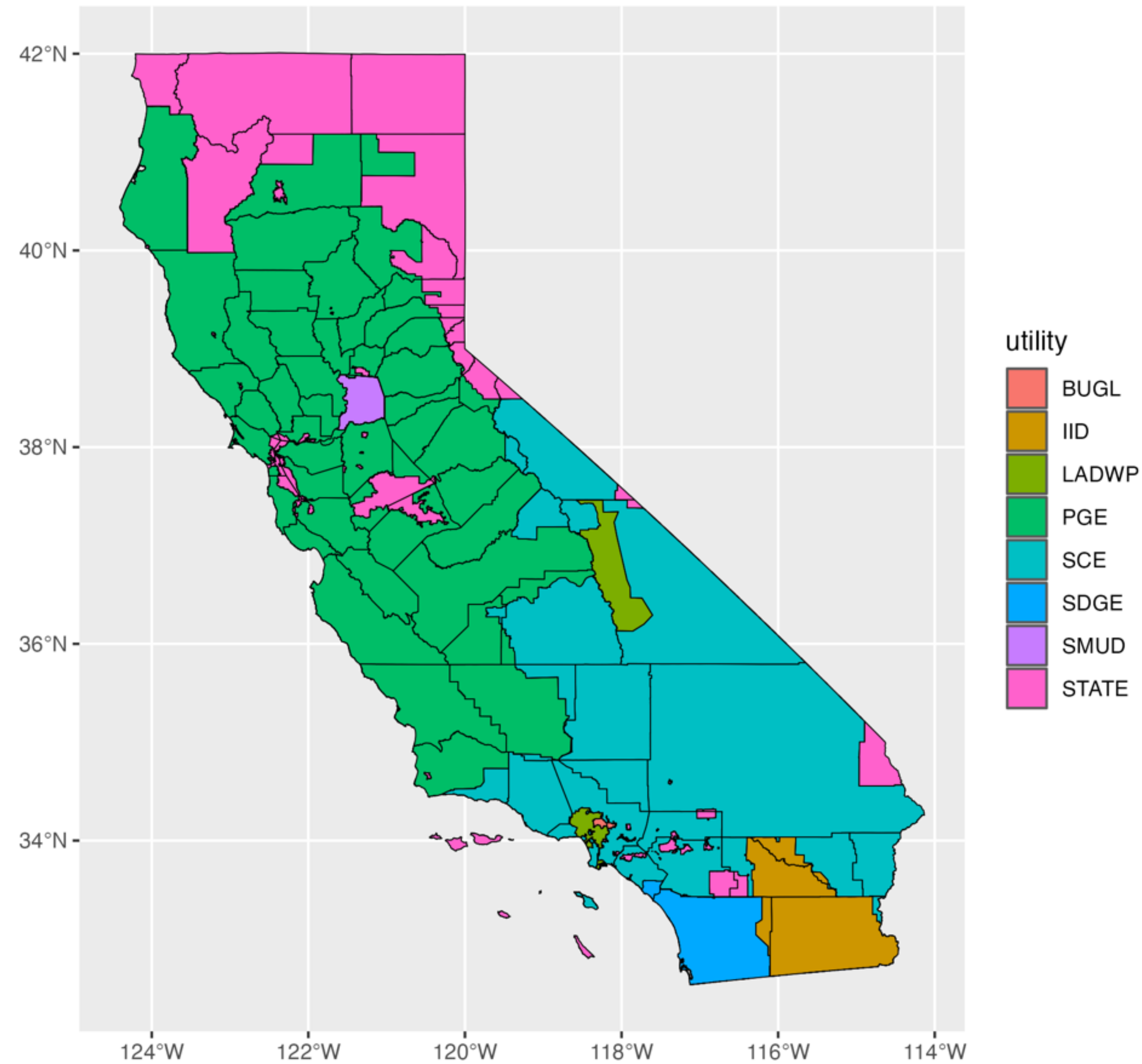


Figure 41. PET TCO model subareas

Notes: The 163 regions distinct regions used in the PET created from the county, air basin, air district, and major utility territory boundaries. Utilities included are: Pacific Gas & Electric (PGE), Southern California Edison (SCE), San Diego Gas & Electric (SDGE), Los Angeles Department of Water and Power (LADWP), Sacramento Municipal Utility District (SMUD), Imperial Irrigation District (IID), and the combined area that includes Burbank Water and Power (BWP), Glendale Water and Power (GWP), and Pasadena Water and Power (PWP). The STATE region captures the remaining areas.

4.1 PET on-road HDV model

4.1.1 HDV model data sources

In this section, we discuss the data sources and methods for the PET. Table 27 provides an overview of data sources, which come from a range of public datasets, references, and work described previously in this report.

Table 27. An overview of the baseline data sources for the PET on-road HDV model

Module	Category	Subcategory	Data sources	Note
TCO	Vehicle	Capital	TRACE2, ICCT (2022)	Three scenarios: base, optimistic, conservative
TCO	Vehicle	Sales tax	CDTFA (2023)	Current sales & use tax rates[44]
TCO	Vehicle	Federal exercise tax	U.S. Code § 4051[45]	12%
TCO	Vehicle	Registration & licensing fees	CA DMV	CA DMV Vehicle Reg. Fee Calc.[46]
TCO	Vehicle	Insurance	Insurance companies	\$5,000/\$12,000 (rough estimates[47])
TCO	Vehicle	Maintenance & repair	ICF (2019); InfoShed	
TCO	Vehicle	Residual value	ANL (2021)	
TCO	Fuel	Fuel costs	TRACE; CEC (2020); EIA (2021); Current utility rate designs; EMFAC2021 v1.0.1	EMFAC used to estimate fuel consumption over time by model year.
TCO	Fuel	Demand charges	Current utility rate designs	
TCO	Infrastructure	Capital	ICF (2019); InfoShed	
TCO	Infrastructure	Maintenance & repair (M&R)	ICF (2019); InfoShed	
TCO	Policy & incentives	HVIP	CARB	Base year: FY 20-21 funding plans
TCO	Policy & incentives	LCFS revenue		Projected
TCO	Policy & incentives	Utility incentives	Utilities	
Fleet turnover	Base-year fleet inventory	Stock base	EMFAC2021 v1.0.1	
Fleet turnover	Base-year fleet inventory	Fleet size distribution		
Fleet turnover	Overall fleet growth		EMFAC2021 v1.0.1	
Fleet turnover	Historical vehicle retirement rate by age		EMFAC2021 v1.0.1	
Fleet turnover	Historical used vehicle imports by age		EMFAC2021 v1.0.1	
Impact analysis	Workforce		IMPLAN	
Impact analysis	Emissions	Emission rates	EMFAC2021 v1.0.1	

We discuss each of these below in the context of their use in the TCO module.

[44] https://www.cdtfa.ca.gov/taxes-and-fees/sales-use-tax-rates.htm
[45] https://www.law.cornell.edu/uscode/text/26/4051
[46] https://www.dmv.ca.gov/wasapp/FeeCalculatorWeb/newVehicleForm.do
[47] https://eastinsurancegroup.com/commercial-truck-insurance-average-cost/

4.1.2 Fleet size

As discussed in Section 1.4, fleet size has increasingly become a policy parameter as the State recognizes how the LCT transition may disrupt the existing economics of heavy-duty fleets. Fleet size impacts both TCO (in terms of differential costs as well as differential incentives) and fleet turnover (in terms of when regulations apply). Given that the PET is specifically intended to evaluate policy designs, it is critical for the model to be able to represent fleet size and its impacts on policy response. In our review of policies, we noted that there are existing policy carveouts for both small and large fleets including regulatory exemptions, incentive eligibility or amounts. The definitions of what constitute "small" and "large" may vary across policy and over time. As such, we sought a sufficient range of fleet sizes for representing likely policy targets.

Fleet size is a difficult variable to collect data on because there is no single data source that captures this information canonically, particularly at the vocational level. We used two sources of data that were indirectly available. For line-haul and construction vehicles, CARB staff used internal DMV data along with Dun and Bradstreet entity information[48] to obtain medium and heavy-duty fleet size distributions for calendar year 2020. To align with our policy modeling needs, we collapsed into the fleet size distributions shown in Table 38. Table 39 provides similar data for drayage trucks in the state using internal data from the California ARB Equipment Registration (ARBER) system (CARB, 2023c), which registers all in-use drayage trucks in California.

Table 28. Fleet size distributions for construction and line-haul trucks

Fleet size	# fleets	% fleets	T4-T7 counts	(%)
1	783,860	80.78%	783,860	18.26%
2-10	176,822	18.22%	512,797	35.13%
11-20	5,918	0.61%	83,908	10.06%
21-50	2,787	0.29%	83,609	11.26%
51-100	623	0.06%	42,893	6.43%
101+	405	0.04%	149,038	18.87%
Total	**970,415**	**100.00%**	**1,656,105**	**100.00%**

Source: Provided by CARB staff using California DMV data and Dun & Bradstreet business entity data.

48 https://www.dnb.com/

Table 29. Fleet size distributions for drayage trucks

			drayage (T6-T7)	
Fleet size	**# fleets**	**% fleets**	**counts**	**(%)**
1	7,340	55.90%	11,044	7.86%
2-10	4,315	32.86%	19,560	13.92%
11-20	634	4.83%	9,290	6.61%
21-50	494	3.76%	15,497	11.03%
51-100	194	1.47%	12,713	9.05%
101+	154	1.17%	72,396	51.53%
Total	**13,130**	**100.00%**	**140,500**	**100.00%**

Source: Provided by CARB staff using California ARB Equipment Registration (ARBER) data (CARB, 2023c).

We note that these are relatively coarse estimates, but they do allow the PET to differentiate costs and regulations along with their associated impacts based upon fleet size. In the current model, we assume that fleet size distribution is static because a fully-specified representation of individual fleets and their decisions to grow or shrink the number of trucks they own is beyond the current scope.

4.1.3 The HDV TCO Module

This section describes the models and underlying assumptions in the HDV TCO module. Where parameters are known and fixed, they are described and justified here. Where parameters are a user-defined input (such as analysis period, financing rates, and discount rate), they are left as variables in this section and explored in more detail in Section 5.

4.1.3.1 Vehicle costs

In the TCO module, vehicle costs include vehicle capital costs, city and county sales and use tax, federal excise tax, registration and licensing fees, insurance costs, and maintenance and repair costs. We estimated vehicle retail prices using vehicle production costs under three scenarios (i.e., base, conservative, and optimistic) obtained from TRACE's forecasts of vehicle manufacturing costs (Section 2.4.2), which were then adjusted with retail markup rates of 40% in 2021-2029 and 35% in 2030-2050 over the manufacturing costs (Figure 42). These markup rates are based on the International Council on Clean Transportation's review of purchase costs for zero-emission trucks (Sharpe & Basma, 2022), in which they define an "integration factor that includes research and development, marketing, insurance, and assembly…[representing]…the difference between the manufacturing cost and the price to be paid by the consumer" (p8).

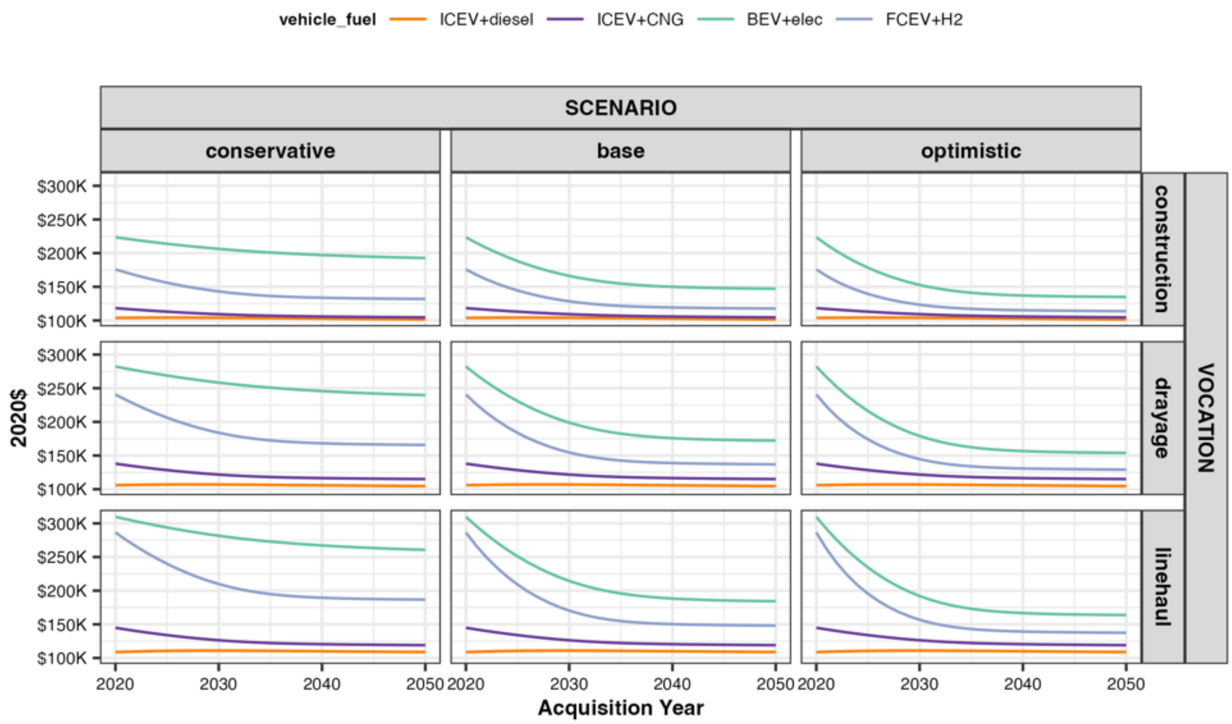


Figure 42. Projected vehicle retail prices, 2020-2050

Source: TRACE model results (Section 2.4.2) with retail markup rates of 40% (2021-2029) and 35% (2030-2050)

Vehicle acquisition is assumed to be purchases that are financed, which result in a series of annual payments (Eq. 18).

$$AVPC_{i,j,k,m} = \frac{((VC_{i,j,k} - \text{DP\_v}_m) * (1 + T_m + FET)) * r1}{1 - (1 + r1)^{-t1}} \qquad \textbf{Eq. 18}$$

where,

$AVPC_{i,j,k,m}$ – Annual vehicle purchasing cost of technology *i* for vocation *j* in year *k* and region *m*;

$VC_{i,j,k}$ – Vehicle retail prices of technology *i* for vocation *j* in year *k* (based upon the scenario selected from Figure 42)

DP_v_m - Down payment made to reduce loan principal. We assume this is 10% of the vehicle purchase cost;

T_m – Sales and use tax rate in region *m*;

FET – Federal exercise tax on heavy-duty trucks (12%);

$r1$ – Vehicle financing annual percentage rate;

$t1$ – Vehicle financing term in years;

City and county sales and use tax rates (effective Jan 1, 2022) were obtained from the California Department of Tax and Fee Administration.

We estimated the residual values following work conducted by ANL (Burnham et al., 2021), as shown in Eq. 19, where exp(A) is the price retention factor based on age and exp(M) is the price retention factor based on mileage.

$$res_{i,j} = \exp\left(A_{i,j} * l_j + M_{i,j} * \frac{\sum_{t=1}^{l_j} aVMT_{j,k,t}}{1000}\right) \qquad \textbf{Eq. 19}$$

where,

$res_{i,j}$ – Residual value rate of technology *i* for vocation *j* at the end of first-owner life;

$\exp\,(A_{i,j})$ – percentage price retention based on vehicle age of technology *i* for vocation *j*;

$\exp\,(M_{i,j})$ – percentage price retention based on vehicle mileage (in 1000 miles) of technology *i* for vocation *j*;

$aVMT_{j,k,t}$ – Annual vehicle miles traveled in ownership year *t* for vocation *j* purchased in year *k*;

l_j – First-owner life for vocation *j* in years.

The parameter values for exp(A) and exp(M) were based on Burnham et al. (2021) and are shown in Table 30.

Table 30. Parameter values of the effect of age (A) and mileage (M) on price retention

Vocation	Exp(A)	Exp(M)
drayage	0.9113	0.9991
linehaul	0.9071	0.9990
construction	0.9220	0.9999

Data source: ANL (Burnham et al., 2021)

To compute registration and licensing fees, we followed CARB's methodology (CARB, 2020b), splitting them into fixed fees tied to the fuel type, vehicle weight, and location, and variable licensing fees tied to the vehicle age. Registration fees were estimated using the Vehicle Registration Fee Calculator maintained by the California Department of Motor Vehicles (California DMV, 2023) for each fuel type and county and are assumed to remain constant in 2020$ during all years modeled. The values obtained are summarized in Figure 43.

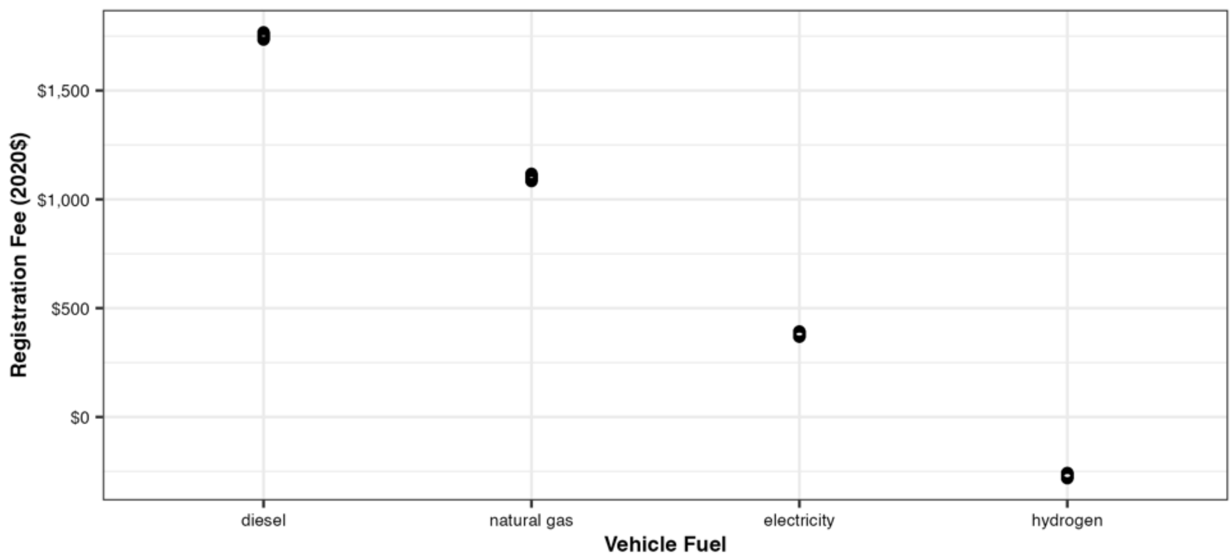


Figure 43. Vehicle registration fees by fuel type

Source: Vehicle Registration Fee Calculator maintained by the California Department of Motor Vehicles (California DMV, 2023). The range of values obtained for all counties is shown for each fuel. Due to the small variation in these values across counties, the points are blurred together.

The annual licensing fees are computed as 0.65% of the original vehicle price times the age reduction percentages shown in Table 31.

Table 31. Vehicle license fee schedule (VLFS)

Year	1	2	3	4	5	6	7	8	9	10	11+
Percentage of price	100%	90%	80%	70%	60%	50%	40%	30%	25%	20%	15%

Source: (CARB, 2020b)

Combining these values, we have:

$$AVRC_{i,j,k} = \sum_{t=1}^{l} RF_{i,k,t} + 0.0065 \times \mathrm{VLFS(t)} \times VC_{i,j,k} \qquad \textbf{Eq. 20}$$

where:

$AVRC_{i,j,k}$ – Annual registration and licensing fees for technology *i* and vocation *j* purchased in year *k*;

$RF_{i,k,t}$ – Vehicle registration fee for vehicle technology *i* and vocation *j* purchased in year *k*;

$VLFS(t)$ – Vehicle license fee schedule percentage for vehicle age *t* from Table 31

Maintenance and repair (M&R) costs on the per mile basis were based on ICF (2019) and the InfoShed outputs. Annual M&R costs were estimated by multiplying M&R costs on the per mile basis and annual VMT (Eq. 21).

$$AVMC_{i,j,k} = \sum_{t=1}^{1} aVMT_{j,k,t} * MC\_permile_{i,j,t} \qquad \text{Eq. 21}$$

Maintenance costs per mile for different vehicle technologies were obtained from ICF (2019) and assumed to be constant over time such that $MC\_permile_{i,j,t} = MC\_permile_{i,j}$ with the values shown in Table 32.

Table 32. Maintenance costs in dollars per mile by vocation and vehicle technology

Vocation	ICEV+diesel	BEV+elec	ICEV+CNG	FCEV+H2
Drayage	0.20	0.17	0.22	0.17
Linehaul	0.19	0.17	0.19	0.17
Construction	0.19	0.17	0.19	0.17

Source: Drayage = "Class 8 Drayage" and Linehaul and Construction taken as "Class 8 SH" from Table II-11 in ICF (2019),

Total vehicle costs are estimated by the sum of the net present value of each cost component discussed in this section (Eq. 22). Residual values of vehicles at the end of first-owner life are included as a benefit that offsets vehicle costs.

$$\begin{aligned} TVC_{i,j,k,m} = {} & \mathrm{DP\_v}_m + AVPC_{i,j,k,m} \times \frac{1-(1+r_{disc})^{-t1}}{r_{disc}} \\ & + \left(AVRC_{i,j,k} + AVIC_j + AVMC_{i,j,k} \right) \\ & \times \frac{1-(1+r_{disc})^{-l_j}}{r_{disc}} - \frac{VC_{i,j,k} * res_{i,j}}{(1+r_{disc})^{l_j}} \end{aligned} \qquad \text{Eq. 22}$$

where,

$AVMC_{i,j,k}$ – Annual vehicle maintenance and repair cost of technology i for vocation ˆ purchased in year k;

$MC\_permile_{i,j,k}$ – Vehicle maintenance and repair cost per mile of technology i for vocation j in purchased year k;

$TVC_{i,j,k,m}$- Total vehicle cost (purchase) of technology i for vocation j in purchased in year k and region m;

$AVRC_{i,j,k}$ – Annual registration and licensing fees of technology *i* for vocation *j* purchased in year *k* (note, this is a function of vocation only because registration fees are a function of vehicle cost, which is vocation-specific);

$AVIC_j$ – Annual insurance costs for vocation *j*; (see (CARB, 2019b) for alternative method)

r_{disc} – Discount rate;

4.1.3.2 Infrastructure costs

Fleets may choose to purchase refueling infrastructure for alternative fuel technologies for both cost and operational reasons. Infrastructure capital and maintenance costs were obtained from ICF (2019). Additional assumptions on infrastructure lifespan and vehicle-to-infrastructure ratio are shown in Table 33. We assume that infrastructure capital costs are financed throughout the infrastructure lifespan (Eq. 23). Total infrastructure costs are estimated as the net present value of annual capital and maintenance costs throughout the first-owner life (Eq. 24).

Table 33. Inputs and baseline assumptions on infrastructure costs

Infrastructure type (at depot)	Capacity/ Power	Capital costs ($)	Installation costs ($)	Annual maintenance costs ($)	Infrastructure lifespan (years)	Vehicle-to-infrastructure ratio
EVSE	200 kW	50,000	55,000	5,500	10	1
Hydrogen Station	230 kg/day	1,250,000	1,250,000	152,000	20	20
CNG Station	1 million DGE/yr	1,000,000	1,000,000	115,000	20	20

Source: ICF (2019)

$$AIC_{m,n} = \frac{(IC_n - DP_{i_{m,n}}) * (1 + T_m) * r2}{1 - (1 + r3)^{-t2}} \qquad \textbf{Eq. 23}$$

$$TIC_{m,n} = DP\_i_{m,n} + \left(AIC_{m,n} + AIMC_{m,n}\right) * \frac{1 - (1 + r_{disc})^{-l_j}}{r_{disc} * r_{vti}} \qquad \textbf{Eq. 24}$$

where,

$AIC_{m,n}$ – Annual infrastructure capital cost of fuel *n* in region *m*;

IC_n - Infrastructure capital cost of fuel *n*;

$\mathrm{DP\_i}_{m,n}$ - Down payment made to reduce infrastructure loan principal at purchase time. We assume this is 10% of the capital and installation costs from Table 33 plus taxes;

T_m – Sales and use tax rate in region *m*;

$r2$ – Infrastructure financing annual percentage rate;

$t2$ – Infrastructure financing term in years (by default we assume this to be the same as the infrastructure lifespan);

$TIC_{m,n}$ – Total infrastructure cost of fuel *n* in region *m*;

$AIMC_{m,n}$ – Annual infrastructure maintenance cost of fuel *n* in region *m*;

r_{disc} – Discount rate;

l_j – First-owner life for vocation j in years;

r_{vti} – Vehicle-to-infrastructure ratio (used for splitting costs among vehicles).

In some cases, smaller fleets may forego the purchase of infrastructure due to the high cost of investment. In the PET, if the fleet size grouping being modeled is smaller than the vehicle to infrastructure ratio in Table 33, infrastructure is assumed to not be purchased and a retail fuel markup is applied to the fuel costs, which we discuss in the next section.

4.1.3.3 Fuel costs

Fuel costs were estimated for each fuel type using a range of input data depending on the fuel. Multiple data sources were used for the projection of commercial EV electricity prices. We first estimated average cost of electricity for fleet owners and operators of various sizes (i.e., 1 vehicle, 10 vehicles, 50 vehicles, 100 vehicles, and 200 vehicles) using specific utility rate designs in 2021-2022. The values of these estimates serve as the base-year electricity costs for fleets. For 2021-2030, annual growth rates under three scenarios (i.e., low demand case, mid demand case, and high demand case) as specified in the commercial electricity rates from the California Energy Demand 2020-2030 Baseline Forecast (CEC, 2020b) were used to project future growth in electricity costs. Average annual growth rates between 2018 and 2030 were used for 2031-2060 to project electricity costs in the longer run. This approach has been applied to nine major electric utilities, including PGE, SCE, SDGE, LADWP, SMUD, IID, BWP, GWP, and PWP. State-wide estimates were also constructed to represent other parts of the state that are outside the service territories of the five major utilities. Projected electricity costs are shown in Figure 44.

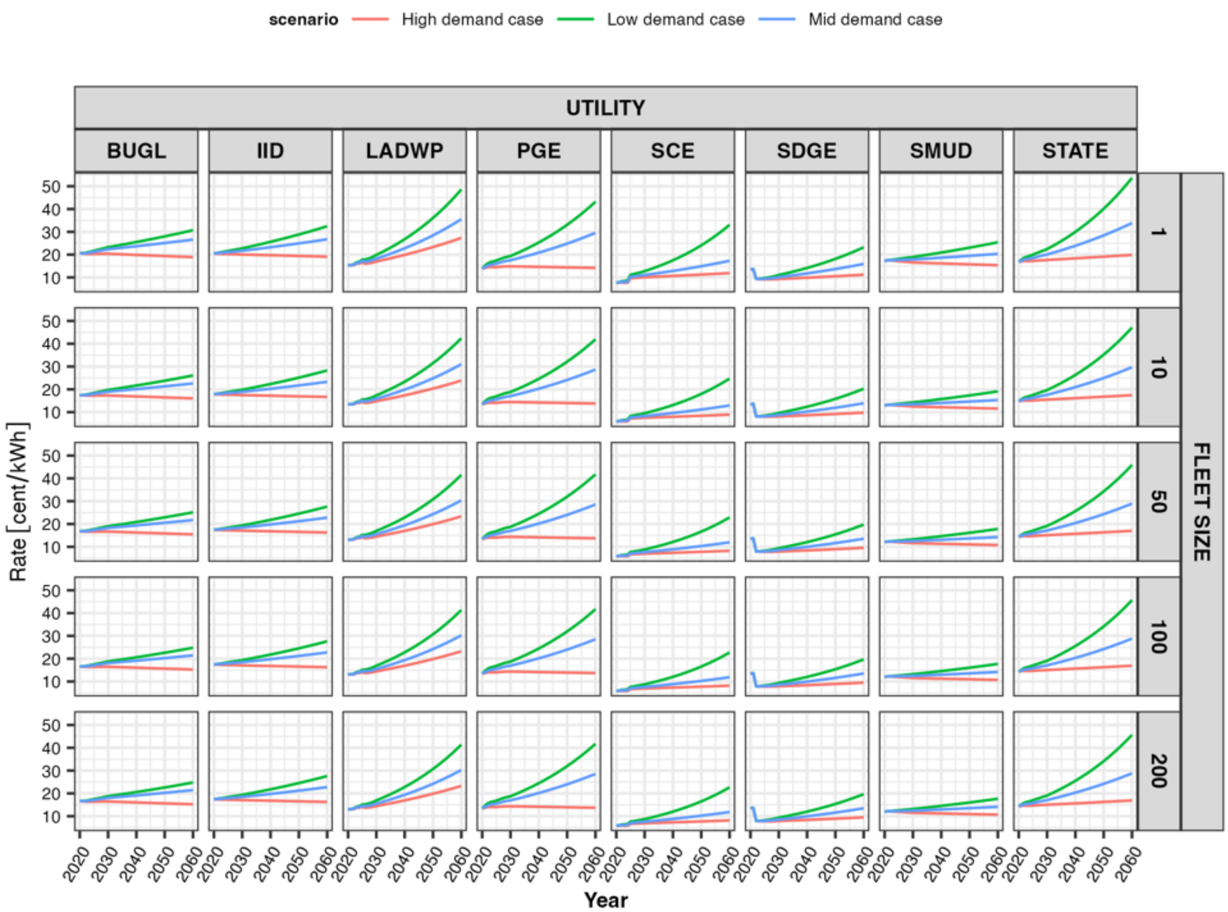


Figure 44. Projected electricity rates, 2020-2060

Source: Baseline rates estimated using utility-specific rate designs from 2021-2022. From the baseline, pre-2030, CED 2019 baseline forecast annual growth rates and post-2030: extended with average annual growth rates between 2018 and 2030.

For diesel and CNG prices, observed retail prices in 2020 and annual growth rates from annual energy outlook (AEO) 2021 (US EIA, 2021) were used to project prices in 2021-2050. We also assume the 2050 rates stay constant from 2051 through 2060. Projected costs for hydrogen, renewable diesel, and substitute natural gas (renewable natural gas and biogas) were extracted from TRACE outputs, previously discussed in Section Alternative Fuel and Technology Cost Projections, using the weighted average of the TRACE scenario that achieves 80% GHG reduction from 1990 levels by 2050.

Putting these all together, projected fuel prices for the base scenario and statewide averages are shown in Figure 45 alongside forecasts from TCO work from CARB (CARB, 2021d) and ANL (Burnham et al., 2021). The PET forecasts show good consistency with ANL's forecast for hydrogen with CARB's hydrogen forecast significantly below both for 2025 before it becomes more in line around 2030. The PET's mean electricity rates lie between ANL's (lower) rates and CARB's higher rates for 2025 through 2035. The high end of the electricity rates for the PET eventually exceeds CARB's forecast around 2040 (assuming CARB's rates remain flat from 2035 onward). Diesel prices for the PET closely track CARB's from 2025 through 2035, while ANL's are significantly lower, which likely reflects the difference between national and California diesel costs. Finally, ANL did not forecast natural gas rates, but the PET's forecasts are slightly higher than CARB's. Overall, the fuel price forecasts from TRACE compare favorably to these recent values from the literature.

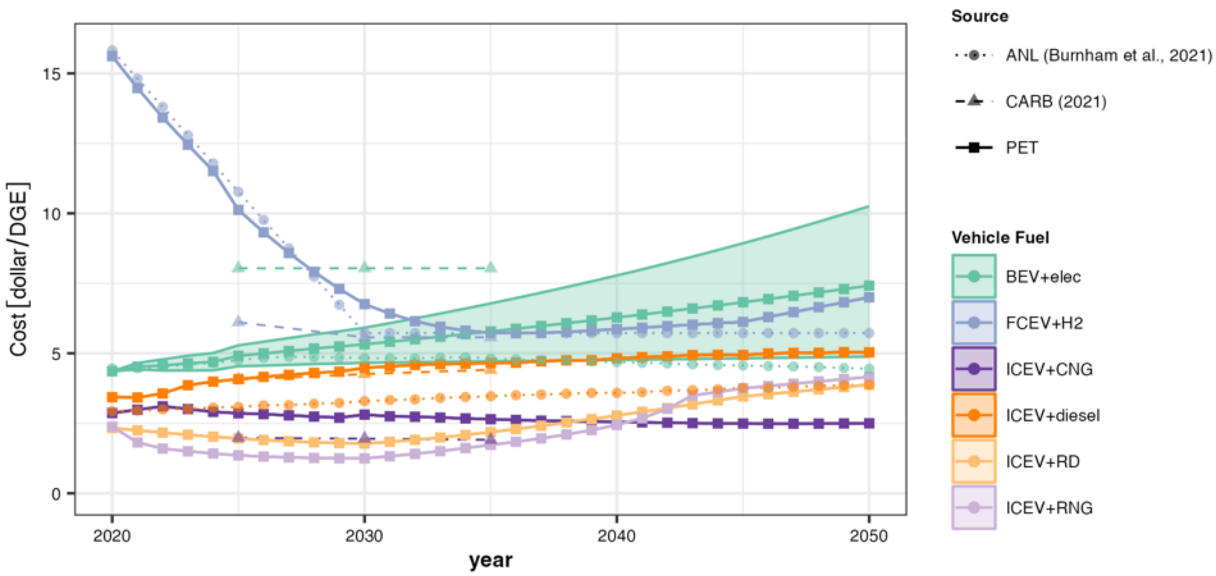


Figure 45. Projected fuel prices, 2020-2060.

Sources: CNG=Compressed Natural Gas, H2=Hydrogen, RD=Renewable Diesel, RNG=Renewable Natural Gas. Diesel and CNG costs from observed retail prices and growth factors from AEO 2021 (US EIA, 2021); H2, RD, and RNG prices include LCFS and RFS credits and are taken from TRACE outputs (Section 2.3.5); electricity rates shown here are statewide averages for each demand case in Figure 44 (weighted by base fleet populations) and do not include LCFS credits. CARB (CARB, 2021d) and ANL (Burnham et al., 2021) and ANL values provided for comparison.

Annual fuel costs for vehicles are estimated by multiplying annual fuel consumption by fuel prices (Eq. 25). Total fuel costs are estimated by the sum of the net present values of annual fuel costs throughout the first-owner life (Eq. 26).

$$AFC_{i,j,k,m,t} = aVMT_{j,k,m,t} \times FE_{i,j,k,m} \times P_{m,n,t} \times MU \qquad \textbf{Eq. 25}$$

$$TFC_{i,j,k,m} = \sum_{t=1}^{l_j} \frac{AFC_{i,j,k,m,t}}{(1 + r_{disc})^t} \qquad \textbf{Eq. 26}$$

where,

$AFC_{i,j,k,m,t}$ – Fuel cost in ownership year *t* of fuel for technology *i* and vocation *j* purchased in year *k* and region *m*;

$aVMT_{j,k,m,t}$ – Vehicle miles traveled in ownership year *t* for vocation *j* purchased in year *k* and region *m*;

$FE_{i,j,k,m}$ – Fuel economy of technology *i* for vocation *j* in purchased year *k* and region *m*;

$P_{m,n,t}$ – Price of fuel *n* in ownership year *t* and region *m*;

MU – Retail markup of fuel. This depends on whether infrastructure is purchased (see Section 4.1.3.2). If infrastructure is purchased, the value is 1.0, if not, the value is 1.5 for gaseous fuels.

$TFC_{i,j,k,m}$ – Total fuel cost of fuel for technology *i* and vocation *j* in purchased in year *k* and region *m*;

r_{disc} – Discount rate.

Generally, $aVMT_{j,k,m,t}$ is assumed to come from the EMFAC forecasts of VMT by vocation (grouped into the PET's three vocational classes). For a vehicle purchased in year *k*, *t*=1 corresponds to *k*, *t*=2 corresponds to *k*+1, and so on up to the vehicle life (l_j). As an example, if we were modeling a vehicle purchased in year 2025 with a 7-year vehicle life, we would use VMT from EMFAC for that vehicle's vocation starting in 2025 and going through year 2031. However, analysis of the VMT data in EMFAC showed that some unexplained data gaps existed for specific vocations/region/year combinations as illustrated in the margin plot in Figure 46.

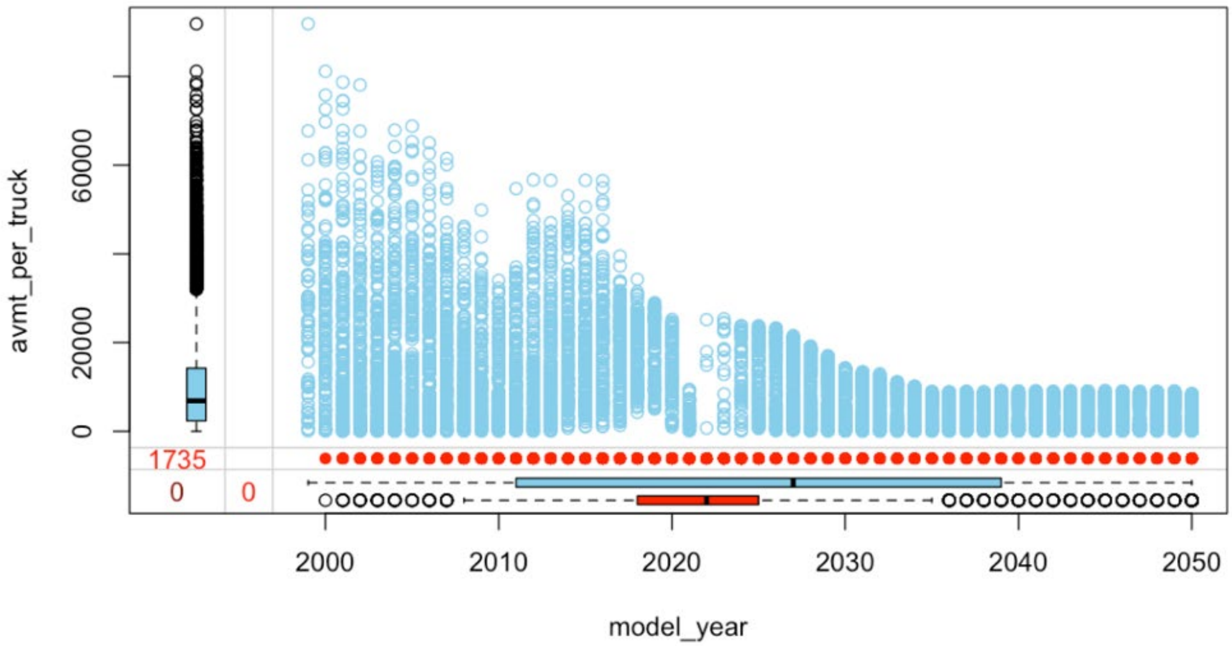


Figure 46. Margin plot of annual VMT per truck for construction

Source: EMFAC2021 v1.0.1 (CARB, 2021a). Each blue circle shows an estimated aVMT for a given vocation and subarea. The notable gap in data between 2021 and 2023 leads to lower estimated aVMT for these years, which impacts elements of TCO sensitive to aVMT.

To obtain more stable estimates of VMT for vehicle model years throughout the range of years modeled, we took the 4-year rolling average of VMT by vehicle age as the VMT determining annual vehicle activity for TCO calculations. Thus, for a vehicle purchased in 2025, the first year VMT was taken as the average of the VMTs for vehicles of age 0 in calendar year 2022 through 2025. Figure 47 shows how this smoothed the missing data from Figure 46. Similar smoothing was applied to each of the three vocations. For cases where acquisition years plus vehicle lifetime exceed 2050, the 2050 VMT is replicated until all needed data is available. For example, for an acquisition year of 2047 with a 7-year vehicle lifetime, the 2050 VMT is repeated for years 2051 through 2053.

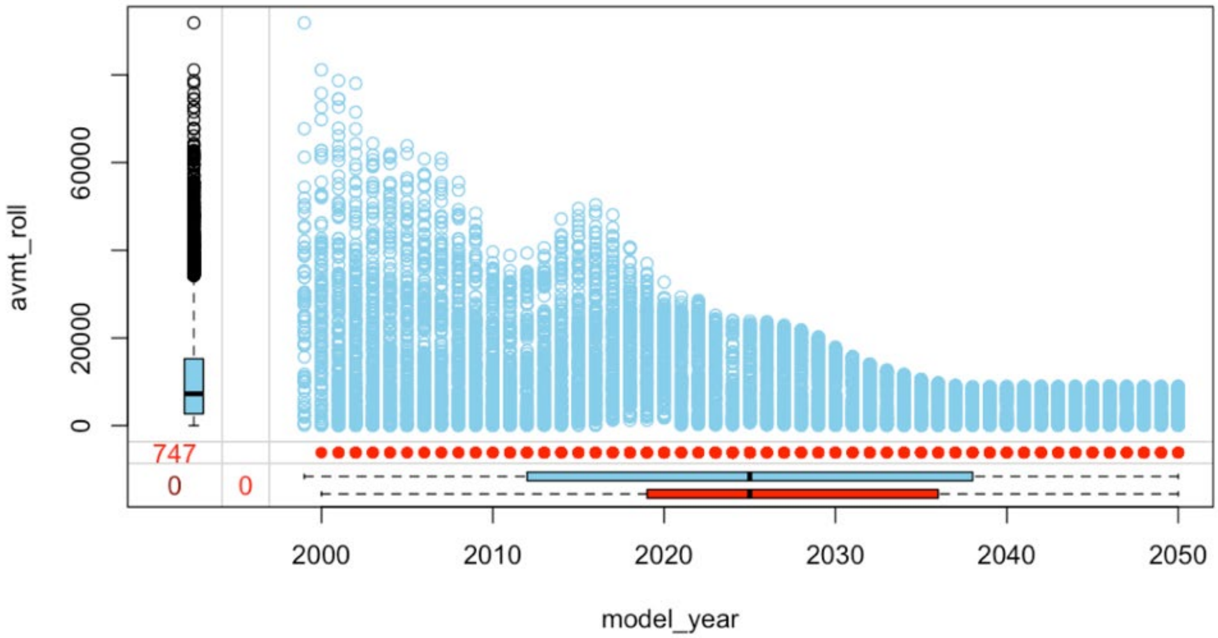


Figure 47. Margin plot of 4 year rolling average of annual VMT per truck for construction

Source: EMFAC2021 v1.0.1 (CARB, 2021a). Each blue circle shows the 4 year rolling average of estimated aVMT for a given vocation and subarea. The notable gap in data between 2021 and 2023 apparent in Figure 46 has been smoothed away.

One note on the lifetime VMTs produced using this method is that they tend to be lower than values typically seen in the literature, especially for the later purchase years. For instance, CARB's Advanced Clean Fleets TCO analysis (CARB, 2021d) used a value of 599,280 miles traveled for day cab tractor over a 12-year lifetime for a vehicle purchased in 2025. Figure 48 shows the mean 12-year VMT across all regions for each vocation derived from EMFAC where the drayage (day cab) total is 484,866 miles in 2025.

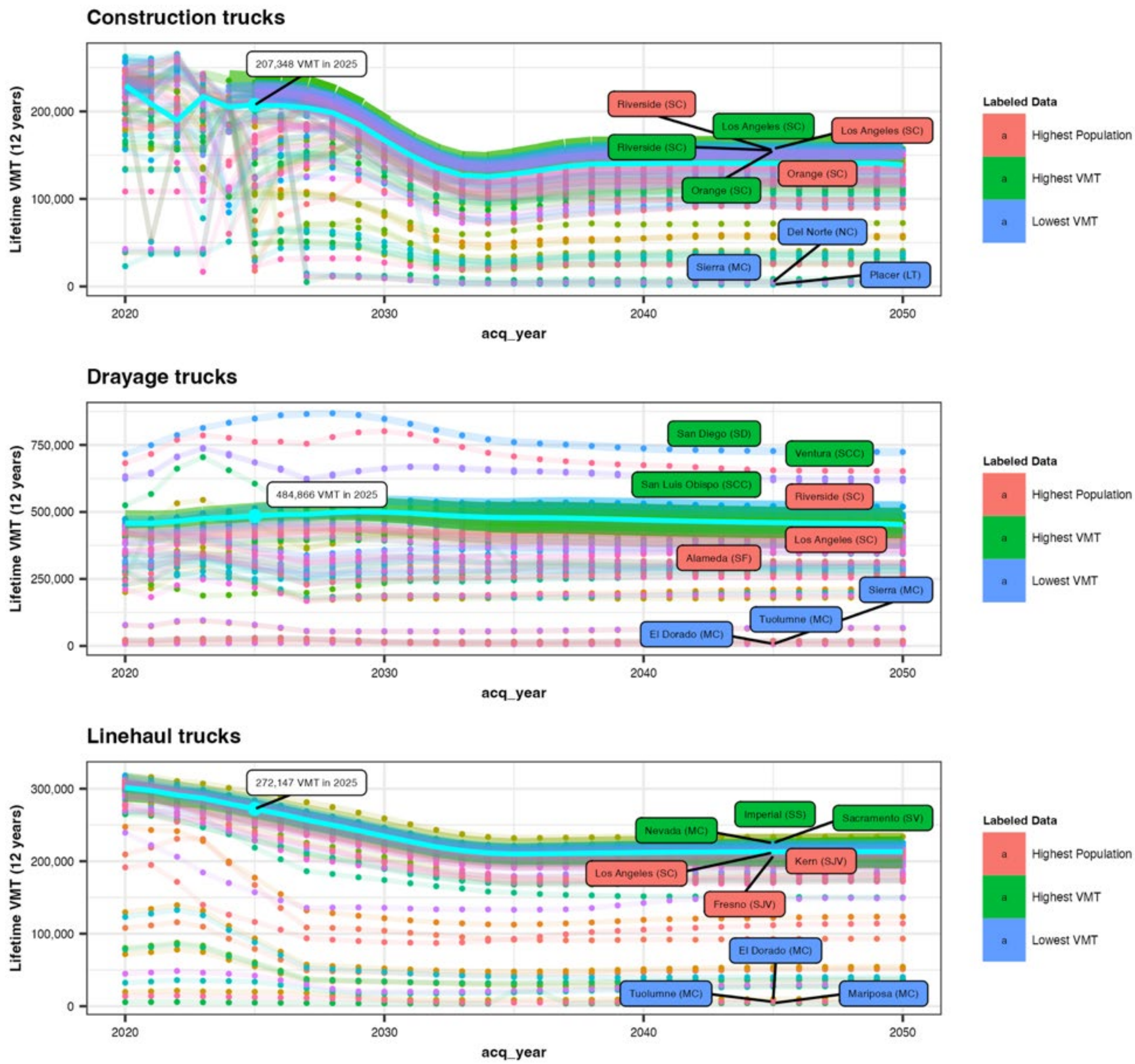


Figure 48. Lifetime (12 year) vehicle miles traveled by acquisition year

Note: Figure shows the statewide weighted mean of truck lifetime VMTs for each acquisition year and vocational class weighted by truck population each region. Region-specific lifetime VMTs are shown for context with those with the highest population (heaviest weight) and highest and lowest VMTs identified.

Given the importance of VMT in determining TCO, the PET is designed to allow the user to scale the baseline VMTs to hit specific VMT targets for a given vehicle life. This can facilitate comparisons with other TCO estimates in the literature that use different activity schedules (we leverage this feature in Section 5.2). This feature, however, does not scale the VMT used to compute fuel consumption and emissions in the impact analysis described in Section 4.3 as this is designed to be consistent with EMFAC VMTs. This differentiation is acceptable because it is reasonable to assume that fleets evaluate TCO on the basis of VMT assumptions that may not materialize.

4.1.3.4 Policy & incentives

Policy and incentives considered in the current version of the TCO module include the HVIP, projected LCFS revenue, as well as CEC and utility incentives for infrastructure. The module also has the capacity to model the effects of subsidized finance rates for both vehicles and infrastructure through sensitivity analysis. The voucher amounts from HVIP in 2020 and 2021 are based on the FY 2020-21 and FY 2021-22 funding plans. Voucher amounts for any future year and any vehicle-fuel combination, or the addition of new programs can be specified as an input by the user under various criteria including acquisition year, vocation, fleet size, and location.

The current LCFS regulation extends to 2030. At this time, it is unclear how the regulation might continue past 2030. To address this uncertainty, we provide three different policy scenarios (Figure 49) that the user may choose between: (1) the CI standard remains constant at 2030 levels until 2050, (2) the CI standard declines from 2030-2040 at the same average rate of change as it did between 2020 and 2030 (default), or (3) The CI declines to zero by the 2045 (to meet net zero targets).

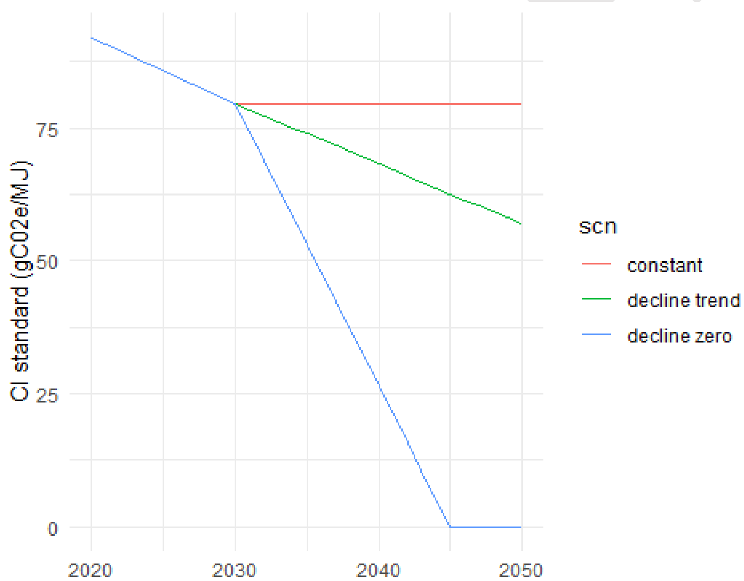


Figure 49. Carbon intensity policy scenarios.

In addition to regulatory uncertainty, the market-based compliance mechanism makes the future value of LCFS credits difficult to predict. Without any policy or market changes, declining carbon standards will increase the cost of credits because more credits will be demanded by high-CI fuels and fewer credits will be generated by low-CI fuels. Conversely, as vehicles switch to alt-fuel powertrains, demand for credits for conventional fuels will fall and production of credits will increase, leading to lower credit prices. Moreover, exogenous supply and demand of credits from other fuel markets will also influence LCFS credit prices. However, modeling these dynamics of the LCFS regulation are beyond the scope of this project. Instead, we supply the user with three alternative scenarios for future LCFS price: (1) prices remain similarly near the regulatory price cap as they have historically (default), (2) prices decline 25% between 2020 and 2050, and (3) prices decline 50% between 2020 and 2050.

We base prices on the spot market as a proxy for the average cost of compliance and the average benefit to opt-in fuels. However, some fuel suppliers may produce both high and low CI fuels and internally offset their deficits from fossil fuel with credits from alt-fuels. We assume that the shadow price of this method of LCFS compliance is equal to the average LCFS credit cost.

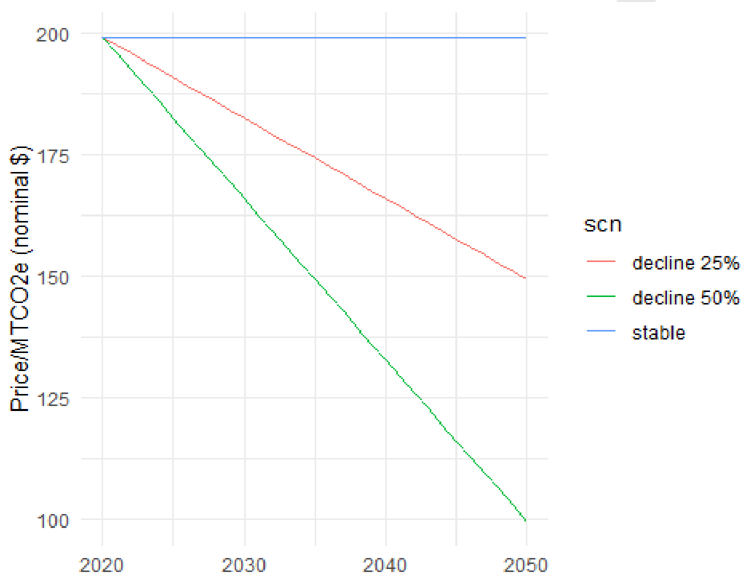


Figure 50. LCFS credit price scenarios.

We calculate the credit/deficit generation for each fuel in each year based on the scenario CI standard, the CI of the fuel for each year, and the fuel specific energy efficiency ratios. Credits will return positive values while deficits are negative values. LCFS credits and deficits are calculated using the following equation:

$$Credit/Deficit = (EER_{fuel} \times CI_{standard} - CI_{fuel}) \times MJ_{fuel} \times 1e - 6 \qquad \textbf{Eq. 27}$$

Credits and deficits are then multiplied by the scenario price to return the subsidy or penalty for each fuel in each year. Projected costs or subsidies from the LCFS for the base scenario are shown in Figure 51.

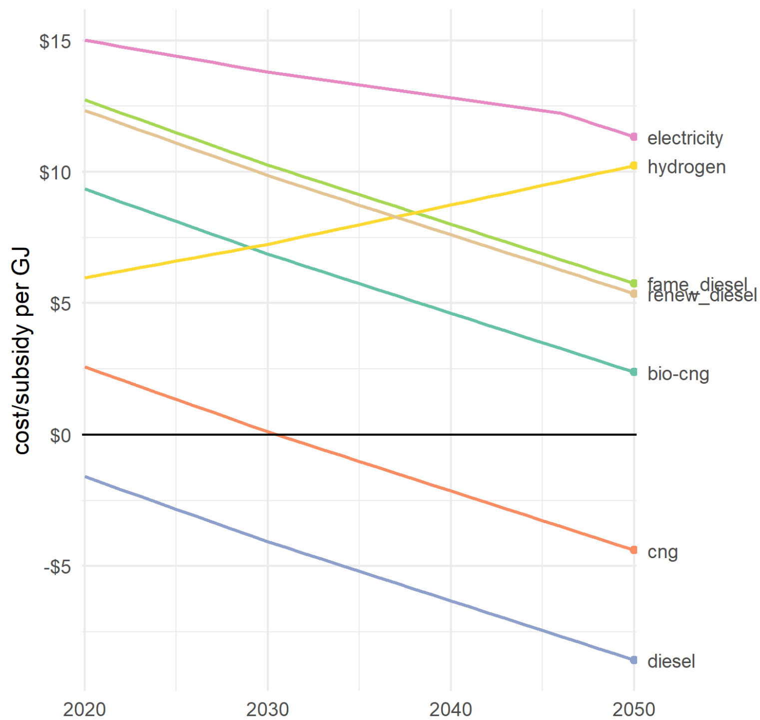


Figure 51. Subsidy value/deficit of select fuels 2020-2050 (base scenario).

Applying LCFS to the total cost of ownership of each fuel type is simple for electric trucks because fleets can access those credits directly, making the credits a simple subsidy based on the price of fuel. However, for liquid and gaseous fuels, the regulated parties are the fuel sellers, who will incorporate the costs/benefits of the credits and deficits into the cost of fuel.

One complicating factor is that many low-CI fuels are perfect or nearly perfect substitutes for high-CI fuels. For example, Bio diesel (FAME) may be substituted for diesel up to 20% of the total volume of fuel, renewable diesel is a 1:1 replacement for fossil diesel, and bio-CNG can be used in place of regular CNG. A second factor is that the cost (shadow or market) of LCFS is already baked into current fuel prices in California, meaning that LCFS compliance costs cannot simply be layered on top of fuel prices.

In addition to the vehicle and LCFS incentives, rebates are available to offset the costs of installing EVSE and hydrogen refueling stations, which we summarized in Section 1.2. The PET has been designed as a flexible tool and incentive designs can be specified to include infrastructure as well as vehicle incentives. Table 34 shows the input for specifying incentive designs, which includes both vehicle and infrastructure incentives. Incentive amounts available per year are specified per fuel and can be tailored (or limited to) specific vocations, regions (or utilities), and fleet sizes. This allows for policy sensitivity across a range of design options. Additional design features, such as incentive caps, can be added on a case-by-case basis.

Table 34. Representative incentive design specification for the PET

Category	Program	Vocation	Fuel	Fleet Size	Utility	2020	2021	2022		2050
vehicle	HVIP	drayage	electricity	1		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	electricity	2-10		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	electricity	11-20		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	electricity	21-50		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	electricity	51-100		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	electricity	101+		120,000	150,000	150,000	...	0
vehicle	HVIP	drayage	hydrogen	1		240,000	240,000	240,000	...	0
vehicle	HVIP	drayage	hydrogen	2-10		240,000	240,000	240,000	...	0
vehicle	HVIP	drayage	hydrogen	11-20		240,000	240,000	240,000	...	0
vehicle	HVIP	drayage	hydrogen	21-50		240,000	240,000	240,000	...	0
vehicle	HVIP	drayage	hydrogen	51-100		240,000	240,000	240,000	...	0
vehicle	HVIP	drayage	hydrogen	101+		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	1		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	2-10		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	11-20		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	21-50		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	51-100		240,000	240,000	240,000	...	0
vehicle	HVIP	linehaul	hydrogen	101+		240,000	240,000	240,000	...	0
...	...	...	...	...	...	...	...	...	...	...
Infr	utility		electricity		PGE	9,000	9,000	9,000	...	0
Infr	utility		electricity		PGE	24,000	24,000	24,000	...	0
Infr	utility		electricity		PGE	34,000	34,000	34,000	...	0
Infr	utility		electricity		PGE	51,000	51,000	51,000	...	0
Infr	utility		electricity		SCE	3,000	3,000	3,000	...	0
Infr	utility		electricity		SCE	23,000	23,000	23,000	...	0
Infr	utility		electricity		SCE	41,000	41,000	41,000	...	0
Infr	utility		electricity		SCE	70,000	70,000	70,000	...	0
...	...	...	...	...	...	...	...	...	...	...
Infr	energiize		hydrogen			1,500,000	1,500,000	1,500,000	...	0

Notes: The input for specifying incentive designs includes both vehicle and infrastructure incentives. Incentive amounts available per year are specified per fuel and can be tailored to specific vocations, regions (and utilities), and fleet sizes allowing for policy sensitivity across a range of design options.

4.1.3.5 *Depreciation of vehicles and refueling infrastructure*

Fleets can achieve cost savings by deducting the depreciation of vehicle value over time. Following CARB (CARB, 2021d), we estimate these savings using the 3-year Modified Accelerated Cost Recovery System (MACRS) depreciation schedule from IRS Publication 946. The cost savings is adjusted using the discount rate.

$$VD_{i,j,k} = \sum_{t=1}^{l} \frac{(VC_{i,j,k} - VI_n) \times MACRS_3(\mathrm{t}) \times R_{corp}}{(1 + r_{disc})^t} \qquad \textbf{Eq. 28}$$

where,

$VD_{i,j,k}$ – Savings due to depreciation for technology *i* for vocation *j* purchased in year *k*;

VI_n – Vehicle incentive amount (e.g., HVIP or other programs) for fuel *n* (see below)

$MACRS_3(t)$ – Depreciation percentage for ownership year t from IRS 3-year MACRS schedule;

R_{corp} – Combined state and federal corporate tax rate. California's state corporate tax rate is 8.84 percent[49], while the federal rate is 21 percent[50], resulting in a 29.84 percent total rate.

We use a similar approach to model infrastructure depreciation except we use the 7-year MACRS depreciation schedule following IRS guidelines.

$$ID_n = \sum_{t=1}^{l} \frac{(IC_{i,j,k} - UI_o) \times MACRS_7(\mathrm{t}) \times R_{corp}}{(1 + r_{disc})^t} \qquad \textbf{Eq. 29}$$

where,

ID_n – Savings due to depreciation for infrastructure purchased for fuel *n*;

$MACRS_7(t)$ – Depreciation percentage for ownership year *t* from IRS 7-year MACRS schedule.

4.1.3.6 TCO estimation

The total cost of ownership is estimated by combining the previous terms (Eq. 30).

$$TCO_{i,j,k,m,n} = \left[TVC_{i,j,k,m} + TFC_{i,j,k,m,n} + TIC_{m,n} - VI_n - VD_{i,j,k} - \sum_{t=1}^{l_j} \frac{aLCFS_n}{(1 + r_{disc})^t} - UI_o - ID_n \right] (1 + f_{i,j,k}) \qquad \textbf{Eq. 30}$$

49 https://www.ftb.ca.gov/file/business/tax-rates.html

50 https://www.irs.gov/publications/p542

where,

$TCO_{i,j,k,m,n}$- Total cost of ownership (purchase) of technology *i* and fuel *n* for vocation *j* in year *k* and region *m*;

$TFC_{i,j,k,m,n}$ - Total fuel cost of fuel *n* for technology *i* and vocation *j* in year *k* and region *m*;

$TIC_{m,n}$ - Total infrastructure cost of fuel *n* in region *m*;

VI_n – Vehicle incentive amount (e.g., HVIP or other programs) for fuel n, which may be capped to be no more than the purchase cost differential between a vehicle using fuel n and a vehicle using the baseline conventional technology (diesel), so if the incentive cap is being modeled:

$$VI_n = min(VI_{n,max}, max((VC_{diesel,j,k} - VC_{i,j,k}),0))$$

where $VI_{n,max}$ is the maximum available incentives for vehicles. If it is not being modeled $VI_n = VI_{n,max}$;

$aLCFS_n$ - Annual LCFS revenue for fuel *n*;

UI_o - Incentives from utility *o*;

r_{disc} - Discount rate;

l_j - First-owner life for vocation *j* in years;

$f_{i,j,k}$ – Technology adjustment factor, or technology premium, for technology *i* and fuel *n* for vocation *j* in year *k*.

The technology adjustment factor is used to consider the impact on TCO of the operational limitations of specific technologies for specific applications. This is useful, for example, to reflect increased costs to fleets operating BEVs that are not explicitly represented in the PET's model of capital and operating expenses and that were identified in our interviews (see Section 3) as important to fleets. For instance, increase in weight due to heavier batteries can cause range limitations and reduce payload capacity. Burnham et al. (2021) conducted a detailed analysis of payload capacity loss resulting from heavy batteries and found they can increase total TCO by over 10% for large batteries, though this is expected to improve over time, with Burnham et al. removing the payload penalty in their 2025 and later day cab TCO estimates. Challenges are expected to remain for linehaul trucks for longer. Based on this, we selected the technology adjustment factors shown in Figure 52 for BEV HDVs. All other technology and vocation combinations are assumed to have a technology adjustment factor of 0% for all years.

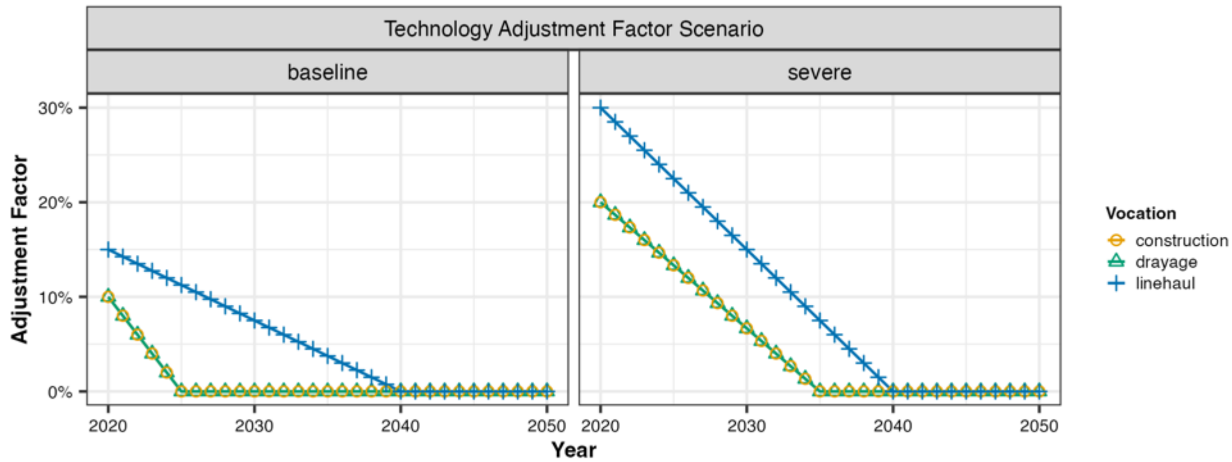


Figure 52. Baseline technology adjustment factors for BEV

Note: Values derived from Burnham et al. (2021, see page xxiii in the Executive Summary) based upon consideration of payload capacity loss. Reductions based upon TCO estimates from the same source showing the payload penalty dissipating over time.

4.1.4 Truck turnover module

As noted earlier, the fleet turnover module models vehicle turnover as a stock and flow system focusing on "active" truck stock. We define active truck stock as all registered trucks less than 20 years old. While trucks retire from active use at varying ages, by 20 years, most trucks are out of active revenue service based upon VMT estimates in EMFAC. Those still in use are likely used for very low mileage applications such as farm use or as backups when primary vehicles are being serviced. We model active trucks only because they are the trucks that contribute the most mileage (and thus produce the most emissions impacts). The module starts with the active truck stock for 2020 as the baseline inventory for the start of the turnover model. Because it sets the initial conditions for truck turnover, model outputs are very sensitive to this starting condition. The three vocations modeled in this tool are defined using the EMFAC vehicle class categorization (Table 35).

Table 35. Vocation and vehicle class categorization.

Vocation	EMFAC202x vehicle class
Drayage	T7 POAK Class 8, T7 POLA Class 8, T7 Other Port Class 8
Linehaul	T7 Tractor Class 8
Construction	T7 Single Concrete/Transit Class 8, T7 Single Dump Class 8

Disaggregation of EMFAC vehicle stocks is achieved by assigning stocks proportionally by area to the PET regions discussed previously in Figure 41.

For each region, we calculate net stock loss rate from historical data on net stock flows of class 8 trucks from 2000 to 2019. Year over year, the stock of model year cohorts change. For example, in 2015 there were 6,648 2005 model year trucks registered in California. In 2016, that number had shrunk to 5,714 for a net loss of 934 or a net percentage loss of 14.05%. While the net loss figure does not contain any information on the fate of individual trucks (deregistration could mean retirement/scrappage or sales out of state), it does provide a basis for projecting stock flows out of the California active truck fleet.

By averaging the percentage change in stock over truck age across multiple years of turnover, we generate a generalized by-age retirement function for trucks which can be applied to future truck populations of that age to project future truck retirement.

$$avg\_net\_change_{j,m,a} = \frac{\sum_{y=2}^{N} pop_{j,m,a,y} - pop_{j,m,a,y-1}}{N} \qquad \textbf{Eq. 31}$$

where:

$pop_{j,m,a,y}$ is the fleet population in year *y* of trucks in vocation *j* operating in region m that have age a;

N is the number of years over which we are averaging population change data.

$avg\_net\_change_{j,m,a}$ is the computed average of population changes of trucks in vocation *j* operating in region *m* that have age a. The average is computed only over positive population changes.

Because there are few (or zero) alternative-fuel trucks in the historical inventory, we base truck turnover rates on combined data, making the implicit assumption that the retirement patterns for alternative-fuel technologies are similar to diesel trucks. Because the underlying data used to create this loss rate is based on net changes in overall vehicle stock (and not individual trucks moving out of the fleet), and California is a net importer of used trucks, this approach cannot model retirements until there is a net loss of those trucks across the whole fleet. In the historical data, that does not occur until trucks reach age 8 on average. Any churn in vehicles prior to 8 years of age are thus masked by imports of used trucks of the same age.

In the model, these annual retirement rates are applied to current year inventories to forecast the portion of trucks of each given age that leave the active fleet each year. For example, if the inventory in year n has 10,000 8-year-old trucks, and net losses for 8-year-old trucks are 2%, then 200 of those trucks will be removed from the inventory in the next year to account for those losses. In year n + 1 those same model year trucks will be 9 years old, and thus will be reduced again, this time by 4%, leaving 7,680 trucks in year n + 2. This pattern repeats until trucks reach 20 years old trucks where any remaining trucks are removed. Because we do not have sufficient historical data to identify trends over time, this set of retirement functions is static. This means the model will not capture potential changes in retirement patterns that might occur due to technological factors.

In addition to replacing retired trucks, the truck fleet will also grow in response to economic and population growth and changes in the logistics industry caused by the continued growth of e-commerce. We extracted fleet growth trends using projected vehicle population from EMFAC2021 for years from 2021 to 2050 and apply it incrementally, starting with the base year of 2020, to compute the population for each vocation in each year and determine the number of net trucks added to the fleet in each vocation in each year.

This net inflow of vehicle stocks represents vehicles brought into the California fleet in each given year. For example, Figure 53 shows the net change of vehicles by age for the calendar years 2015-2019 and the 2010-2019 mean year over year change according to the EMFAC database. The data show that on average California's class 8 fleet increases for trucks with ages ranging from -1 to 6, where age is defined as calendar year-model year and decreases for older trucks. Assuming vehicles of with ages of 1 or less are new vehicles added to the fleet, we can see that California is a net-importer of used Class 8 trucks with ages ranging from 2-6 years. This means that in any given year, trucks added to the fleet are a mixture of both new trucks delivered from OEMs and used trucks which were initially sold new outside of California.

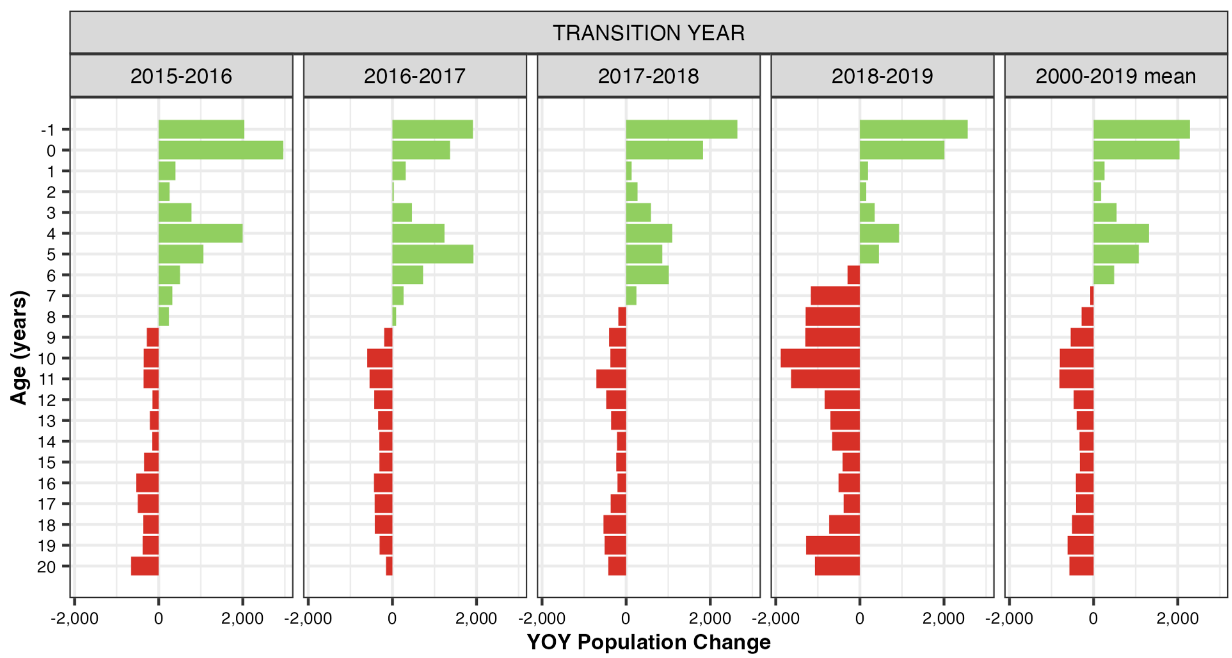


Figure 53. Net change in vehicle stock by inventory year for California Class 8 Fleet between 2015 and 2019, with the 2000-2019 mean.

Source: EMFAC (CARB, 2021a). Changes shown for all vocations modeled in the PET. The mean on the right is computed for years 2000-2019, prior years shown to illustrate the annual variations.

The quantity of vehicles brought into the fleet each year is the sum of the number of retired trucks (replacements) and the net growth of the overall active fleet. To determine how many of the inflow vehicles are new versus how many are used, we rely on the average shares of net-inflow vehicles observed in historical data illustrated in Figure 53. We calculate this distribution in a similar manner as the retirement functions described above. Net inflows are measured by comparing the number of each model year from one year to the next. We take the historical average number of net inflow trucks by age and divide it by the total net inflow to calculate the share of inflow trucks of each age. Because next model year vehicles are typically released in the middle of the prior year and because vehicles can remain unsold beyond their model year, we assume that all changes in the quantity of prior, current, and next model year trucks are new purchases. For example, between 2025 and 2026, we assume that all 2025, 2026 and 2027 model year vehicles are bought new. Increases in 2024 and older models are assumed to be used vehicle purchases. For the PET model, we compute these new and used vehicle gain parameters for each vocation using EMFAC fleet stock data for the relevant EMFAC classes for the years 2000-2019. The result is a set of gain shares specified as follows:

$$gainshare_{j,m,a} = \frac{avg\_net\_change_{j,m,a}}{\sum_{\forall a} avg\_net\_change_{j,m,a}} \qquad \textbf{Eq. 32}$$

where:

> $gainshare_{j,m,a}$ is the fraction of added vehicles in vocation *j* operating in region *m* that are of age a.

We treat the gain shares for vehicles of age 1 or less to be the new vehicle gains and those for vehicles of age two or more as used vehicles. If we are considering fleet size, it is likely that the distribution of total new and used trucks brought into the fleet is not uniform across fleet sizes. For example, say the model determines that 100 new trucks and 50 used trucks should be added to the fleet in a given year. How many of those new trucks should be purchased by fleets of what size? If, for instance, it is more likely that small fleets purchase used vehicles than large fleets, then we may want to adjust the shares of new and used purchases assigned to fleets of specific sizes. This is potentially important because large fleets are subject to different requirements than small fleets under the ACF regulations. The PET allows this to be handled through a parameter that determines what fraction of new trucks should be assigned to fleets of specific sizes.

4.1.5 HDV TCO and fleet turnover integration

The fleet turnover model provides in each simulation year the number of new and net used vehicles added to the fleet for each region and vocation. In each of these cases, we need to determine the fuel type splits to forecast stock changes by fuel type. For new vehicles, we model the impact of different TCOs on the market shares of different technology and fuel type combinations in the fleet stock. To do this we had hoped to build on a model estimated using revealed fuel type choices from the work described in Section 1.6, but as noted there the available data was insufficient for that purpose. As an alternative, we adapted the choice formulation used by the Global Change Analysis Model (GCAM) version 6 (Bond-Lamberty et al., 2022). A similar formulation is also used in the TEMPO model (Muratori et al., 2021) that, among other things, projects vehicle ownership and technology adoption decisions similar to the goals in this project. For the PET, we selected the modified logit model used in GCAM over the standard logit (Clarke & Edmonds, 1993) to determine the fuel type market shares in new truck purchases annually. The suitability of this formulation for this case follows the justification in the GCAM model where they note that if prices do not approach zero, the modified logit "is much less sensitive to incremental differences in the choice indicator [which has the effect] of allowing high-cost technologies to retain more market share than they would in the [standard] logit case." In our adaption of this model, the share of a certain vehicle technology is estimated by:

$$S_{i,j,k,m,n} = \frac{\alpha_{i,j,k,m,n} * (TCO_{i,j,k,m,n})^{\gamma}}{\sum_{\forall q \in \mathrm{Q}} \alpha_{i,j,k,m,q} * (TCO_{\mathrm{i},j,k,m,q})^{\gamma}} \qquad \textbf{Eq. 33}$$

where,

$S_{i,j,k,m,n}$ - the share (as a percentage) of technology *i* and fuel *n* for vocation *j* in year *k* and region *m* in new truck purchase;

$\alpha_{i,j,k,m,n}$ - the share weight of technology *i* and fuel *n* for vocation *j* in year *k* and region m;

$TCO_{i,j,k,m,n}$ - the TCO of technology *i* and fuel *n* for vocation *j* in year *k* and region *m*;

γ - the logit exponent

Q – is the set of fuel types available

To select the logit exponent, γ, we note that a negative value (γ <0) means that lower costs will be preferred to higher costs in the choice model whereas a positive value (γ>0) would model the opposite. The magnitude γ determines how aggressive switching behavior will be with changing costs. In our model, we follow the GCAM model's parameter for class 8 freight trucks (>32tons)[51] and select γ = -8 as the default, which reflects a relatively aggressive behavior.

We used the share weights (α) to calibrate the model using observed historical data through 2020 and represent the effect of specific preferences for certain choices beyond economic considerations. The share weights also provide a mechanism for new technologies to be

[51] See https://github.com/JGCRI/gcam-core/blob/f8138153e52b5e875b1775406d2de70868587149/input/gcamdata/inst/extdata/energy/A54.tranSubsector_logit.csv

gradually phased in. Figure 54 shows the default share weights assigned where the base year (2020) is historically calibrated. We have adjusted the weights based for future milestone years (2026, 2031, 2041) using logistic curves based on findings from the qualitative interviews discussed in Section 3.4 as well as additional interviews conducted by the team in related work with fleets who were operating CNG HDVs across a range of vocations (Bae, Rindt, et al., 2022). The respondents were asked to provide their impressions of various alternative fuels for HDV operations looking out to the 2030s. The default values in the PET are assumed to be the same across all vocations except for FCEV being slightly more favorable in the linehaul vocation than in the other vocations starting in 2031. Note that the share weights for ICEV+RD and ICEV+RNG are the same for all years. If a fuel type is disallowed by regulation for a particular vocation, year, and region combination, we set the share weight for that option to be zero. We discuss this in more detail in the next section.

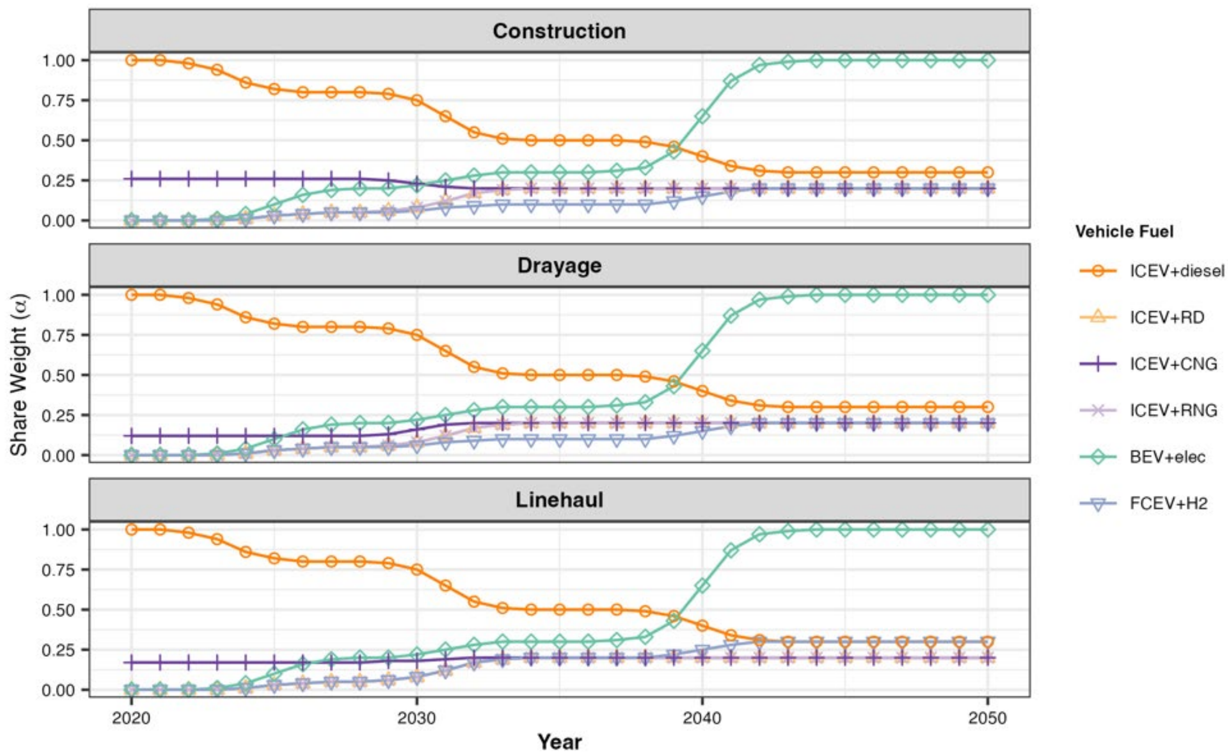


Figure 54. Default share weights for each fuel type.

For used trucks, we need to keep in mind that we are modeling *net* changes in used vehicle stock and therefore additions to the used fleet must come from outside of California and that we therefore need to determine the fuel type distribution of these used truck imports. Our approach is to assume that this distribution matches the distribution of some lagged prior period. For instance, if we are adding trucks that are 6 years old, we assume that the distribution of fuel types for those trucks should match the distribution of fuel types for new trucks added to the fleet six years prior. This is applied except when regulatory rules restrict used vehicles to particular fuel types, which we discuss in the context of modeling the Advanced Clean Fleets regulation in the next section.

4.1.6 Regulatory impacts on fleet turnover

A range of regulatory policies impacting fleet turnover in California is summarized in Section 1.1. These impacts are represented in two ways within the PET: through forced retirements and through fuel technology choice set restrictions. Table 36 summarizes the regulations that are represented in the PET, which we discuss in detail below.

Table 36. Summary of regulations modeled in the PET

Regulation	Rule	Modeled	Comments
Truck and Bus	HDV compliance schedule	Yes	Older diesels retired from the fleet in 2021-2023
Advanced Clean Trucks	Manufacturer targets	No	The PET does not represent supply-side OEM decision making
Advanced Clean Fleets	Manufacturer sales mandate	Yes	Limits choice sets for all HDV to ZEV-only starting in 2036
Advanced Clean Fleets	Drayage fleet requirements	Yes	Limits choice sets for all HDV to ZEV-only starting in 2024
Advanced Clean Fleets	Priority fleet requirements	Partially	Represents the Model Year Schedule option by limiting HDV choice sets for large fleets (50+) to ZEV-only starting in 2024. The PET does not include public vehicle so the impact of this regulation on federal fleets is not modeled. The ZEV Milestones option is not modeled. (We assume all affected fleets follow the Model Year Schedule.)
Advanced Clean Fleets	State and local agency requirements	No	The EMFAC classes represented in the PET do now include public vehicles.

The **Truck and Bus Regulation** (CARB, 2008c) falls into the first category and is modeled in the turnover module by implementing a set of forced retirements of trucks as follows:

- In simulation year 2021, all trucks model year 2004 and older are retired.
- In simulation year 2022, all trucks model year 2006 and older are retired.
- In simulation year 2023, all trucks model year 2009 and older are retired.

The **Advanced Clean Trucks regulation** (CARB, 2019a), which requires manufactures to increase the fraction of zero-emission trucks they sell in California from 2024 onward is not explicitly modeled by the fleet turnover model. This is because the model does not explicitly represent vehicle makes nor supply-side decisions by manufacturers and therefore cannot represent their behavior directly.

However, the recently passed **Advanced Clean Fleets Regulation** (CARB, 2023b) is modeled through a combination of retirements and choice set restrictions. First, the *manufacturer sales mandate* requires manufacturers to only sell zero-emission heavy-duty vehicles starting in 2036. This is represented in the model as follows:

- From simulation year 2036, we remove all combustion vehicles from the available fuel choices, leaving only BEV and FCEV as options for new vehicles.

The *drayage fleet requirements* limit new drayage truck registrations to zero-emission only starting in 2024. The rule also mandates that all drayage trucks (new or used) must be zero emission starting in 2036. This is represented in the model as follows:

- In simulation year 2035, all non-ZEV drayage trucks are retired.
- From simulation year 2024 onward:
  - we limit the fuel choice for new drayage trucks to BEV or FCEV.
  - we limit the fuel choice for used drayage trucks to BEV or FCEV. However, since the market for used ZEV trucks will lack inventory (particularly from out of state) for some time, we convert any used truck additions predicted by the gain shares into new vehicle purchases. This conversion is carried out until 2030 after which we assume there will be a functioning used vehicle market for ZEVs.

High priority and federal fleets are required to phase-in the use of ZEVs starting in 2024. Here, high-priority fleets "are entities that own, operate, or direct at least one vehicle in California, and that have either $50 million or more in gross annual revenues, or that own, operate, or have common ownership or control of a total of 50 or more vehicles (CARB, 2023b)." Two compliance options are available for these fleets. The first is the Model Year Schedule in which these high priority fleets "must purchase only ZEVs beginning 2024 and, starting January 1, 2025, must remove internal combustion engine vehicles at the end of their useful life as specified in the regulation" (CARB, 2023b). Alternatively, the ZEV Milestones Option allows fleets to meet ZEV targets as a percentage of the total fleet starting with vehicle types that are most suitable for electrification per the schedule outlined in Table 37.

Table 37. ZEV fleet milestones by milestone group and year

Percentage of vehicles that must be zero-emission	10%	25%	50%	75%	100%
Milestone Group 1: Box trucks, vans, buses with two axles, yard tractors, light-duty package delivery vehicles	2025	2028	2031	2033	2035+
Milestone Group 2: Work trucks, day cab tractors, buses with three axles	2027	2030	2033	2036	2039+
Milestone Group 3: Sleeper cab tractors and specialty vehicles	2030	2033	2036	2039	2042+

Source: CARB Advanced Clean Fleets Regulation Summary (CARB, 2023b)

The PET can only model a portion of these high-priority fleet compliance mechanisms. First federal fleets are not explicitly modeled in the PET so we ignore those impacts. Second, regarding high priority fleets, data on fleet revenues are not available to identify the portion of fleets subject to these rules. Instead, we used two sources of data identify high priority fleets by fleet size. For line-haul and construction vehicles, CARB staff used internal DMV data along with Dun and Bradstreet entity information to obtain medium and heavy-duty fleet size distributions for calendar year 2020 that we collapsed into the fleet size distributions shown in Table 38. Table 39 provides similar data for drayage trucks in the state using internal data from the California ARB Equipment Registration (ARBER) system (CARB, 2023c), which registers all in-use drayage trucks in California. Because the previously mentioned drayage fleet requirements apply to all fleets, regardless of size, they will supersede the high priority fleet requirements. For completeness, however, we do model fleet size drayage so we can track technology distribution over time by fleet size since electricity rates differ by fleet size in this model as well as model differential incentive policy such as HVIP, that offers higher incentives for small fleets.

Table 38. Fleet size distributions for construction and line-haul trucks

Fleet size	# fleets	% fleets	T4-T7 counts	(%)
1	783,860	80.78%	783,860	18.26%
2-10	176,822	18.22%	512,797	35.13%
11-20	5,918	0.61%	83,908	10.06%
21-50	2,787	0.29%	83,609	11.26%
51-100	623	0.06%	42,893	6.43%
101+	405	0.04%	149,038	18.87%
Total	**970,415**	**100.00%**	**1,656,105**	**100.00%**

Source: Provided by CARB staff using California DMV data and Dun & Bradstreet business entity data.

Table 39. Fleet size distributions for drayage trucks

Fleet size	# fleets	% fleets	drayage (T6-T7) counts	(%)
1	7,340	55.90%	11,044	7.86%
2-10	4,315	32.86%	19,560	13.92%
11-20	634	4.83%	9,290	6.61%
21-50	494	3.76%	15,497	11.03%
51-100	194	1.47%	12,713	9.05%
101+	154	1.17%	72,396	51.53%
Total	**13,130**	**100.00%**	**140,500**	**100.00%**

Source: Provided by CARB staff using California ARB Equipment Registration (ARBER) data (CARB, 2023c).

Of the two compliance mechanisms for priority fleets, the ZEV milestones option is more difficult to represent because it applies at the individual fleet level, requiring fleets to hit ZEV percentage targets within their fleets according to the schedule in Table 37. Modeling this effectively would require modeling individual fleets in addition to individual trucks. While this would be a potentially interesting addition, it would require modeling individual firms over time, which would expand the scope of the model unreasonably. Instead, we focus on the model year schedule, and model a restricted choice set by partitioning the new vehicles added to each vocational fleet each year into fleet sizes according to the fractions in Table 38. We model priority fleets as follows:

- From 2024 onward, construction/line-haul fleet sizes greater than 50 have their choice set restricted to ZEVs only.
- From simulation year 2024 onward:
    - we limit the fuel choice for new construction/line-haul with fleet sizes greater than 50 trucks to BEV or FCEV.
    - we limit the fuel choice for construction/line-haul with fleet sizes greater than 50 trucks to BEV or FCEV. However, as above, since the market for used ZEV trucks will lack inventory (particularly from out of state) for some time, we convert any used truck additions predicted by the gain shares into new vehicle purchases. This conversion is carried out until 2030 after which we assume there will be a functioning used vehicle market for ZEVs.

The final component of Advanced Clean Fleets applies to *state and local agencies*, requiring "state and local government fleets…to ensure 50 percent of vehicle purchases are zero-emission beginning in 2024 and 100 percent of vehicle purchases are zero-emission by 2027, or following the ZEV Milestones Option in Table 37. Public class 8 trucks are captured by the "T7 Public" EMFAC category, which is not among the EMFAC categories included in the PET (per Table 35), so this mechanism is not currently represented, but could be if T7 Public was added to the model later.

4.2 PET off-road equipment model

The development of the off-road model followed the design of the on-road model closely. Necessary modifications in methodology (e.g. equipment cost estimation, incentives, etc.) and data were introduced to adapt the on-road model for off-road equipment. One major difference is that limitations in available data limit the ORE model to statewide scope only, as opposed to the regional breakdowns in the on-road model. The ORE module is also limited to only modeling diesel equipment and battery-electric equipment.

The spectrum of off-road equipment covers a lot more equipment types, and similar data from zero-emission equipment operation is not generally available. For conducting any such analysis, a general approach that can utilize available data, and applies to all types is needed. In this work, this is achieved by using activity data of diesel equipment for estimating costs for battery electric equipment through a general framework. Using this approach, we developed the PET TCO model for the equipment types identified in Section 2.5.1. Each of the studied types also has horsepower bins (HP bins), along which equipment activity and costs vary. We used the availability of data to determine which specific bins to consider as described below and shown in Table 40.

4.2.1 ORE data sources

Activity data for the studied equipment types was collected from the EMFAC2021 database for calendar years 2020-2050 (CARB, 2021a). This data provides population, activity, and emission data across calendar years for multiple HP bins and model years of equipment.

This study focuses on heavy-duty equipment, and thus data for HP bins 25 and below are removed, as those pertain to compact equipment. The EMFAC2021 data also has an HP bin of 9999, which basically includes any equipment with HP rating over 750. It was removed too, as it can lead to overestimation. Data for equipment using fuels other than diesel was removed as those are not the focus of this study. Equipment age in each calendar year was calculated as the difference of that calendar year and equipment model year:

$$\text{age} = \text{calendar year} - \text{model year} \qquad \textbf{Eq. 34}$$

Data for only the new equipment (having ages -1 and 0) in each calendar year were taken. The age of -1 exists because the next model year generally becomes available in advance, e.g., model year 2021 is available in calendar year 2020. Data with zero equipment population were also removed. After all this filtration, we retained 60 equipment type/HP bin combinations for modeling during calendar years 2020-2050 as shown in Table 40.

Table 40. Equipment types and HP bins included in the PET ORE model

Equipment type	#	HP bins
Agricultural - Agricultural Tractors	7	50, 75, 100, 175, 300, 600, 750
Cargo Handling Equipment - Port Forklift	6	50, 75, 100, 175, 300, 600
Cargo Handling Equipment - Port RTG Crane	4	175, 300, 600, 750
Cargo Handling Equipment - Port Truck	6	50, 75, 100, 175, 300, 600
Cargo Handling Equipment - Port Yard Truck	3	175, 300, 600
Construction and Mining - Crawler Tractors	6	50, 100, 175, 300, 600, 750
Construction and Mining - Excavators	7	50, 75, 100, 175, 300, 600, 750
Construction and Mining - Graders	6	50, 75, 100, 175, 300, 600
Construction and Mining - Rubber Tired Loaders	6	50, 100, 175, 300, 600, 750
Construction and Mining - Skid Steer Loaders	4	50, 75, 175, 300
Construction and Mining - TractorsLoadersBackhoes	5	50, 100, 175, 300, 600
Total	**60**	

4.2.2 The ORE TCO module

The literature discussed previously at the top of Section 4 focused on TCO analyses of on-road EVs. Similar analyses for off-road electric equipment are less common. A technical report from the National Renewable Energy Laboratory, published in 2013, evaluated TCO for hydrogen fuel cell forklifts, using data collected from projects deploying these equipment at eight commercial warehousing and distribution centers (Ramsden, 2013). With that said, recent work by Boriboonsomsin et al. (2022) provides a useful framework.

The cost components considered here are presented in Figure 55 and include vehicle and infrastructure capital costs, maintenance costs, fuel costs as well as residual value at end of owner lifetime and any incentives available for capital costs (e.g., the CORE program) or fuel costs (like LCFS). These cost components were calculated for each equipment type and HP bin in each calendar year, for both battery electric and diesel equipment only.

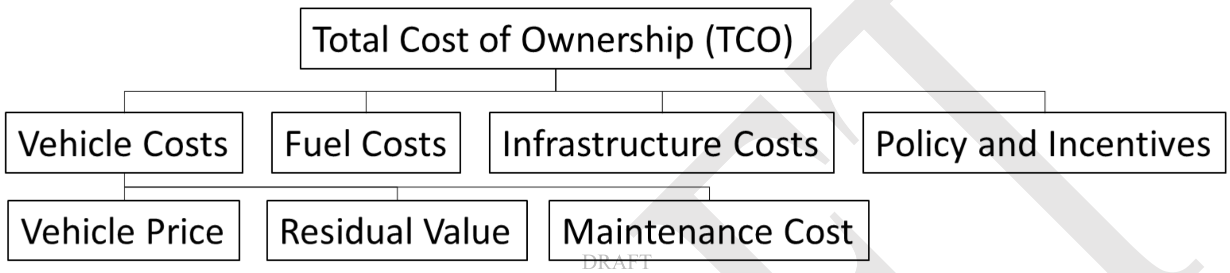


Figure 55. Cost elements for ORE TCO model

This framework is compatible with the TCO methodology used for the on-road HDV module, which simplifies implementation of the PET as code can be consolidated.

4.2.2.1 Equipment Costs

We estimated equipment retail prices using equipment production costs developed earlier in Section 2.5.2. Recall that these are based on energy requirements obtained from the OFFROAD database, which were converted into component costs for batteries (for electric equipment) and fuel tanks (for diesel equipment). Following the baseline assumptions for on-road equipment, these were adjusted with retail markup rates of 40% in 2021-2029 and 35% in 2030-2050 over the manufacturing costs (Sharpe & Basma, 2022).

4.2.2.2 Residual Value, Maintenance and Repair Costs

Parameters such as residual values and maintenance and repair cost, which depend on the vehicle usage, needed to be distinguished between two major categories of equipment studied. One general category comprised of the majority of equipment types, the other one contained trucks (e.g. port yard truck). We address each in turn below.

Equipment was assumed to be purchased with residual values at the end of first-owner life included to offset the capital costs. Generally, the residual value depends on vehicle age and usage. For all equipment types, the age is already determined by the equipment bin (Eq. 34 above).

Usage is determined differently for general and truck types, but they both start with the annual vehicle operating hours ($aVOH$) from the OFFROAD database. For equipment type j and HP bin k in year m we used a similar approach to obtaining a representative annual estimate for operating hours as we did to determine the fuel consumption in our component cost calculations in Section 2.5 (Eq. 7) whereby we take the maximum over all years of the $aVOH$ projected for new equipment:

$$aVOH_{j,k,m} = \max_{\text{all years}}(aVOH_{j,k,m,age=-1}, aVOH_{j,k,m,age=0}) \qquad \textbf{Eq. 35}$$

To compute residual values for general equipment types we determined the residual value percentage (percentage of initial value) by computing the linear combination of two residual value component functions estimated by Zong (2017), with one based upon age and one based upon operating hours as follows (and see Figure 56):

$$res_{j,k,m} = res_A(l) + res_H(aVOH_{j,k,m} \times l) \qquad \textbf{Eq. 36}$$

$$res(A) = -62.4 \times exp(-0.2366A) + 62.96 \times exp(-0.2351A); \qquad \textbf{Eq. 37}$$

$$res(H) = 6.408 \times exp(-5.837E-5 \times H) - 6.008 \times exp(-5.739E-5 \times H) \qquad \textbf{Eq. 38}$$

where,

l = equipment age for equipment type j and HP bin k in year m, which for TCO is assumed to be a user-defined parameter for first owner life, with a default of 10 years (Un-Noor et al., 2023).

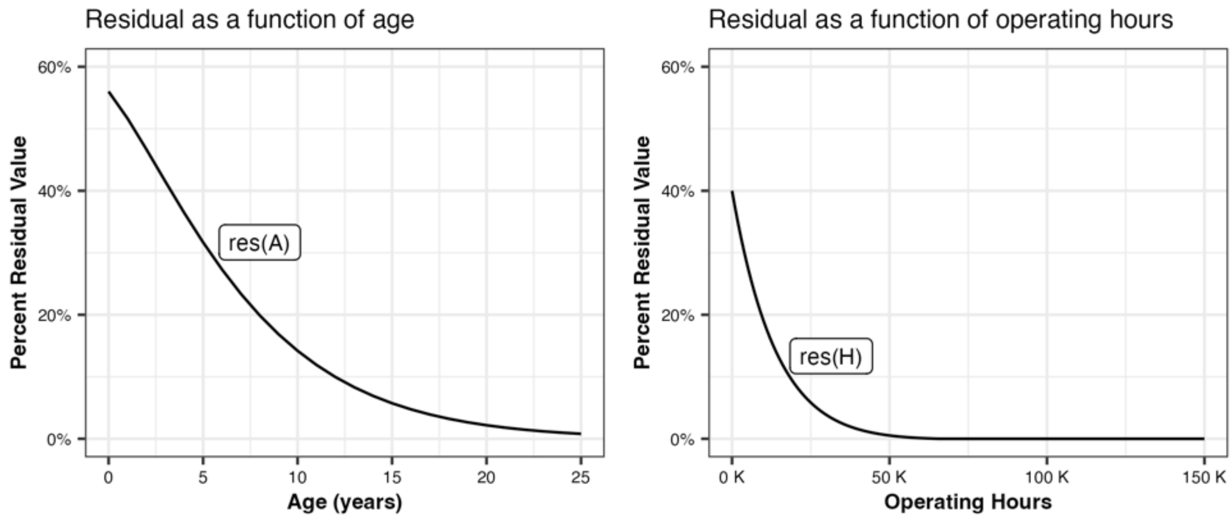


Figure 56. Residual value components for general equipment category

Source: Residual value functions as a function of age and operating hours fit to observed data (Zong, 2017). Adding res(A) and res(H) produces the residual value percentage estimate.

For the truck category, vehicle miles travelled (VMT) was the usage indicator. Annual VMT was calculated by converting the annual operating hours obtained from Eq. 35 using the median speed for yard tractors, which was found as 4.22 miles per hour from activity data (Johnson, 2021).

$$aVMT_{j,k,m} = aVOH_{j,k,mz}/4.22 \qquad \textbf{Eq. 39}$$

We then followed ICF (2019), using the procedure outlined for HDV in Section 4.1.3.1. Again, we computed the residual value rate of equipment type *j* and HP bin *k* at the end of first-owner life using the following (which is the same as Eq. 19), and applying the parameter values for drayage from Table 30:

$$res_{j,k} = exp\ (A_{i,j} \times l_j + M_{i,j} \times \frac{aVMT_j \times l_j}{1000}) \qquad \textbf{Eq. 40}$$

where,

$res_{i,j}$ - Residual value rate of technology *i* for vocation *j* at the end of first-owner life;

exp $(A_{i,j})$ - percentage price retention based on vehicle age of technology *i* for vocation *j*=drayage: 0.9113

exp $(M_{i,j})$ - percentage price retention based on vehicle mileage (in 1000 miles) of technology *i* for vocation *j* = drayage: 0.9991

$aVMT_j$ - Annual vehicle miles traveled for vocation j;

l_j - First-owner life for vocation j in years, assumed to be 10 years for equipment.

Per-hour maintenance and repair costs calculations also differed between general equipment and truck types. For equipment types in the general category, they were calculated based on annual operating hours using a relationship computed by Bayzid (2014) from data collected on 150 HP graders to determine maintenance costs per hour as a function of aVOH:

$$MC\_perhour_{j,k,m} = 6E-8 \times {aVOH_{j,k,m}}^2 + 3E-5 \times aVOH_{j,k,m} + 9.4091 \quad \textbf{Eq. 41}$$

Total annual maintenance cost was then obtained as:

$$AVMC_{j,k,m} = aVOH_{j,k,m} \times MC\_perhour_{j,k,m} \quad \textbf{Eq. 42}$$

For the truck types, annual maintenance cost was obtained as a function of VMT:

$$AVMC_{i,j,k,m} = aVMT_{j,k,m} \times MC\_permile_i \quad \textbf{Eq. 43}$$

where the per mile maintenance costs followed values identified by ICF (2019) for class 8 drayage as $MC\_permile_{BE} = 0.17$, $MC\_permile_{ICE} = 0.2$.

4.2.2.3 Total Vehicle Costs

Equipment purchases are assumed to be financed and paid through annual payments for a given term. The financing rate and term are user inputs with defaults of 3% and 10 years, respectively. Total vehicle costs were estimated by the sum of the net present value of each cost component. The tax was assumed to be 2% (CDTFA, 2023). As off-highway vehicles do not require regular vehicle registration, licensing fees were not considered. Thus, we compute the annual vehicle purchase cost and total vehicle costs as follows:

$$AVPC_{i,j,k,m} = \frac{VC_{i,j,k,m} * (1 + R_m + FET) * r1}{1 - (1 + r1)^{-t1}} \quad \textbf{Eq. 44}$$

$$TVC_{i,j,k,m} = \left(AVPC_{i,j,k,m} + AVIC_j + AVMC_{j,k,m}\right) \times \frac{1 - (1 + r_{disc})^{-l}}{r_{disc}} - \frac{VC_{i,j,k} * res_{j,k,m}}{(1 + r_{disc})^l} \quad \textbf{Eq. 45}$$

where,

$AVPC_{i,j,k,m}$ - Annual vehicle purchasing cost of technology i for equipment type j and HP bin k in year m

$VC_{i,j,k,m}$ – Vehicle capital costs of technology i for equipment type j and HP bin k in year m

R – Sales and use tax rate = 0.095

FET - Federal exercise tax = 0.12

$r1$ - Vehicle financing annual percentage rate = 0.03; a user input

$t1$ - Vehicle financing term in years = 10; a user input

$TVC_{i,j,k,m}$ - Total vehicle cost of technology i for equipment type j and HP bin k in year m

$AVMC_{j,k,m}$ – Annual vehicle maintenance cost for equipment type j and HP bin k in year m

$AVIC$ - Annual insurance costs = $3,000 (Insuranks.com, 2023)

r_{disc} – Discount rate = 0.01 (Boriboonsomsin, Un-Noor, Scora, Wu, et al., 2022)

l – First-owner life in years = 10

$res_{j,k,m}$ – Residual value for equipment type j and HP bin k in year m

4.2.2.4 Fuel Costs

Fuel costs were estimated on the annual basis by multiplying annual fuel consumption by fuel prices. Fuel costs for all fuels except electricity were sourced from the TRACE model outputs described in Section 1.6. Electricity rates were taken as yearly average across Californian utilities. Total fuel costs were estimated by the sum of the net present values of annual fuel costs throughout the first-owner life. The diesel annual fuel consumption (*aFC*) for equipment type j and HP bin k in year m was calculated first:

$$aFC_{Diesel,j,k,m} = \max\left(aFC_{Diesel,j,k,m,age=-1}, aFC_{Diesel,j,k,m,age=0}\right) \times N \qquad \textbf{Eq. 46}$$

where *N* is the number of operating days in a year, again assumed to be 186 as in the vehicle component cost calculations in Section 2.5.

The energy content of the consumed fuel was then converted into GJ by multiplying with 0.14652 (USGal/GJ), to use per-GJ costs to calculate annual fuel costs:

$$AFC_{ICE,j,k,m,Diesel} = aFC_{ICE,j,k,m} \times 0.14652 \times P_{m,Diesel} \qquad \textbf{Eq. 47}$$

For electric equipment, electric energy consumption was calculated considering diesel engine and electric motor efficiencies (as done for battery sizing above), then following the same procedure:

$$AFC_{BE,j,k,m,Electricity} = aFC_{ICE,j,k,m} \times \frac{0.35}{0.72} \times 0.14652 \times P_{m,Electricity} \qquad \textbf{Eq. 48}$$

where, $P_{m,Diesel}$ and $P_{m,Electricity}$ are fuel price per GJ in year m.

Total fuel cost of fuel n for technology i, equipment type j and HP bin k in year m:

$$TFC_{i,j,k,m,n} = \sum_{1}^{l} \frac{AFC_{i,j,k,m,n}}{(1 + r_{disc})^{l}} \qquad \textbf{Eq. 49}$$

4.2.2.5 Infrastructure Costs

As with on-road vehicles, infrastructure capital and maintenance costs were obtained from ICF (2019) as previously summarized in Table 33. Electric equipment infrastructure equipment cost was assumed to be $50,000, installation costs $55,000, maintenance costs of $5,500 per year, infrastructure lifespan of 10 years and vehicle-to-infrastructure ratio of 1. We assumed that infrastructure capital costs were financed throughout the infrastructure lifespan. Total infrastructure costs were estimated as the net present value of annual capital and maintenance costs throughout the first-owner life. Infrastructure costs for diesel equipment was assumed to be 0, thus the equations below only need to be applied for electric equipment infrastructure costs.

$$AIC_{n} = \frac{IC_n \times (1 + R) \times r3}{1 - (1 + r3)^{-t3}} \qquad \textbf{Eq. 50}$$

$$TIC_{n} = (AIC_{n} + AIMC_n) \times \frac{1 - (1 + r_{disc})^{-l}}{r_{disc} \times r_{vti}} \qquad \textbf{Eq. 51}$$

where,

AIC_n - Annual infrastructure capital cost of fuel n

IC_n - Infrastructure capital cost of fuel n

R – Sales and use tax rate = 0.095

$r3$ - Infrastructure financing annual percentage rate = 0.03 by default

$t3$ - Infrastructure financing term in years (assumed to be the same as the infrastructure lifespan) = 10

TIC_n - Total infrastructure cost of fuel n

$AIMC_n$ - Annual infrastructure maintenance cost of fuel n

r_{disc} - Discount rate = 0.01 (Boriboonsomsin, Un-Noor, Scora, Wu, et al., 2022)

l - First-owner life in years = 10

r_{vti} - Vehicle-to-infrastructure ratio (used for splitting costs among vehicles)

4.2.2.6 Policy and Incentives

Policy and incentives considered in the ORE TCO module include Clean Off Road Equipment Voucher Incentive Project (CORE) and projected LCFS credits and revenue. Only battery electric equipment was assumed to be eligible to receive incentives. Thus, incentive values for diesel equipment were assumed to be $0. CORE incentives were calculated as the price premium of battery electric equipment compared to diesel equivalents (with a maximum of $500,000 per piece of equipment):

$$CORE_{i,j,k,m} = \min(\$500000, VC_{BE,j,k,m} - VC_{ICE,j,k,m}) \quad \textbf{Eq. 52}$$

Following the on-road analysis, we assumed an average utility incentive (UI) of $42,750 based upon the average value utility incentives identified in Figure 4. Annual LCFS credit for battery electric equipment was calculated using energy usage and credit provided per unit energy:

$$aLCFS_{i,j,k,m,n} = aFC_{ICE,j,k,m} \times \frac{0.35}{0.72} \times 0.14652 \times C_m \quad \textbf{Eq. 53}$$

where C_m is per GJ LCFS credit in dollars in year m.

4.2.2.7 TCO Estimation

The total cost of ownership was estimated as:

$$TCO_{i,j,k,m,n} = TVC_{i,j,k,m} + TFC_{i,j,k,m,n} + TIC_n - CORE_{i,j,k,m} - UI - \sum_{1}^{l} \frac{aLCFS_{i,j,k,m,n}}{(1 + r_{disc})^l} \quad \textbf{Eq. 54}$$

where,

$TCO_{i,j,k,m,n}$- Total cost of ownership of technology i and fuel n for equipment type j and HP bin k in year m

$TVC_{i,j,k,m}$ - Total vehicle cost of technology i for equipment type j and HP bin k in year m

$TFC_{i,j,k,m,n}$ - Total fuel cost of fuel n for technology i and fuel n for equipment type j and HP bin k in year m

TIC_{n} - Total infrastructure cost of fuel n

$CORE_{i,j,k,m}$ – CORE incentive amount for technology i for equipment type j and HP bin k in year m

$aLCFS_{i,j,k,m,n}$ - Annual LCFS revenue for technology i and fuel n for equipment type j and HP bin k in year m

r_{disc} - Discount rate

l - First-owner life in years

For representative results from the TCO module, please see the ORE impacts module discussion in Section 4.4.

4.2.3 Equipment turnover module

The development the ORE fleet turnover model followed the same logic as the HDV fleet turnover model described in Section 4.1.4, except that it is applied statewide rather than by region. As with the HDV model, 20 years of active equipment stock were represented, beginning with the active equipment stock from the OFFROAD2021 database in the baseline year of 2020. Retirement rates were similarly drawn from average rates for 2000-2019, with future year fleet growth rates tracking those from OFFROAD2021. However, the relative sparsity of many equipment populations in OFFROAD's stratified bins produces unreliable population fleet turnover forecasts. Additional refinements to the ORE turnover model are needed, which may include modeling fewer stratifications to account for these smaller populations. As such, completion of the ORE turnover is left for future work.

4.3 HDV Impacts module

The impacts module is applied to the results of the HDV and ORE fleet turnover model to generate the program performance metrics. The following subsections discuss each of the components of the impact module and provide some illustrative results for a same PET case. Additional results will be provided in Section 5 as we illustrate how to deploy the PET to develop incentive strategies.

4.3.1 HDV TCO estimates

The TCO model is the primary driver of fleet transition, so clarity on how it forecasts costs is critical for understanding how the attractiveness of different vehicle technologies over time evolve as the market interacts with regulatory and incentive policies. The impact module generates two main outputs that demonstrate TCO evolution at varying levels of detail.

4.3.1.1 Statewide TCO estimates

Statewide TCO estimates over time are generated by computing the statewide weighted averages of TCO for each vocation and technology across all regions in each year:

$$\overline{TCO}_{i,j,k,n} = \left(\sum_{\forall m} TCO_{i,j,k,m,n} \, w_m \right) / \sum_{\forall m} w_m \qquad \textbf{Eq. 55}$$

where,

$\overline{TCO}_{i,j,k,n}$ is the average statewide TCO of technology i using fuel type n for vocation j in year k

w_m is the weight of region m. We use the base year (2020) total truck population in each region from EMFAC as the weight.

The PET generates a plot of the evolution of $\overline{TCO}$ over time by fuel type and vocation as estimated by the model, an example of which shown in Figure 57. In this base case, no incentives are modeled, and the vehicle cost evolution and electric rates are assumed to be neutral.

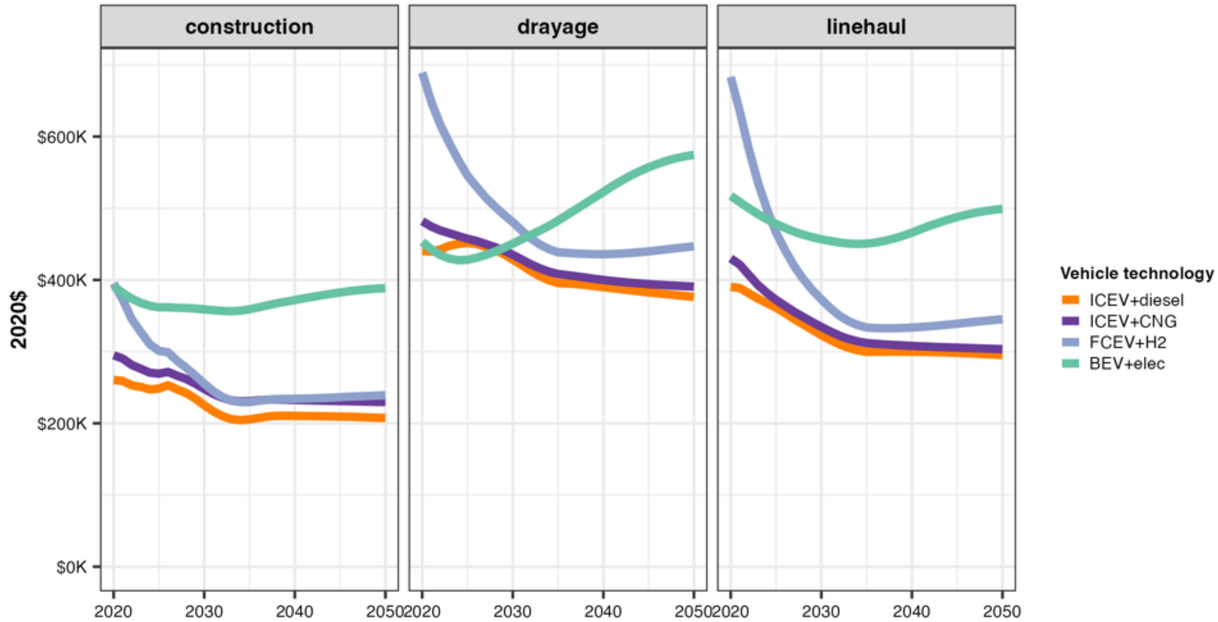


Figure 57. Example of TCO over time as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec.

We can also view the discounted cash flow for vehicle purchases as shown in Figure 58 for an example scenario in 2025. Here, we model a vehicle purchase with a loan term of 5.25 years. The first year sees a high cost in fees, which includes taxes in this rendering, and afterwards the amortized vehicle purchase cost through the first five years. The vehicle payment is slightly higher in year 1 due to an assumed 10% down payment. We can also see the vehicle depreciation tax benefits represented in the first four years. The differential fuel costs are highlighted in these plots as well, with hydrogen clearly the most expensive fuel at this stage in 2025. LCFS credits help to further offset fuel costs for the duration of the BEV vehicle's life. The large negative downturn in the final year is the residual value of the vehicle as it is sold. No purchase incentives are modeled here, which explains why, as we look at Figure 59's rendering of cumulative cash flows over time for these same vehicles, the BEV+elec vehicle's TCO is consistently higher than the other alternatives. We will explore the role of incentives in detail later in Section 5.

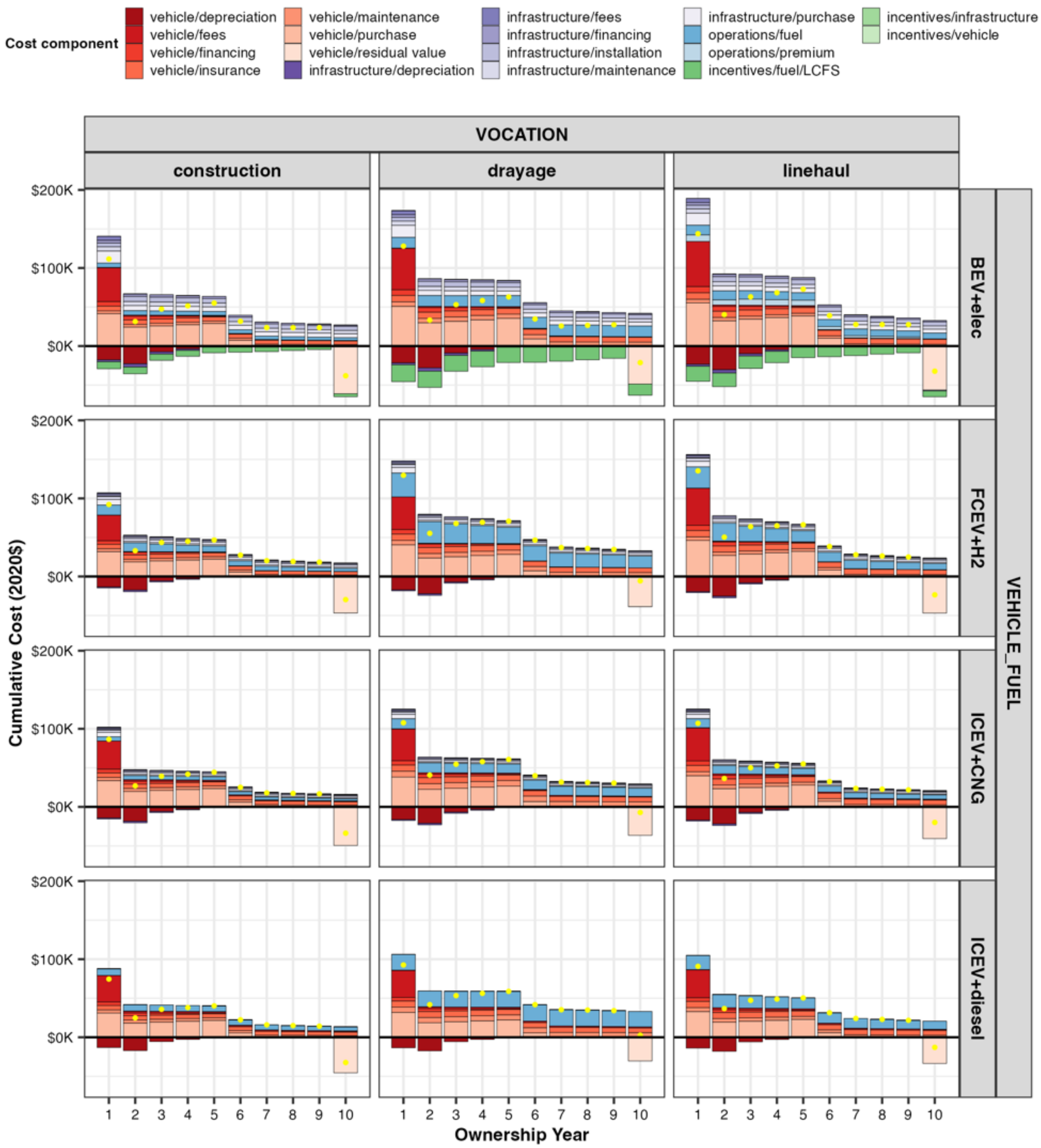


Figure 58. Example of discounted cash flow for vehicle purchases as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec. A 10-year first ownership life is assumed.

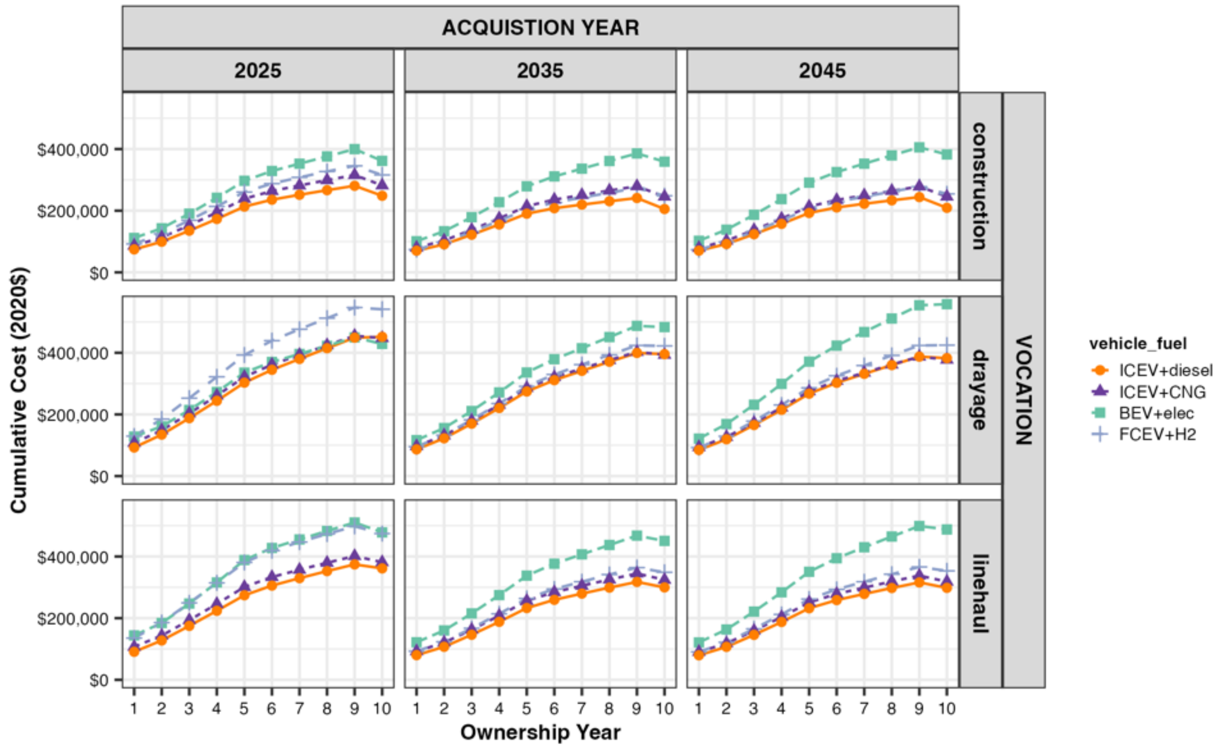


Figure 59. Example of cumulative cash flows for truck purchases as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec. A 10-year first ownership life is assumed.

4.3.1.2 Regional TCO estimates

The PET interface allows the user to select specific regions for which to generate plots of TCOs computed for each vocation and technology in that region. For each region, sub plots can be generated for the specified years (2025, 2035, and 2045 by default).

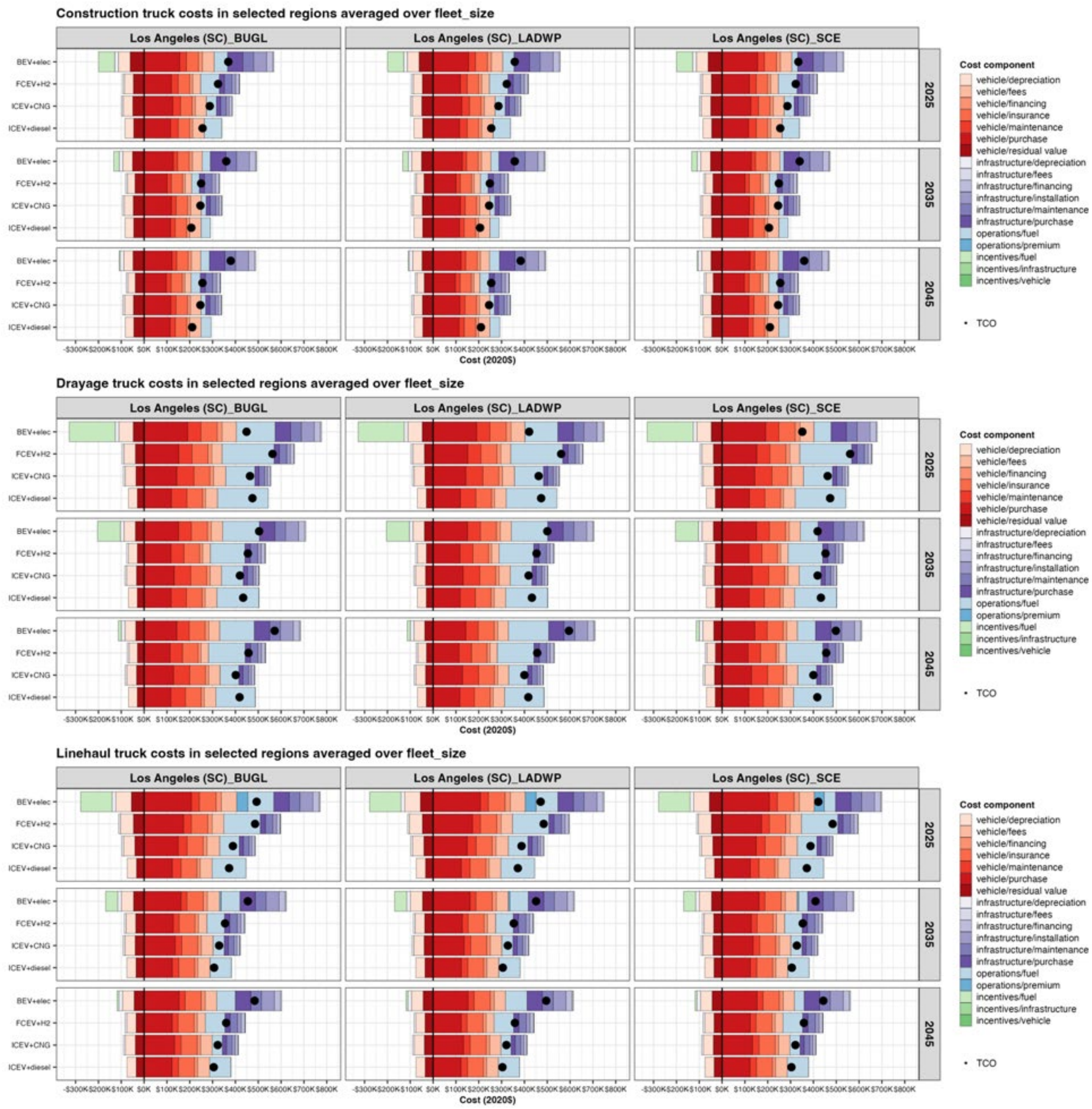


Figure 60 shows the TCO components for the three vocations for three different utility areas in Los Angeles. For each vocation, year, and region combination, the specific cost components that make up the TCO of each technology type are shown. These include vehicle costs (purchase, fees, and maintenance) and value (residual value), infrastructure costs (purchase, installation, and maintenance), fuel purchase costs, incentives (LCFS, vehicle purchase incentives from HVIP, and utility incentives). The operations premium associated BEVs is also included.

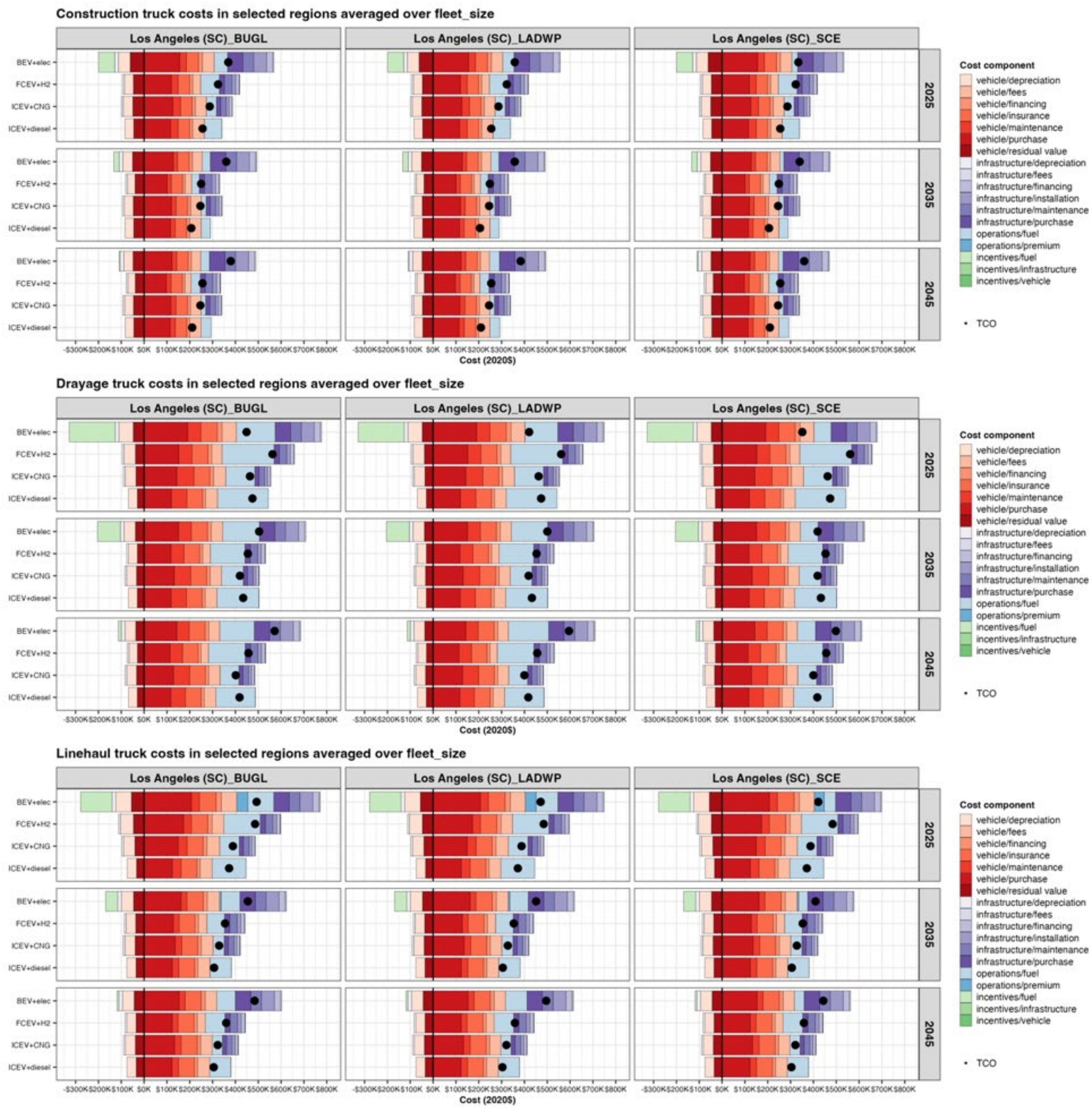


Figure 60. TCO components in three utility areas in Los Angeles as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec. The significant impact of LCFS credits can be seen in 2025 for BEV+elec trucks, which is particularly pronounced in drayage operations, which have the highest VMT for the vehicles modeled.

4.3.2 Technology uptake by fleets

The interaction between the TCO model and the fleet transition model described in Section 4.1.5 produce specific outputs of interest. First, by applying the choice model on the TCOs for each region we can compute technology shares as shown in Figure 61. The variable impact of regulation on different vocations and fleet sizes is evident in the removal of non-ZEV options for large construction and linehaul fleets as well as for all drayage fleets. The gradual removal of LCFS credits for BEV vehicles in this scenario leads FCEV becoming more attractive over time in all vocations.

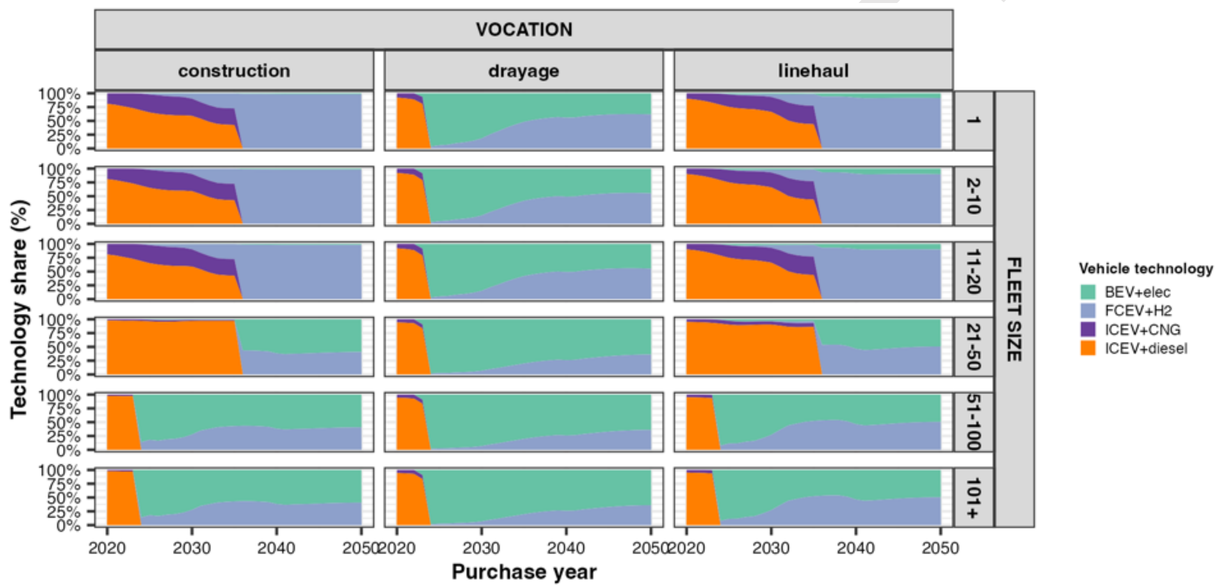


Figure 61. Technology shares over time by fleet size as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec.

The impact of these technology shares on fleet uptake is shown in plots of new and total truck stock by fuel technology as seen in Figure 62, which shows how the technology shares manifest in fuel technology splits in new vehicle purchases. Note that the “spikes” in the new truck sales are largely driven by retirements forced by policy. The new diesel truck sales in 2021 and 2023 stem from modeling of the Truck and Bus regulation’s forced retirements of older trucks in these years. There is no corresponding spike in 2024 when the ACF regulation mandates that many fleets (drayage and large fleets) can only purchase ZEVs from that year forward.[52] This is because the truck turnover model is governed by a requirement to ensure the total truck stock meets the average growth rate derived from truck populations during 2000 through 2019. Thus, when there are additional retirements forced by regulatory policy those trucks must be replaced in order to meet the growth rate target, which results in these discontinuities.

[52] We acknowledge that under the ZEV Milestones option, ACF does not strictly mandate ZEV replacements, but as previously noted the PET cannot model the fuel splits of individual fleets in a way tha would allow the ZEV Milestones option to be represented.

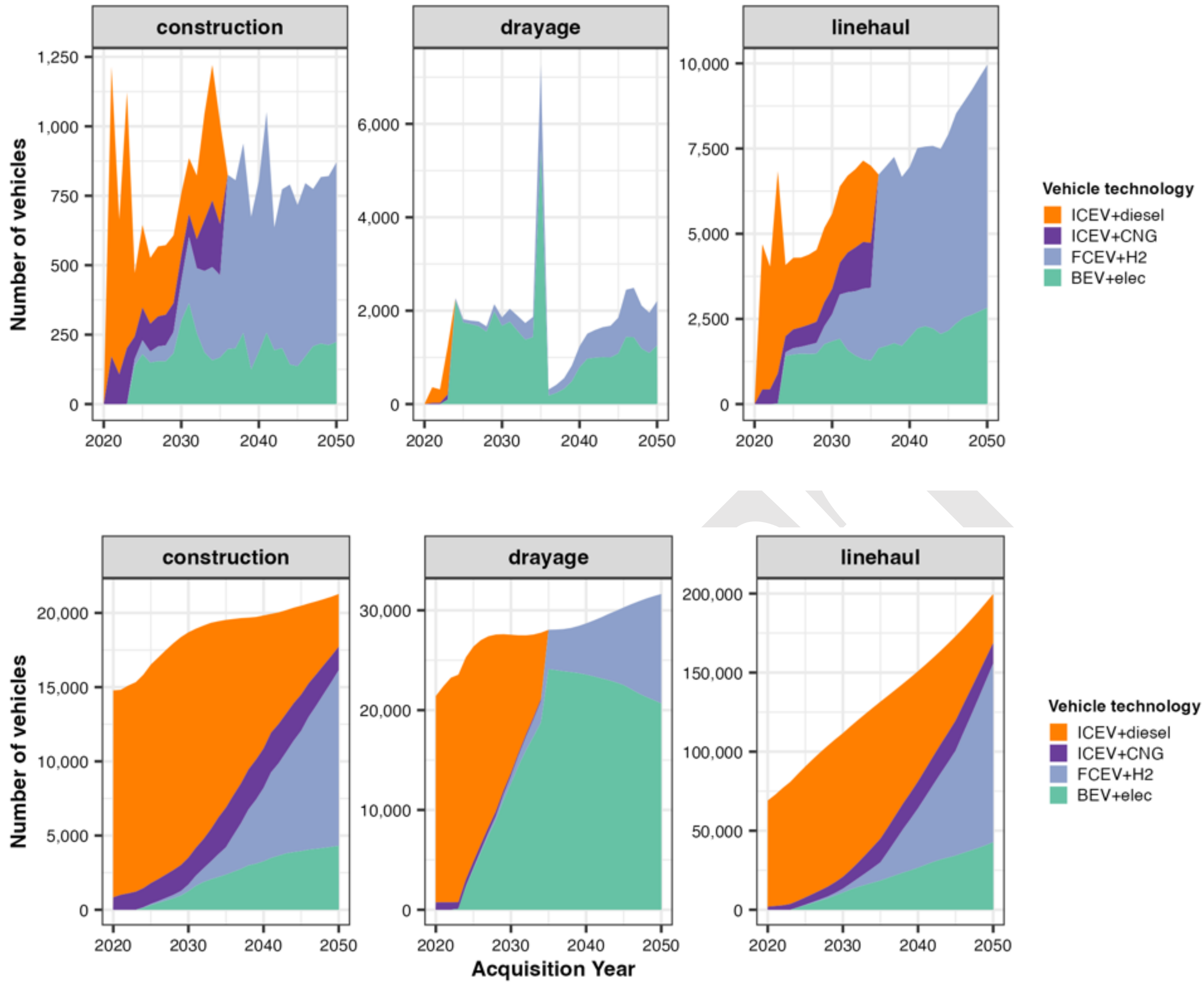


Figure 62. Projected new truck sales and truck stock as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec. The forced retirements from the ACF regulation are apparent, particularly for drayage in 2035. Note that we assume the fleet population tracks the growth rates in EMFAC. If there are forced retirements (as in 2035) the assumption means that the forced retirements cause a sales spike to keep stock tracking the growth rate. Note that the vertical scales differ between the plots horizontally.

4.3.3 Emissions impact analysis

With the estimated vehicle technology splits, the PET generates VMT by vehicle technology.

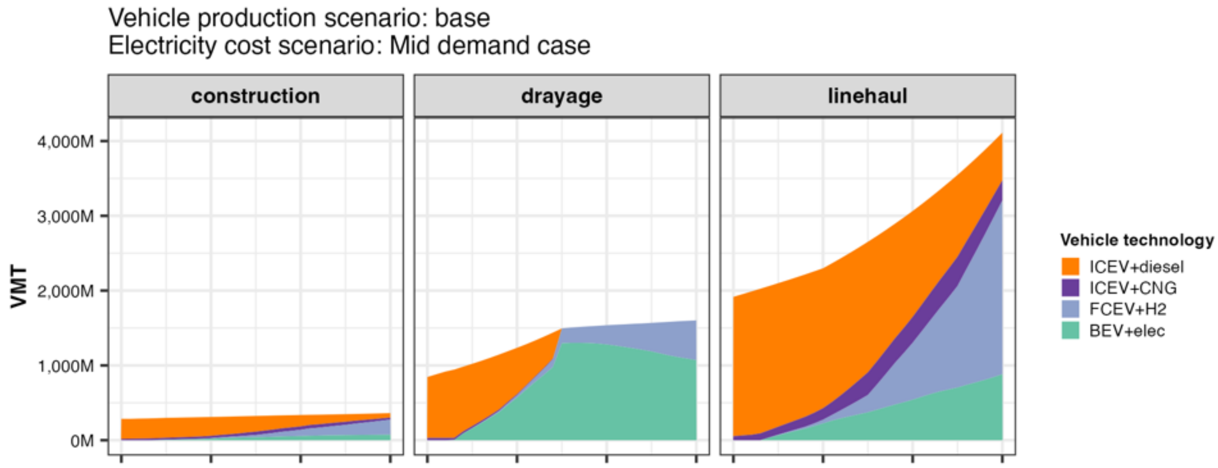


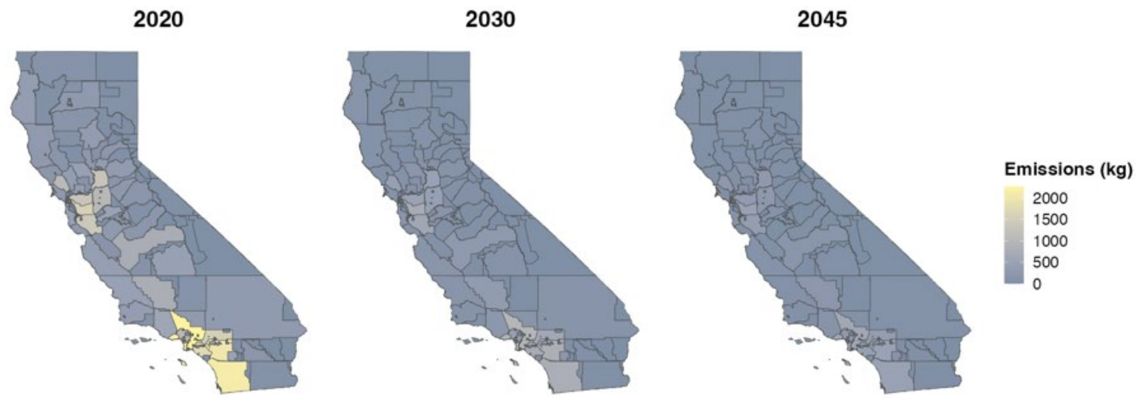
Figure 63. Projected VMT shares as modeled in the PET impact module

Notes: Base scenario shown with moderate vehicle development assumptions and mid demand electricity costs. No vehicle or infrastructure incentives are modeled, though LCFS credits are modeled for BEV+elec.

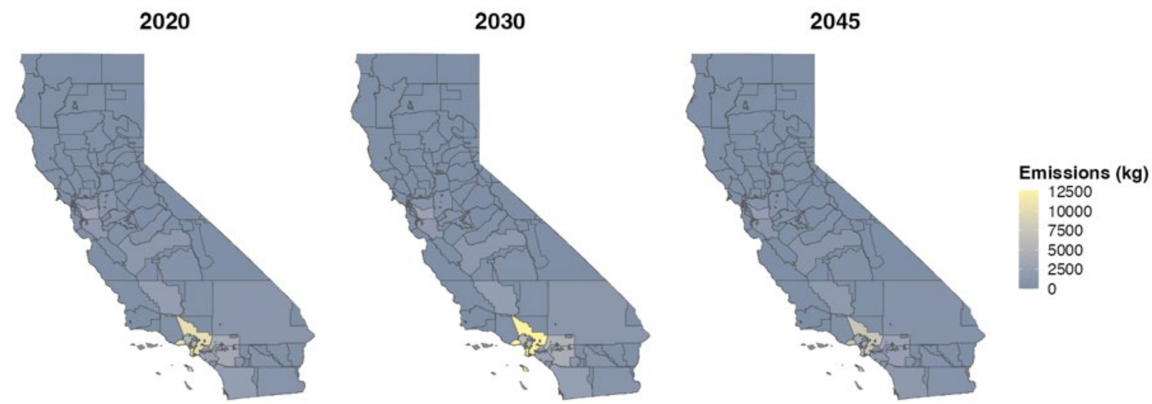
Emissions impacts are computed by applying the emissions rates (ER) from EMFAC2021 (v1.0.1) for the pollutants of interest to the estimated VMT in each region *m* for vehicles in vocation *j* of model year *n* using fuel type *i* as shown in Eq. 56.

$$pollutant_{i,j,k,m,n} = \mathrm{ER}_{\mathrm{pollutant,i,j,k,m,n}} \times VMT_{i,j,k,m,n} \quad \textbf{Eq. 56}$$

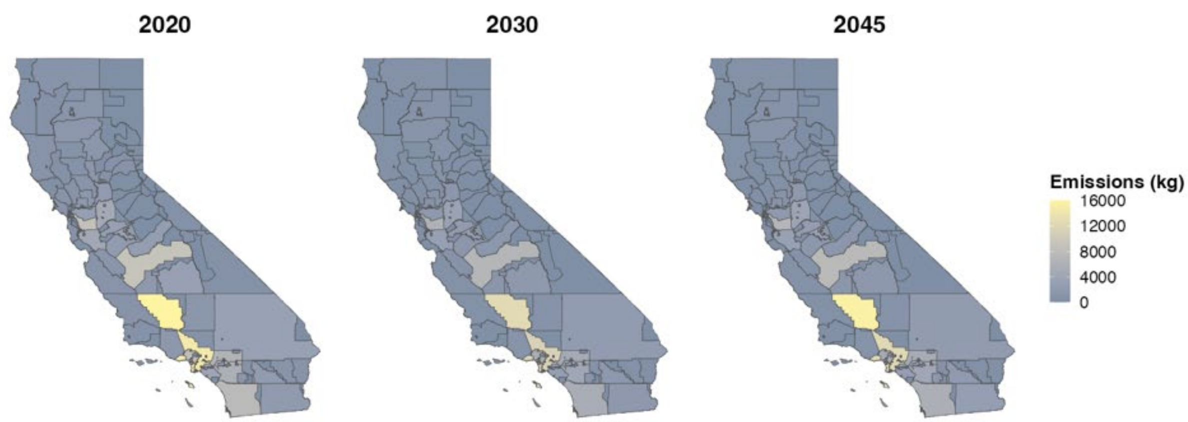
Though the VMT by linehaul trucks is approximately double that of drayage, the spatial distribution of their impacts are notable, as illustrated in Figure 64, where the drayage emissions are concentrated in the LA basin at comparable magnitudes to the emissions of linehaul, which are more dispersed, with highest concentrations in the San Joaquin Valley and the LA basin, but impacts throughout the state.



(a) Construction



(b) Drayage



(c) Linehaul

Figure 64. Visualization of PM2.5 emissions from (a) construction, (b) drayage, and (c) linehaul as modeled in the PET impact module

Note: The PET produces similar plots for PM10, NO_X, CO and GHG. Note that the emissions scale varies between each sub plot.

4.3.4 Workforce impact analysis

This section explains the modeling approach to obtaining the employment impact of investment in different vehicle technologies and sustainment infrastructure, as well as the tools used. The employment impact is measured on a per-unit basis, i.e., the number of Full-time Equivalent jobs (FTEs) per one million dollars invested, or FTE/$1 mil. There are 11 investments modeled: the vehicle cost, fuel/electricity cost and vehicle maintenance cost of ICEV, FCEV and BEV, and two types of sustainment infrastructure, i.e., EVSE and H2 Refueling.

4.3.4.1 Input-output (I-O) Analysis using IMPLAN

Input-output analysis is a generally accepted approach to economic impact analysis (EIA) that estimates based on historical data the total impact of any change or “shock” to the economy of a defined region, e.g., an injection of funds via public investment programs, within a defined period of time. Such impacts are measured by changes in the number of jobs which is the focus of this analysis, value added (GDP), economic output and tax revenue. The I-O analysis on the 11 investment items is conducted using IMPLAN, which is a software for regional economic impact modeling built around the concept of Social Accounting Matrices (SAM). SAM is a widely adopted framework for EIA. SAM utilizes a collection of input-output tables, or I-O tables, called Leontief Inverse Matrices developed by Nobel Laureate Wassily Leontief specifically for macroeconomic analysis and modeling.

Naturally, for any industry to fulfill the direct demand from the “shock” with outputs of goods and services, it needs labor and the outputs from the suppliers as inputs, generating indirect demand upward the supply chain and in the labor market. SAM maps the interdependent relationship among industry sectors and institutions (final consumers of goods and services such as residents, government, export, etc.) by tracking the flow of capital and commodities. It tracks such flows in intra-regional transactions as well as inter-regional trades. In an accounting format, it tells the user the breakdown of every unit of spending in the most recent fiscal period, i.e., the percentages of spent funds among local purchase of goods and service, imports of goods and service, cost of labor, and tax and revenues retained by the producer. In the process, the “ripple effect” of intermediate demands from any “shock” is captured and accounted for.

For the underlying models of IMPLAN to properly represent the regional economy, the cost functions involved are informed by secondary data obtained from multiple government agencies including the Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), etc., who update the data on a yearly basis. Thus, IMPLAN datasets are organized, published and updated each year (hence referred to as “data-year”).

4.3.4.2 Built-in Assumptions and Limitations of IMPLAN

IMPLAN among other SAM-based tools is a cost-effective choice for estimating and forecasting economic impacts in a regional economy where the collection of first-hand data for the same purpose is prohibitively costly. Given the scale and complexity of any regional economy such as California, IMPLAN relies on built-in assumptions that simplifies the economic reality as the models map and represent it. Therefore, there are inherent limitations associated with these assumptions, which are acknowledged as the following:

- **Static Relationships**: IMPLAN datasets are produced and published on a yearly basis. The interdependent relationships between industries and institutions in IMPLAN are static. Each dataset is a snapshot of the regional economy of the data-year. Similarly, IMPLAN does not account for price elasticity. The prices of goods and services are assumed to remain constant.
- **Linearity**: The I-O relationships between industries and institutions in IMPLAN are linear. IMPLAN's estimation of economic outputs and associated employment and GDP impacts follows a constant return-to-scale rule. When a "shock" 10 times as large is modeled, for example, the resulting impact is simply dialed up by 10 times.
- **Timing of Impacts**: IMPLAN does not specify when impacts will actually be realized. However, IMPLAN model results are time-sensitive due to inflation and real price changes induced by other causes, e.g., advancement of technology. IMPLAN compensate this by employing a set of "deflators" for each dataset to adjust user inputs to the data-year of the dataset before running the model. The "deflators" are informed by BEA data for historical price changes and by the BLS employment growth model for forecasted future changes.
- **Geographic Granularity**: IMPLAN does not provide data on the exact location of economic impacts within the defined region.
- **Limited Tracking**: There are certain limits to how far IMPLAN tracks the flow of money and commodities once they start circulating in the economy, especially the flow of money. There are certain accounts in IMPLAN's Social Accounting Matrices where once the money flows into, it is considered "lost" to the economy and is no longer accounted for. Such accounts include sales tax, income tax, import, retained earnings, and capital income including stock dividends and interest payments, etc. This is because an IMPLAN dataset captures only one year of economic activities. It does not account for nor makes any assumptions about how retained corporate earnings, government tax income, and resident savings are spent beyond the data-year.

4.3.4.3 The Process of Multiplier Generation

For each of the 11 investments analyzed, the total cost is distributed across a timeline and among a basket of cost items. A basket of cost items is necessary to assign total cost to IMPLAN inputs that represent the material and labor purchased to fulfill the demand and a timeline is required to forecast the annual impact of the investment as it occurs in the future.

Each commodity and service in the basket is assigned with a percentage to serve as weight which adds up to 100%. The items selected and their respective weights are derived from cost analyses on the technology, e.g., BEV, conducted and published by various agencies and other independent sources as well as previous analysis done by Luskin Center for Innovation. The percentage of some commodities and services are assumed to decrease over a certain period in the timeline as the corresponding technology matures, resulting in slightly different sets of weights to distribute the cost for the same investment across time.

Once the percentage of each cost item is derived for each year along the timeline, they are multiplied by $1 million as a standard unit of investment to generate a set of IMPLAN inputs for that $1 million across different goods and services. A set of Local Purchase Coefficients (LPR) built into IMPLAN models are then applied to determine for each cost item how much of the purchase is sourced locally for local economic impact instead of importing from other states or countries.

Each basket, ready with cost distribution across years and cost items and with LPR assigned to each cost item, is then put into the IMPLAN modeling software to calculate employment impacts. IMPLAN employment impacts are job-counts averaged over full-time and part-time jobs. To convert IMPLAN results into standard FTE units, a job-to-FTE bridge converter provided by IMPLAN is used. Naturally, the FTE numbers are smaller than raw IMPLAN result numbers and this discount varies from industry to industry. A conversion is done for each of the industries presented in the results and aggregated to obtain a total number of FTEs per $1 million of investment.

This process above is repeated for each of the 11 investments twice, once using the 2019 dataset (V1) and once using the 2020 dataset (V2), comparing results based on most recent pre- and post-pandemic data-years for a better understanding and isolation of the disruptive impacts of the COVID-19 pandemic. Based upon this analysis, a third set of factors was generated (V3), which uses the 2020 base year for years 2021-2025 and the 2019 base year for years 2026-2050 to account for COVID-19 impact in the near term but assuming resumption of the pre-pandemic trends thereafter.

To further explore the trend of labor intensity in fulfilling these investments and purchase demands, which is also measured by the amount of human labor required per unit of investment, i.e., FTE/$ 1 mil, the same analysis for each investment is also repeated six times, once for every dataset from 2015 to 2020. Each repetition is done only for the data-year without any forecasts down the timeline. This base-year-only comparison is designed to reveal some fundamental changes such as advancement of technology and change in labor productivity in the past few years.

Figure 65 shows the sample output of annual expenditures forecast by the employment impact model using the 2019 multipliers (V1). In these estimates, the general trend of decreasing economic contributions from ICEV and fossil fuel is offset by increases in BEV and FCEV-related activity.

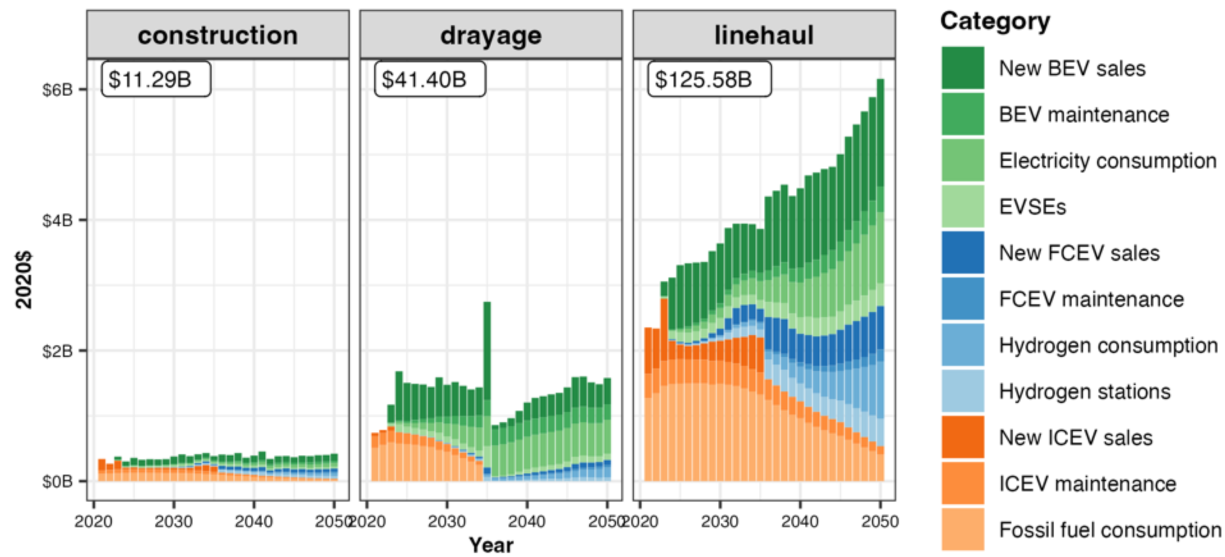


Figure 65. Representative projected annual expenditures by vocation for each of the 11 economic impact areas as modeled in the PET impact module

Figure 66 and Figure 67 demonstrate how these expenditures translate into full-time equivalent (FTE) positions for ZEV-related and ICEV-related expenditures respectively.

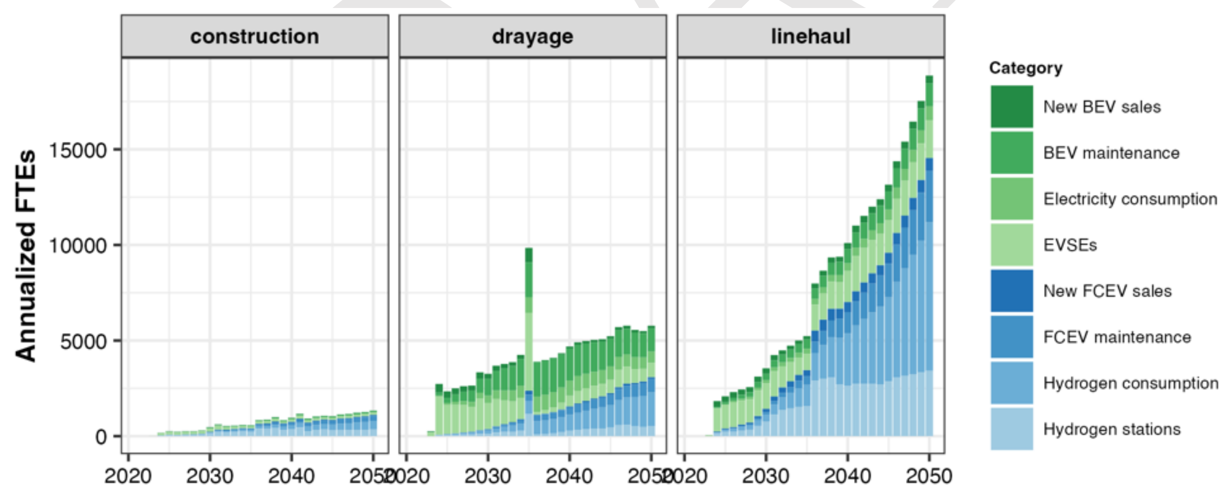


Figure 66. Projected annualized FTEs resulting from ZEV-related expenditures as modeled in the PET impact module

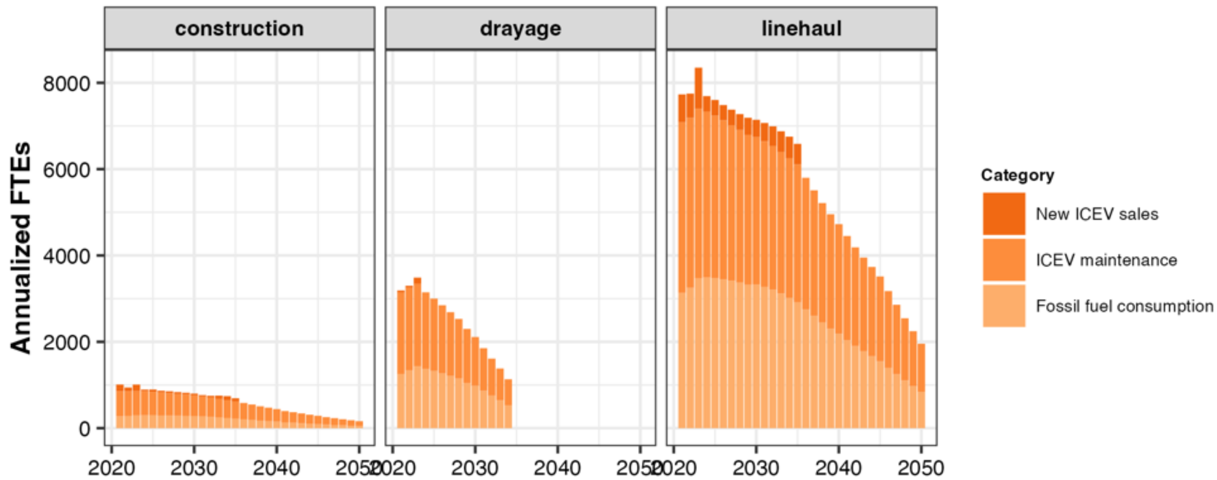


Figure 67. Representative projected annual FTEs resulting from ICEV-related expenditures as modeled in the PET impact module

4.4 ORE impacts module

The impacts module for the off-road equipment calculations is not as comprehensive as the HDV impacts module as the TCO are statewide estimates rather than region-specific and because of the lack of data necessary to build a reliable turnover model. In addition, insufficient data was available to develop distinct employment multipliers for ORE so there is no employment impacts module. Instead, the ORE impacts are analyzed based on relative TCOs for different fuel types over time. TCO estimates are produced for 11 equipment types across 7 HP bins (50, 75, 100, 175, 300, 600, and 750), resulting in 60 cases. PET results from selected equipment types and HP bins are presented in this section.

This analysis presents costs over calendar years for both battery electric and diesel equipment. The calendar years are placed along the x axis with costs shown in 2020 US dollars along the y axis. The results vary across types and HP bins due to different activity demands and component sizes. Figure 68 shows TCO calculations for Tractor/Loader/Backhoe in the 100 HP bin. Although battery electric equipment has lower TCO for purchase years out until approximately 2035, they become increasingly more costly as we approach 2050. Fuel costs for battery electric equipment (cost of electricity consumption for charging) remains cheaper than diesel throughout the years modeled while the LCFS credit for battery electric equipment decreased over time, driven by the estimated LCFS credits generated by the TRACE model (Section 1.6). In this analysis, infrastructure costs and utility incentives were held constant. Overall, as equipment incentives decreased with advancing years, total cost for battery electric equipment increased (notice the pronounced effect of LCFS on total cost). We note that infrastructure costs contribute to driving total cost for battery electric equipment higher than diesel. If infrastructure incentives from utilities were to be discontinued, this difference could be higher. For 50 HP Tractor/Loader/Backhoe and 50 HP Excavator, shown in Figure 69 and Figure 70, respectively, vehicle costs remain high for battery electrics, and with reducing incentives, diesel options get increasingly cheaper.

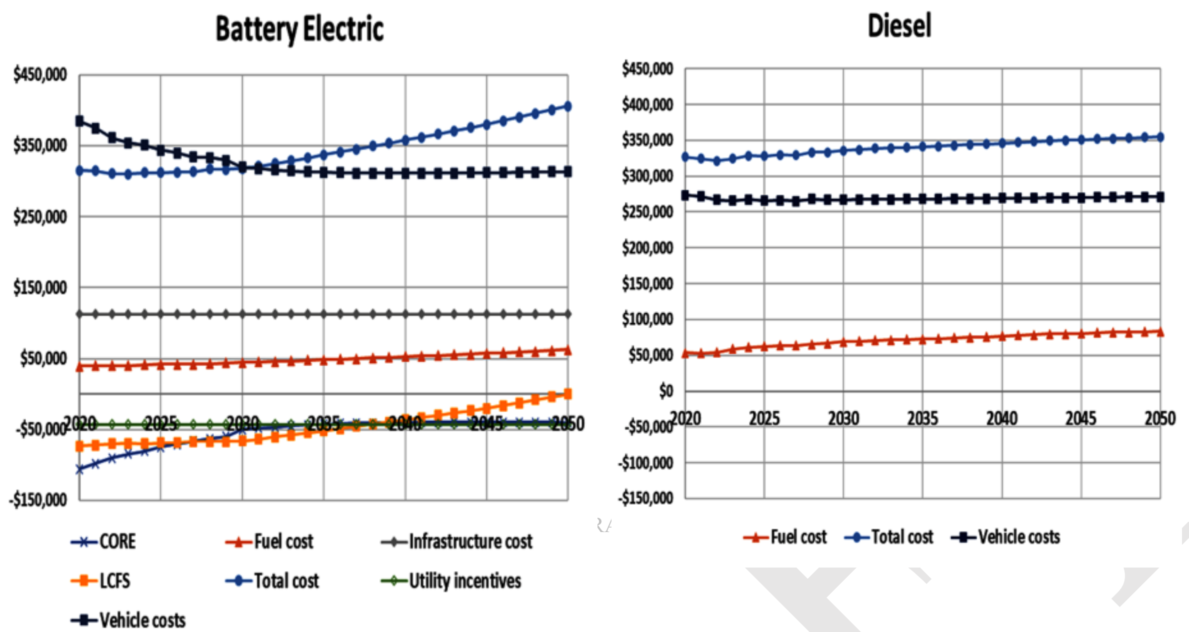


Figure 68. Cost components for Tractor/Loader/Backhoe in 100 HP bin.

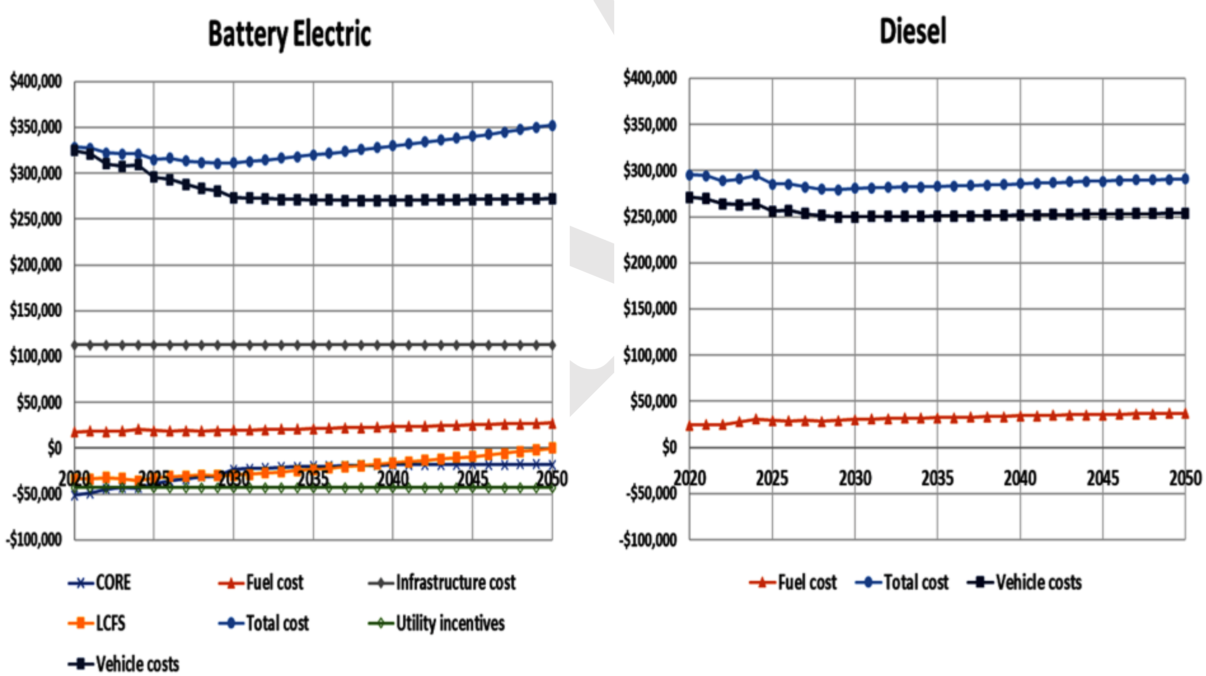


Figure 69. Cost components for Tractor/Loader/Backhoe in 50 HP bin.

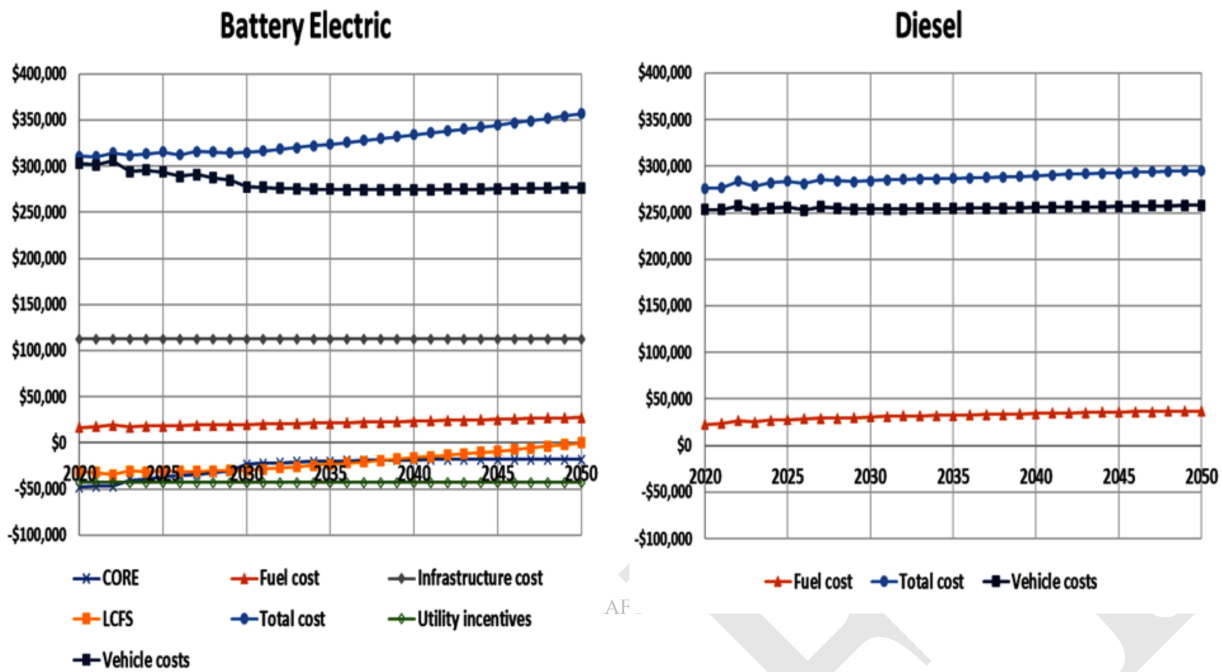


Figure 70. Cost components for Excavator in 50 HP bin.

For 175 HP Port Forklift shown in Figure 71, the costs demonstrate a different pattern from the previous cases; the spikes during 2023, 2027, 2044, and 2048 being the most noticeable. These are driven by the fuel consumption data obtained from OFFROAD, which showed higher fuel consumption for these years that resulted in increased vehicle costs, fuel cost, and LCFS incentives. Accounting for these anomalous variations, for example by using a smoothing approach like that described for HDV in Section 4.1.3.3, is left for future work. However, considering the general trends, the total costs in 2050 indicate that the diesel version of this equipment will be cheaper to own in 2050. Even though in the prior years, battery electric versions generally appear to be cheaper due to incentives and cheaper fuel cost countering the higher vehicle costs.

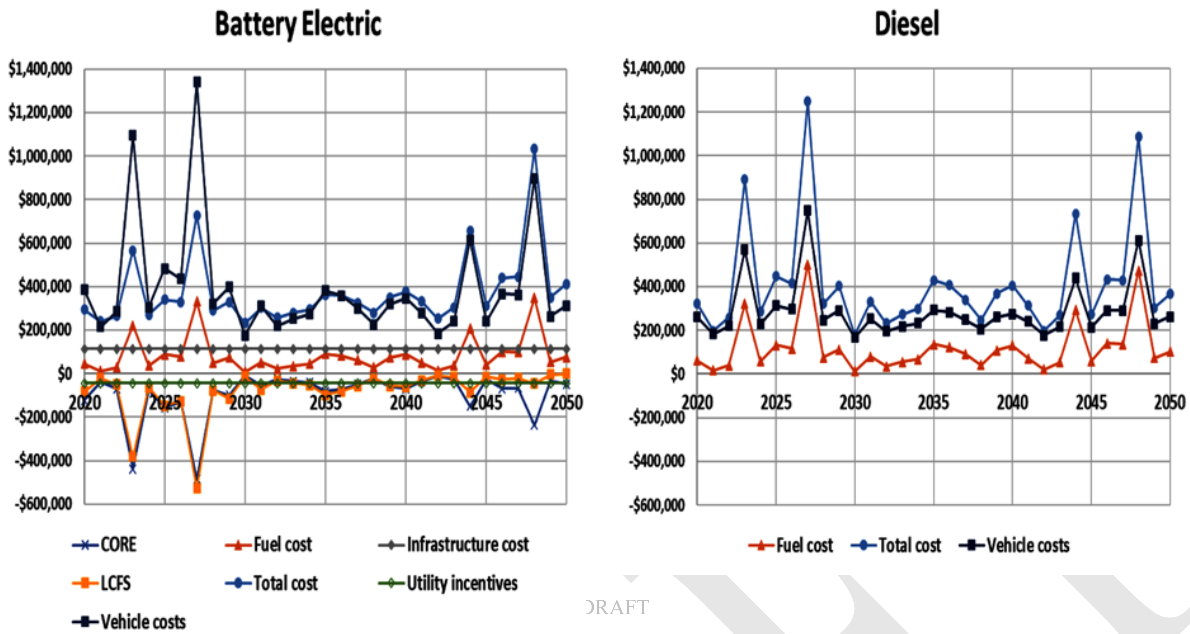


Figure 71. Cost components for Port Forklift in 175 HP bin.

The four cases discussed so far showed that the total cost varies over the calendar years, and either of the two technologies can appear cheaper depending on the different cost components. If we look at the number of cases where total cost for battery electric equipment is less for each calendar year (Figure 72), we see that it echoes the trends seen in the previous four cases. The number of equipment types and sizes that are cheaper as battery electric decreases as the years progress, and only eight remain in 2050. These eight are Agricultural Tractor in HP bins 300, 600, 750, Crawler Tractor in 600 HP bin, Grader in 300 HP bin, Rubber-Tired Loader in 300 and 600 HP bins, and Tractor/Loader/Backhoe in 600 HP bin.

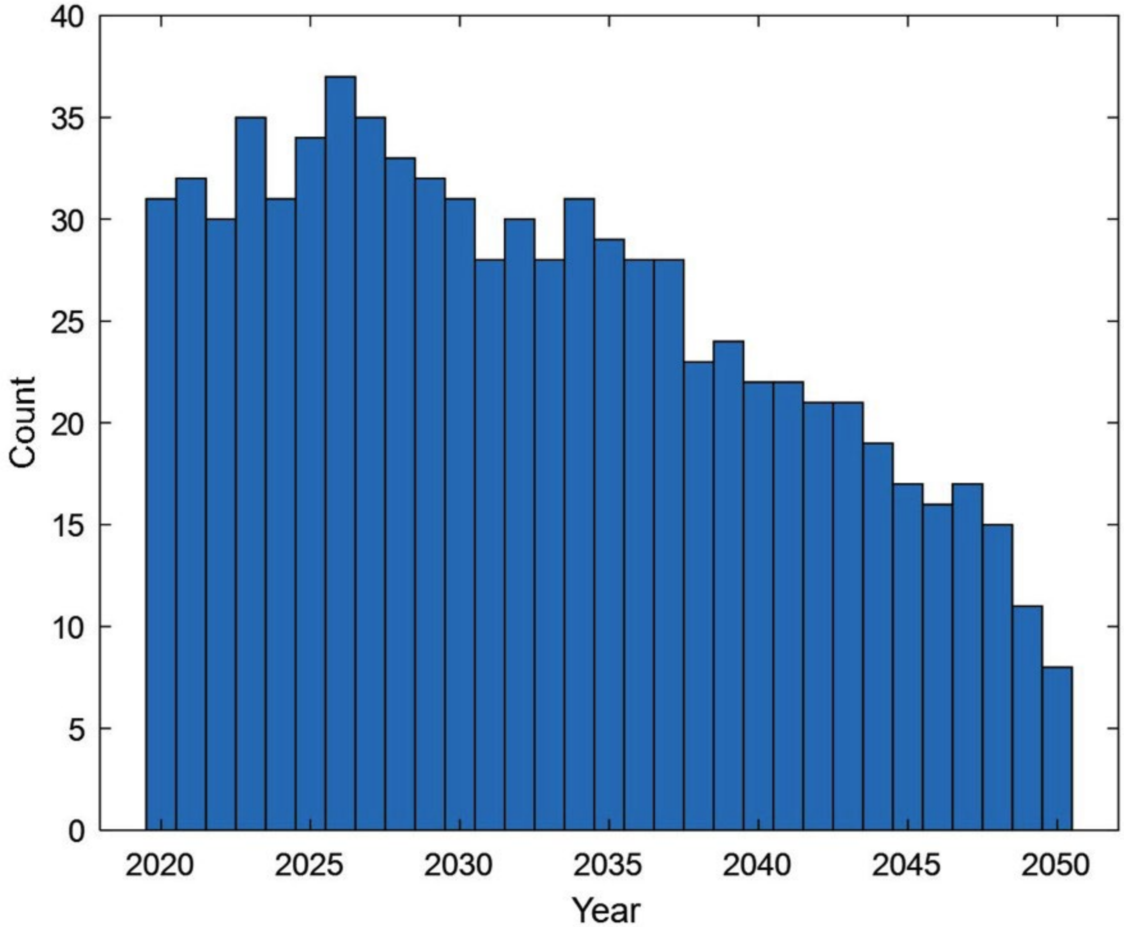


Figure 72. Number of cases in each calendar year with lower total cost for battery electric equipment.

Now, let us take a look at the results from another angle, which involves all the studied types and sizes, not only the four presented above. Figure 73 - Figure 75 provide a look at the extent of differences of total costs for the two technologies, for the two years at both ends of our studied range, and one in the middle (2020, 2035, 2050). Negative values in the figures mean the total cost is less for battery electric equipment. Colored bars indicate the magnitude of price difference: green where battery electric is cheaper, red where it is costlier. The data shown in these tables are modeled costs based upon the methodology described above, including CapEx, OpEx, plus any incentivization (purchase incentives offsetting differential costs along with LCFS credits). Even for the 2020 data, these costs are based upon component sizing derived from OFFROAD activity data and not actual equipment costs identified in the market. Specific bins, particularly in the higher horsepower ranges may be subject to additional constraints that are not reflected here. This is especially true of the 2020 costs where some ZEV equipment may not have been on the market.

Figure 73 shows that total cost for battery electric equipment was cheaper for most of the cases in 2020. In the cases where diesel was cheaper, the margin was very small. This gap generally decreased by 2035 (Figure 74), and cases where diesel equipment appear cheaper show slightly higher magnitude. In 2050 (Figure 75), significantly more diesel equipment were cheaper than battery electric, compared to 2035. For cases where battery electric was cheaper, e.g., Agricultural Tractor and Crawler Tractor in the 600 HP bin, the cost difference decreased. Nevertheless, for some cases, e.g., 750 HP Agricultural Tractor and 300 HP Grader, battery electric appeared cheaper. These findings are consistent with the previous findings shown in Figure 68 - Figure 71: battery electric equipment's total cost were lower than diesel at the beginning of our study timeframe (e.g., 2020) when incentives were higher, incentives decreased as the years progressed (e.g., 2035) – reducing price difference, and diesel appeared cheaper for many cases during the final years (e.g., 2050). The findings of Figure 72 also corroborates with Figure 75: total cost for battery electric equipment remained cheaper for 8 cases in 2050.

2020

	50	75	100	175	300	600	750
Agricultural Tractors	-$16,555	-$66,688	-$126,477	-$221,367	-$584,837	-$1,768	-$185,855
Crawler Tractors	$16,666	N/A	-$5,797	-$115,630	-$257	-$464,940	N/A
Excavators	$14,267	N/A	-$37,267	-$119,959	-$19,953	-$357,744	N/A
Graders	N/A	N/A	N/A	-$18,782	-$3,365	N/A	N/A
Port Forklift	N/A	N/A	N/A	-$7,426	-$423,563	N/A	N/A
Port Truck	N/A	N/A	N/A	-$31,865	N/A	N/A	N/A
Port Yard Truck	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Rubber-Tired Loaders	-$15,121	N/A	-$115,743	-$269,715	-$473,356	-$1,138,346	N/A
Skid Steer Loaders	$36,733	$1,898	N/A	-$19,393	-$6,483	N/A	N/A
Tractors/Loaders/Backhoes	$1,693	N/A	-$56,834	-$16,729	-$26,499	-$376,456	N/A

Figure 73. Total cost difference of battery electric and diesel equipment in year 2020.

Note: Negative values mean total cost is less for battery electric equipment. Colored bars indicate the magnitude of price difference. Green where battery electric is cheaper, red where it is costlier.

2035

	50	75	100	175	300	600	750
Agricultural Tractors	$22,693	-$6,263	-$4,465	-$98,236	-$317,319	-$68,397	-$184,594
Crawler Tractors	$4,937	N/A	$9,167	-$411	-$8,676	-$244,646	N/A
Excavators	$37,414	N/A	$5,985	-$43,258	-$12,912	-$186,879	N/A
Graders	N/A	$48,858	-$2,713	-$17,741	-$184,968	N/A	N/A
Port Forklift	N/A	N/A	N/A	-$6,658	-$423,563	$6,898	N/A
Port Truck	$23,326	N/A	N/A	-$31,865	-$156,832	-$765,587	N/A
Port Yard Truck	-$15,121	N/A	-$115,743	-$269,715	-$12,535	-$663,792	N/A
Rubber-Tired Loaders	-$6,568	$1,898	-$4,178	-$117,463	-$24,153	-$687,148	N/A
Skid Steer Loaders	$49,925	$4,788	-$56,834	$34,394	-$26,499	-$376,456	N/A
Tractors/Loaders/Backhoes	$3,754	N/A	-$3,259	-$55,372	-$86,216	-$19,916	N/A

Figure 74. Total cost difference of battery electric and diesel equipment in year 2035.

Note: Negative values mean total cost is less for battery electric equipment. Colored bars indicate the magnitude of price difference. Green where battery electric is cheaper, red where it is costlier.

2050	50	75	100	175	300	600	750
Agricultural Tractors	$57,583	$49,876	$39,542	$25,472	-$3,400	-$11,133	-$236,493
Crawler Tractors	$64,316	N/A	$53,158	$39,468	$26,839	-$16,668	N/A
Excavators	$6,158	N/A	$52,343	$38,668	$2,249	$319	N/A
Graders	N/A	$6,432	$4,349	$2,522	-$64	N/A	N/A
Port Forklift	N/A	$69,471	N/A	$4,622	$53,956	$41,838	N/A
Port Truck	$23,326	N/A	$66,340	-$31,865	$65,969	-$765,587	N/A
Port Yard Truck	-$15,121	N/A	-$115,743	$67,996	$67,737	-$663,792	N/A
Rubber-Tired Loaders	$49,000	$1,898	$39,422	$18,369	-$1,553	-$138,428	N/A
Skid Steer Loaders	$64,577	$6,287	-$56,834	$6,878	-$26,499	-$376,456	N/A
Tractors/Loaders/Backhoes	$6,180	N/A	$49,759	$35,338	$27,213	-$394	N/A

Figure 75. Total cost difference of battery electric and diesel equipment in year 2050.

Note: Negative values mean total cost is less for battery electric equipment. Colored bars indicate the magnitude of price difference. Green where battery electric is cheaper, red where it is costlier.

These findings suggest that incentive supports will be needed to maintain price parity between the zero-emission and diesel alternatives, otherwise ZE adoption may slow. This echoes existing literature which underscored the necessity of retaining incentives to make BE TCO competitive (Figenbaum, 2022). As it was suggested in by Figenbaum (2022), incentives could be made cost neutral through other sources of earnings, so that they can be sustained in the long term and keep BE TCOs attractive. Another way to interpret our results is that battery electric equipment technology must improve to bring costs down so that they can become cheaper without relying extensively on incentives. However, as TCO depends on many factors, changes in any of them can produce different results. For example, if manufacturers decide to achieve higher profit margins, it can make BEV TCO less competitive, as pointed out by (van Velzen et al., 2019).

The findings here are limited by the available data. With different cost data, the results can be different. The forecasts, particularly beyond 2035, are impacted by significant uncertainties in both equipment component and fuel costs. We note the commercial electric equipment is still not broadly used across all sectors considered, thus vehicle costs can only be estimated. Due to the unavailability of residual value, maintenance and repair cost data of electric equipment, data from diesel equipment were used here. With better data for these variables, the results can be more accurate. The assumptions can also change due to technological developments and breakthroughs reducing vehicle costs, as well as the opportunity to use pre-existing infrastructure that will bring infrastructure costs down. Finally, the aggregate analysis here doesn't fully account for the significant variety of equipment types and applications. We recommend continued research in this area to further refine these results. Still, the similarities of our results with findings from previous independent studies (Figenbaum, 2022; van Velzen et al., 2019) support the efficacy of the current methodology and assumptions.

5 Recommended Incentive Strategies

With the features of our model specified, we now turn to analyzing how different regulatory and incentive designs interact using the PET model to make recommendations about the most effective policy to achieve the State's carbon reduction goals. Due to the limitations with the ORE module noted previously, we focus here only on HDV incentives. This task starts in Section 5.2 with a comparison of the PET's baseline TCO estimates to recent comparable studies in the literature. This is followed in Section 5.1 by a sensitivity analysis of the PET's TCO model to select specific model parameters for the policy design task. In Section 5.2 we identify the baseline scenario for our policy designs based upon the sensitivity analysis results. In Section 5.4 we systematically explore the combinations of regulatory and incentive designs and identify the most promising design using a cost-effectiveness metric. In Section 5.5 we describe a detailed assessment of that policy design based upon PET model outputs from the Impact module.

5.1 TCO Sensitivity Analysis

We conducted a sensitivity analysis of the TCO model to clarify the impact of individual parameters on the costs forecast by the model. After summarizing the parameters we varied in the next section, we present the results of the sensitivity analysis and identify the baseline scenario for considering incentive policy designs.

5.1.1 Parameters considered in the sensitivity analysis

5.1.1.1 Electricity and vehicle production scenarios

As noted previously there are three vehicle technology adoption scenarios and three electricity cost scenarios. The vehicle technology adoption scenarios derive from TRACE outputs (Section 2.3) and are realized in vehicle costs by vocation as summarized in Figure 42 (Section 4.1.3.1). The electricity demand scenarios are summarized in Figure 44 (Section 4.1.3.3). We combined these into the nine cases shown in Table 41.

Table 41. Scenarios used in the incentive strategy analysis

	Electricity Scenario		
Adoption Scenario	**Low-demand**	**Mid-demand**	**High-demand**
Conservative	CL	CM	CH
Moderate	ML	MM	MH
Optimistic	OL	OM	OH

Source: Electricity scenarios are described in Figure 44 in Section 4.1.3.3. Adoption scenarios derive from TRACE outputs

5.1.1.2 Retail/R&D markup parameters

The Retail/R&D markup parameters include a default baseline of 35% markup for all technologies except for BEV and FCEV before 2030, which use a markup of 40% as discussed in Section 4.1.3.1. As alternatives, we've created a 'hi' case that shifts those markups up 15% and a second scenario that shifts them down 15%. These are shown in Figure 76.

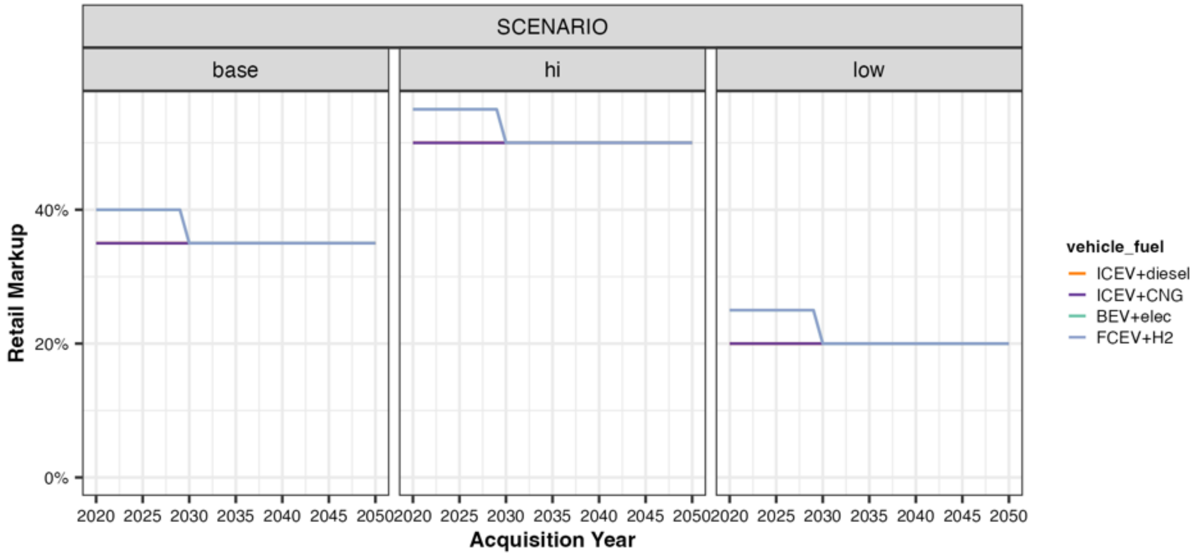


Figure 76. Retail markup scenarios for the PET sensitivity analysis

Note: The markups for BEV+elec are the same as FCEV+H2 and the markups for ICEV+diesel are the same as those for ICEV+CNG.

5.1.1.3 Technology adjustment factor alternatives

The baseline technology adjustment factors described in Section 4.1.5 assume BEVs have a 10% operations premium on the TCO for drayage diminishing to zero through 2025, and construction and linehaul have a 15% premium for line-haul in 2020 and that these diminish over time to 0% at 2035 to represent fleets adapting their operations to ZEVs any functional penalty. We also considered a more severe penalty for BEVs where there was a 20% premium for construction and drayage in 2020 and a 30% premium for line-haul, again with both diminishing to zero at 2035 over time. These alternatives are shown side by side in Figure 77.

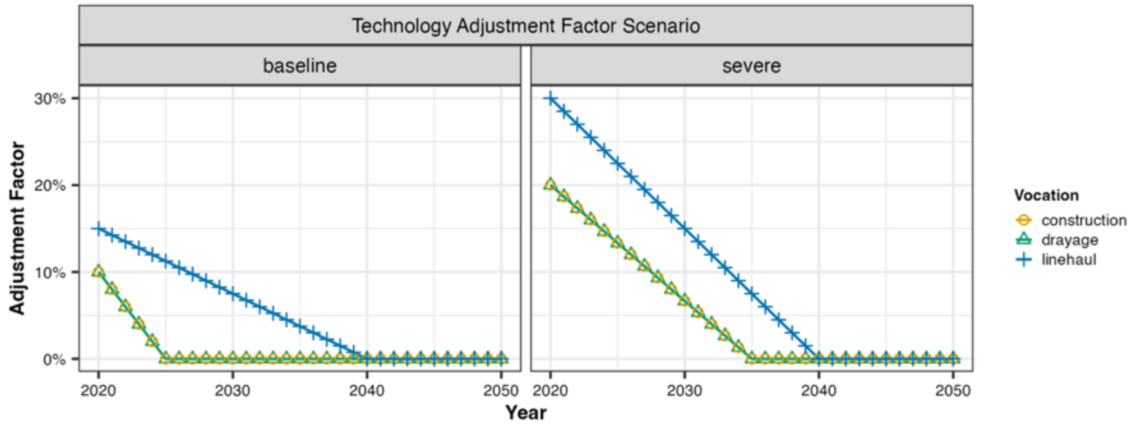


Figure 77. BEV technology adjustment factor alternatives

5.1.1.4 Infrastructure cost alternatives

Only one alternative to the baseline infrastructure costs described in Table 33 (Section 4.1.3.2) was considered and this was to include a 2:1 alternative to the 1:1 baseline for the vehicle to infrastructure ratio parameter for EVSE (but not for H2 dispensers). This alternative represents the assumption that a single EVSE can feasibly charge multiple trucks at a depot during extended dwell periods that are typical of drayage, construction, and to a lesser extent regional line-haul trucking. This advantage does not exist for singleton fleets who install their own EVSE (the model caps the vehicle to infrastructure ratio to the number of vehicles in the fleet), but becomes more likely as fleet size increases allowing a smart charging installation to efficiently distribute power to multiple trucks during the dwell period.

A question remains whether a 2:1 ratio vehicle to EVSE is a reasonable assumption for vocational vehicles. Preliminary evidence using telemetry data from drayage trucks operating out of the Ports of Los Angeles and Long Beach suggests a 2:1 ratio is reasonable for drayage. In this case, 30 days of data for more than 1000 diesel drayage trucks was analyzed to see whether the tours could be performed with a BEV truck. In the analysis, observed VMT was converted to end-of-tour state of charge estimates using a 2.1 kWh/mi assumption. An optimization was performed to determine how many chargers would be necessary to meet the energy demand over time based upon the observed schedules. The findings in Figure 78 show that optimized smart charging can produce EVSE to truck ratios at 0.5 or lower (i.e., the truck:EVSE ratio is 2 or higher), with the ratio improving as the fleet size increases.

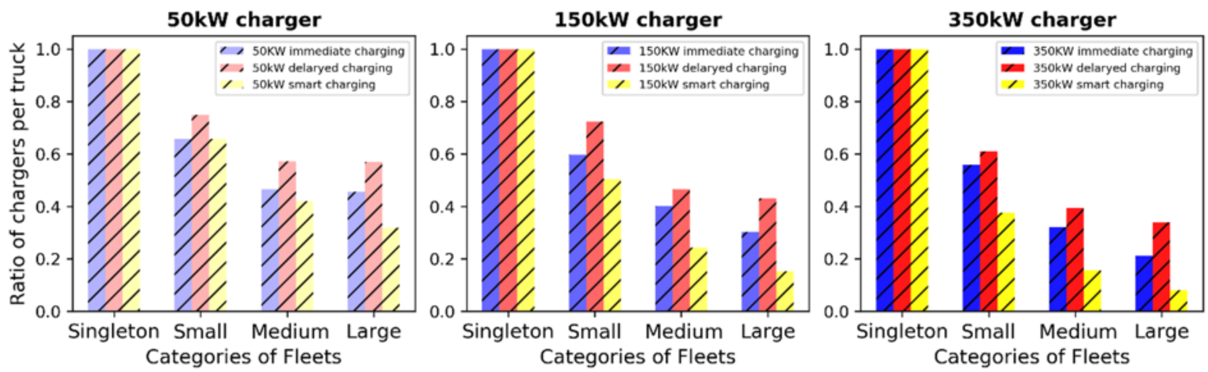


Figure 78. Optimized EVSE to truck ratios for drayage operations

Note: Fleet sizes are small=2-20; medium=21-100; large=100+. All fleets are assumed to have dedicated EVSE. The optimization determines the minimum number needed based upon observed behavior. Note that in these figures the ratio is EVSE:vehicle.

These findings support the use of a 2:1 truck:EVSE ratio for all but singleton fleets so we have included it for sensitivity analysis.

5.1.1.5 Financing parameters

Recall that baseline TCO calculations are dependent upon financing parameters that include the first owner lifetime as well as the APRs and terms for vehicle and infrastructure loans as well as the assumed discount rate. We identified two recent sources in the literature to select potential parameters: ANL's TCO analysis (Burnham et al., 2021) and CARB's ACF discussion document (CARB, 2021d). For vehicle lifetime (while we'll use interchangeably with analysis period), ANL used 10 years while CARB selected 12 years to represent "a middle ground between fleets who operate their trucks for five years before turning them over and those who operate their trucks for 20 or more years until the truck cannot operate." To facilitate comparisons, we selected an analysis period of 10 years as the baseline. Because TCOs using different analysis periods can't be directly compared, we do not vary this across any scenarios.

The discount rate is used to represent the opportunity cost of an investment, in this case vehicles and infrastructure that are financed over some loan period. The ANL analysis provides a comprehensive analysis of data on discount rates, APRs, and loan terms typical for HDV purchases. Accounting for assumed 2% inflation, they select a real discount rate of 3% (5% nominal less 2% assumed inflation), a real loan APR of 4%, and loan term of 5.25 years (63 months).

CARB's ACF analysis uses a discount rate of 0% (following CA Department of Finance guidelines). For financing rates, they assume a slightly higher rate of 7% based upon an assumption that 80% of fleets will receive a 5% rate and 20% will be less credit worth and finance at 15%. Since they do not account for inflation in their analysis, the 7% nominal rate is the same as the real rate.

For our analysis, we adopt ANL's parameters as the baseline case and evaluate the impact of CARB's higher rates as an alternative. Note that to facilitate comparison, we still use vehicle life of 10 years and a 3% discount rate in the CARB case.

Table 42. Financing parameters for the baseline and CARB ACF sensitivity cases

Financing parameters	Baseline	CARB
First owner vehicle life (l)	10	10
Vehicle financing APR	4%	7%
Vehicle financing term	5.25	5
Infrastructure financing APR	4%	7%
Infrastructure financing term	20	20
Discount rate	3%	3%

5.1.1.6 Total VMT

Burnham et al. (2021) noted their models' sensitivity to VMT for TCO and interesting Levelized Cost of Driving (LCOD). It's obvious that TCO would increase with additional driving, but they noted that LCOD drops with more driving since the marginal costs of additional driving once equipment is paid for are better than when financing payments were still being made in the early years of ownership, though this is a diminishing return. To explore the impact of additional mileage on the PET's TCO we computed a scaling factor to convert the total EMFAC-derived drayage VMT in 2025 for the 10-year lifetime to match ANL annual totals for day cab trucks:

$$\text{VMT scale factor} = \frac{573{,}288\ \text{mi}}{484{,}866\ \text{mi}} = 1.236 \qquad \textbf{Eq. 57}$$

We then applied this factor to scale the VMT for all three vocations and used it for the high VMT case. We did not compute a low VMT case.

5.1.2 Sensitivity analysis results

Using the above parameter assessments, we created a range of values for each parameter shown in Table 43. We ran the PET TCO model for the years 2025, 2030, and 2035 for the baseline case, and then in additional runs varied the individual parameters through their alternatives while holding all other parameters in Table 43 to the baseline.

Table 43. Parameter ranges for TCO sensitivity analysis

Parameter	Low	Baseline	High
Electricity Scenario (Figure 44)	High demand case	Mid demand case	Low demand case
Vehicle Production Scenario (Section 2.4.2)	Optimistic	Moderate	Conservative
Incentives	No vehicle incentives	2023 HVIP schedule (Table 45), tapering to zero by 2035.	2023 HVIP schedule (Table 45), tapering to zero by 2050.
Retail markup	20% for ICEV 25% for ZEV until 2030, then 20%	35% for ICEV 40% for ZEV until 2030, then 35%, Source: the ICCT (Sharpe & Basma, 2022)	50% for ICEV 55% for ZEV until 2030, then 50%
Operations premium	No BEV penalty	10% BEV penalty diminishing	20% BEV penalty diminishing
Infrastructure	2:1 EVSE:Truck	Table 33	No high case considered
Vehicle lifetime	5	10	15
Vehicle financing APR	0%	4%	8%
Discount rate	0%	3%	5%
VMT		EMFAC VMT (Section 4.1.3.3)	Scaled drayage VMT to match ANL annual totals

To visualize the impacts of each parameter, we converted the costs into per-mile cost, or LCOD, by dividing the TCO elements by the lifetime VMT for the vocation[53] and then created tornado charts of the resulting LCOD ranges. The tornado charts show the LCOD of the baseline case as a vertical gray line and the variations of the LCOD caused by varying each parameter as horizontal bars to the left and right of the gray line to represent lower and higher LCODs respectively. Because the change in LCOD can be in the opposite direction of TCO (e.g., for parameters that impact VMT), the bars are colored by their impact on TCO (gold is higher, green is lower). In each chart, the parameters have been sorted from top to bottom by widest absolute range of LCOD results to clearly identify the parameters that the model is most sensitive to.

Figure 79 through Figure 81 show tornado charts demonstrating the impact of varying individual parameters on the 2025 LCOD for construction, drayage, and linehaul trucks respectively. All subfigures for a given year have been scaled to the same range to simplify comparison.

[53] Following Burnham et al. (2021), conversion to LCOD used discounted annual VMTs over the vehicle's lifetime.

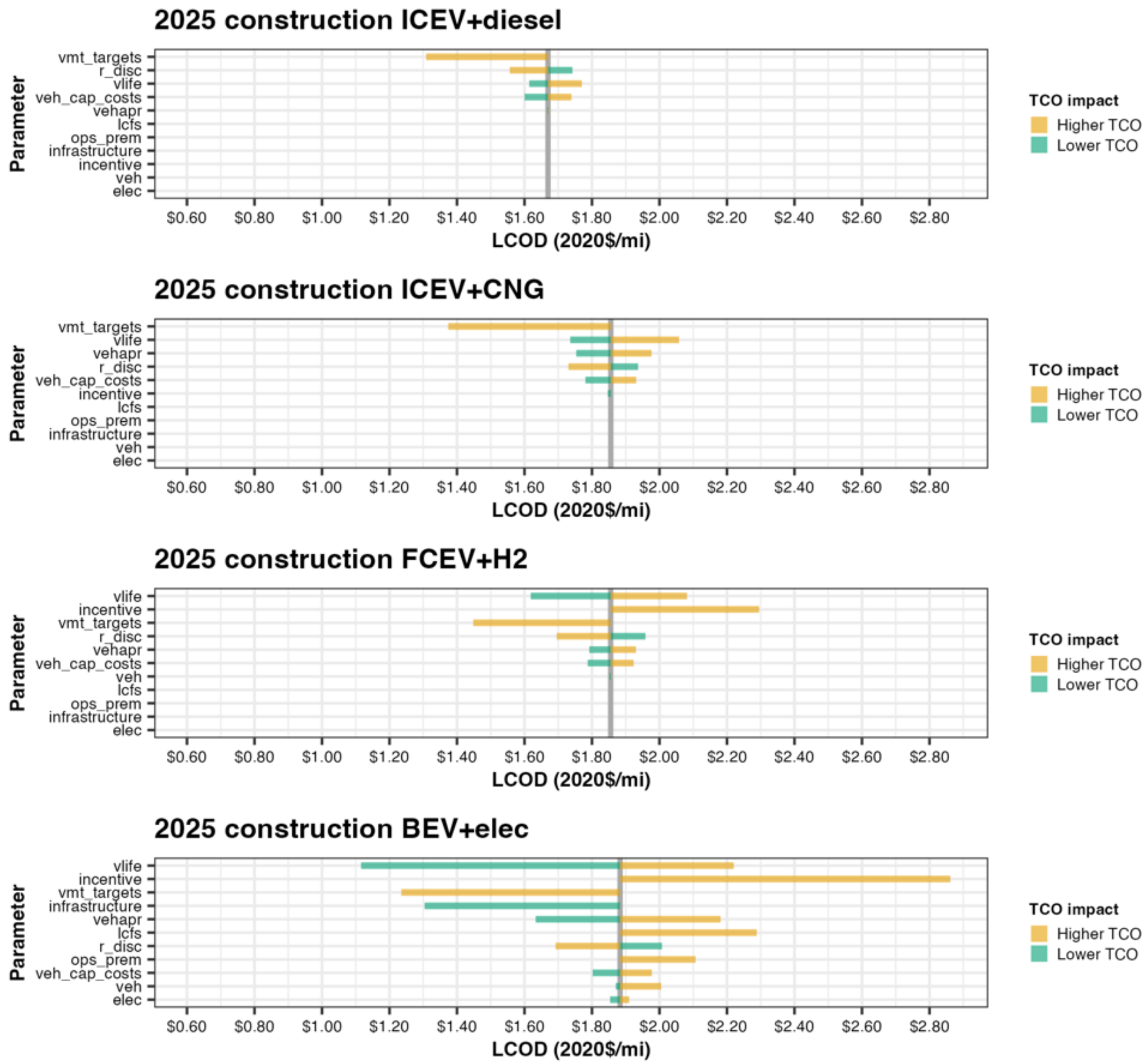


Figure 79. Tornado charts of LCOD for construction trucks in 2025

Note: The vertical gray line in each subplot shows the LCOD for the base case. The yellow and green bars show the impact of setting the associated parameter to the high and low variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, higher or lower. Impact on LCOD can go in the reverse direction.

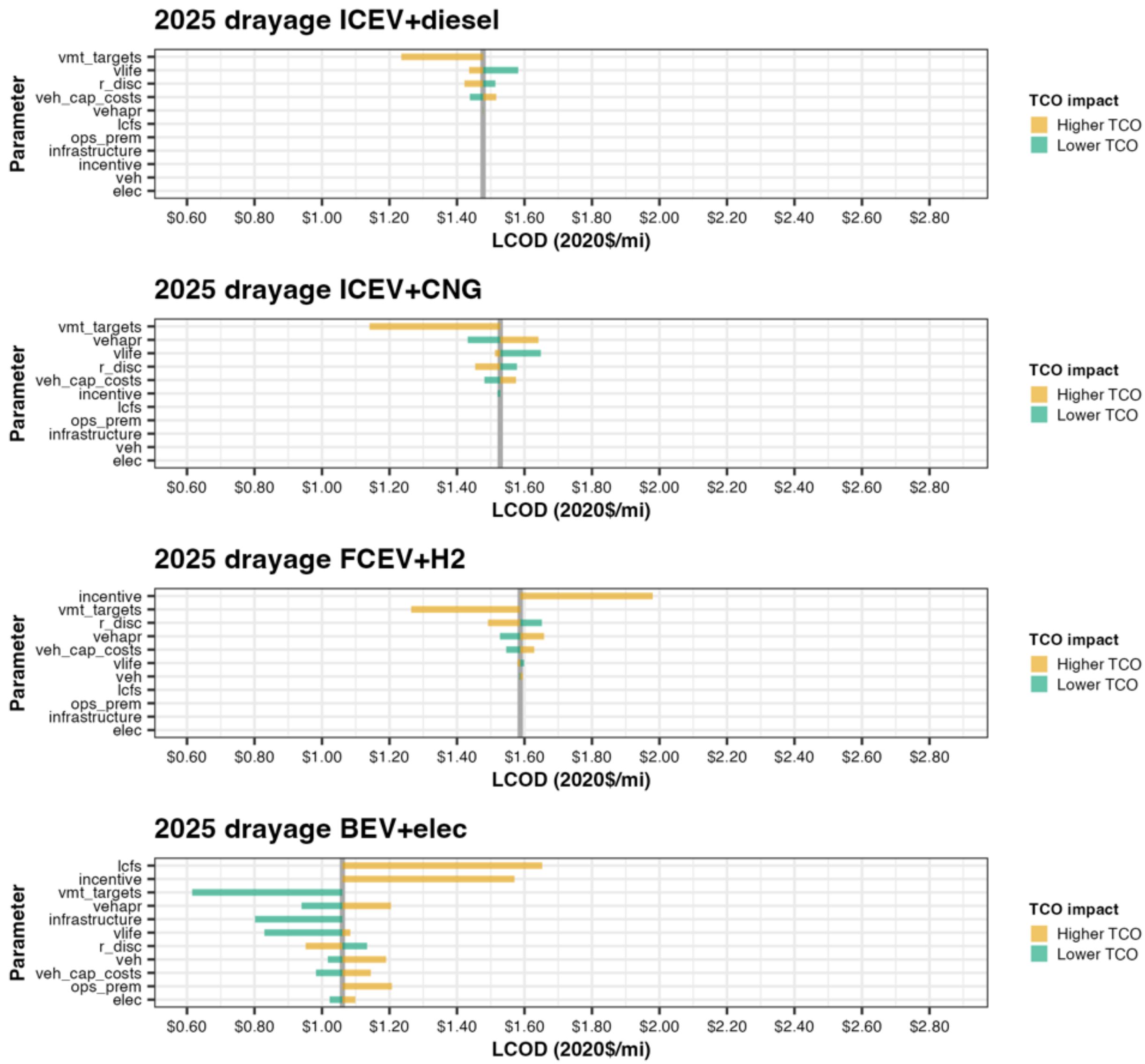


Figure 80. Tornado charts of LCOD for drayage trucks in 2025

Note: The vertical gray line in each subplot shows the LCOD for the base case. The yellow and green bars show the impact of setting the associated parameter to the high and low variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, higher or lower. Impact on LCOD can go in the reverse direction.

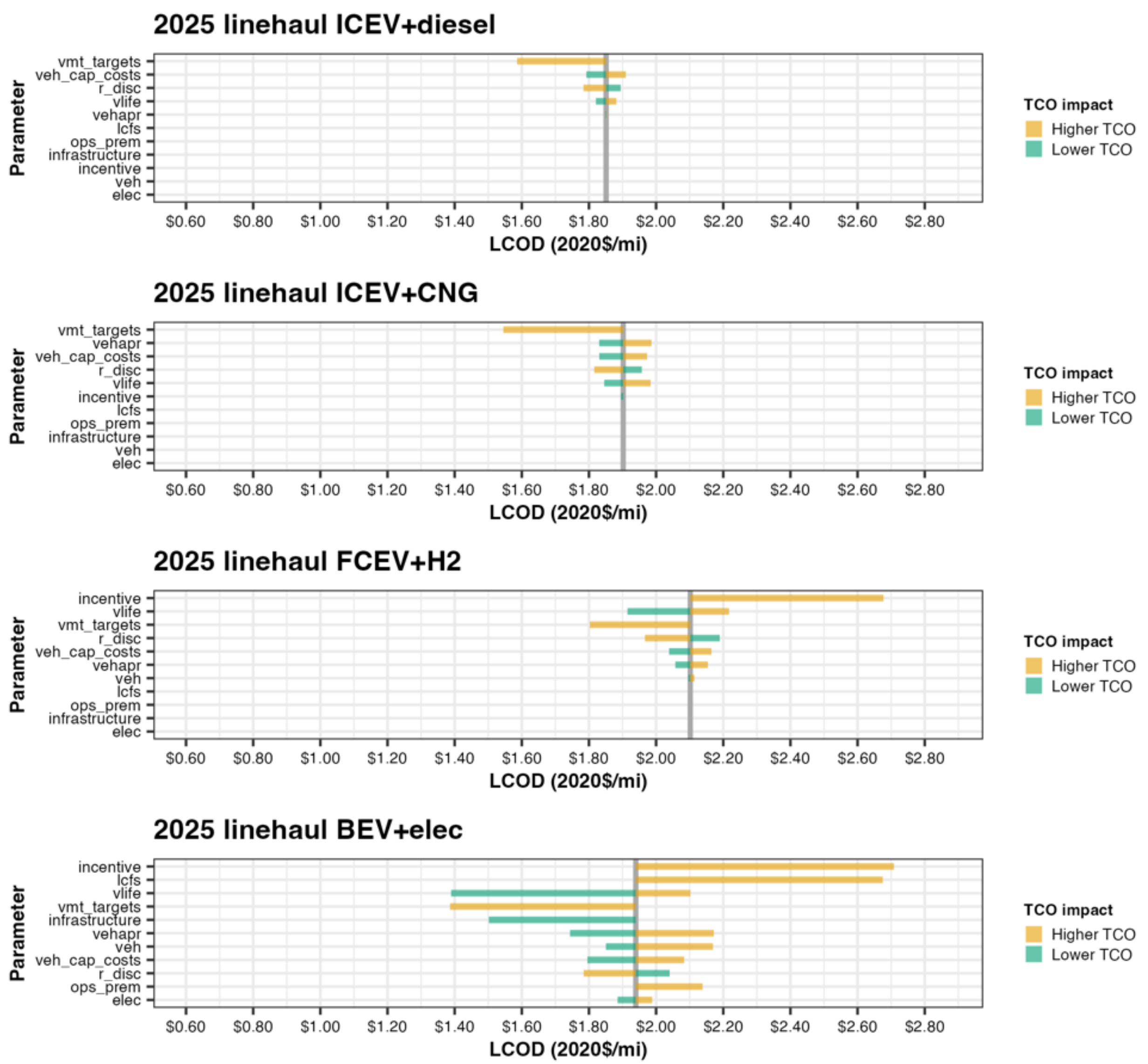


Figure 81. Tornado charts of LCOD for linehaul trucks in 2025.

Note: The vertical gray line in each subplot shows the LCOD for the base case. The yellow and green bars show the impact of setting the associated parameter to the high and low variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, higher or lower. Impact on LCOD can go in the reverse direction.

Looking at the year 2025 figures, we can see parameters impacting VMT are consistently influential. In all cases, at the top of the charts we find either the VMT targets (which inflate base VMTs by about 23.6%) or vehicle life parameters (which add additional operations years to the base case, thus increasing VMT). As VMT increases, TCO increases and LCOD decreases just as Burnham et al. (2021) demonstrated. This highlights that fuel costs are a major determining factor for TCO, even when normalized for VMT.[54] There is little variation for ICEV+diesel and ICEV+CNG in the PET model over the parameters we varied that don't impact VMT. Differences in vehicle capital costs related to the retail markup parameters have a modest impact, though these variations are relatively consistent across all fuel types. The discount rate has a similarly consistent impact as well. For our purposes, however, we are primarily concerned with relative differences in costs between fuels as this is the driver in the choice model applied during fleet turnover. Thus, if the impacts of a parameter are similar across all fuels, they are less likely to influence the turnover model's forecast.

Looking at the ZEV options, we see that the HVIP and infrastructure incentives (which are grouped together in these charts) are the influential factor on TCO and LCOD and, in the case of BEV+elec, LCFS credits. If either of these supports are removed for drayage trucks in 2025, the clear advantage of BEV+elec on TCO and LCOD evaporates, and removing both would dent the competitiveness of this option. This is similarly true for other BEV+elec vocations as well as FCEV+H2, which would move from being "in the ballpark" to uncompetitive across all vocations.

Figure 82 through Figure 84 show the tornado charts for year 2035 where we see similar patterns to those discussed for 2025, with VMT-related parameters being most influential in all cases now, taking over for incentives which have diminished to just infrastructure supports with HVIP tapering to zero across all cases. One factor that is easier to discern in these 2035 charts is that the VMT impacts are greater for BEVs than other fuels, which is consistent with operational costs being lower for BEVs than other alternatives.

[54] ANL (Burnham et al., 2021) make a similar observation in their TCO analysis.

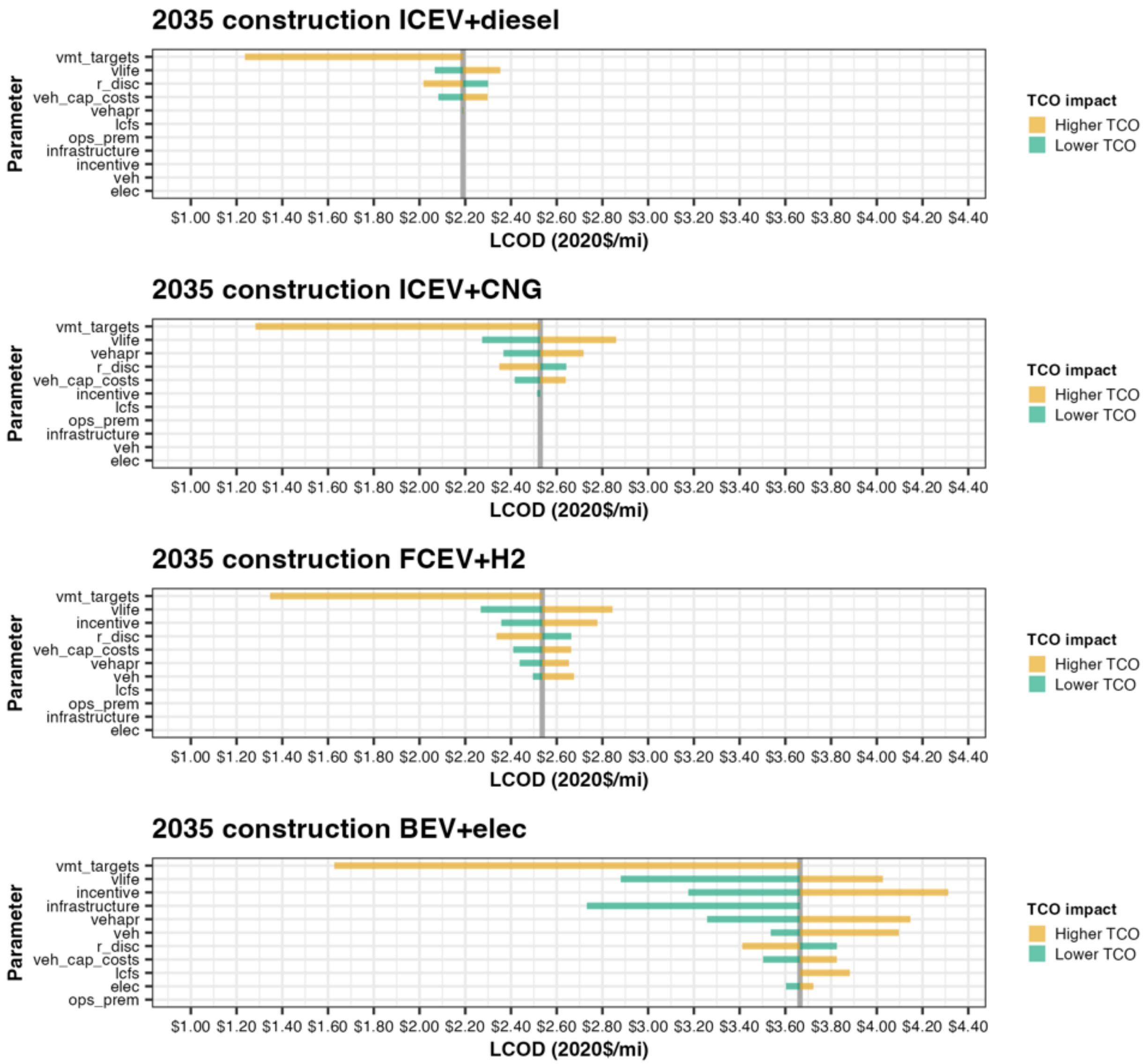


Figure 82. Tornado charts of LCOD for construction trucks in 2035

Note: The vertical gray line in each subplot shows the LCOD for the base case. The red and green bars show the impact of setting the associated parameter to the hi and lo variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, higher or lower. Impact on LCOD can go in the reverse direction.

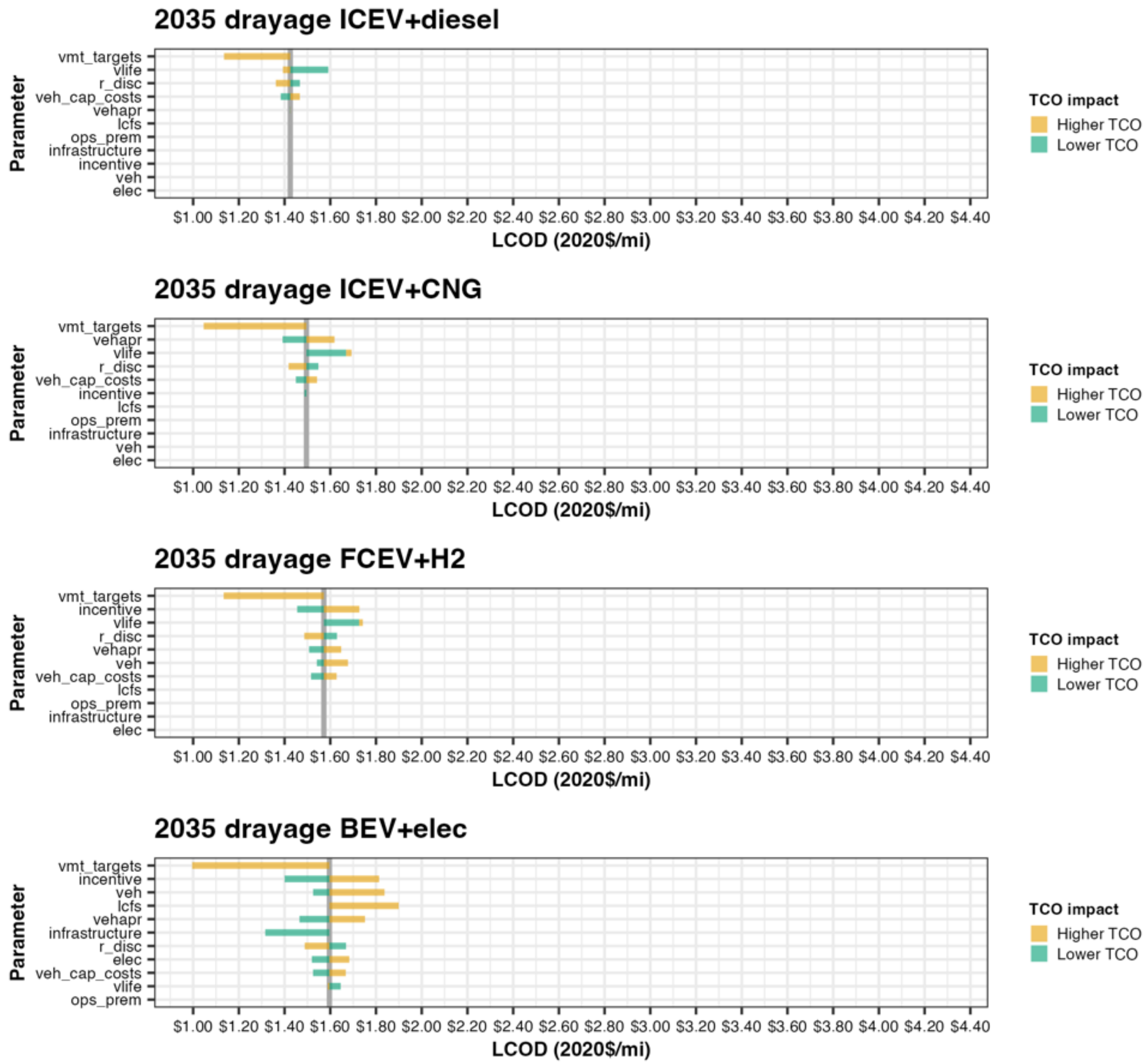


Figure 83. Tornado charts of LCOD for drayage trucks in 2035

Note: The vertical gray line in each subplot shows the LCOD for the base case. The red and green bars show the impact of setting the associated parameter to the hi and lo variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, higher or lower. Impact on LCOD can go in the reverse direction.

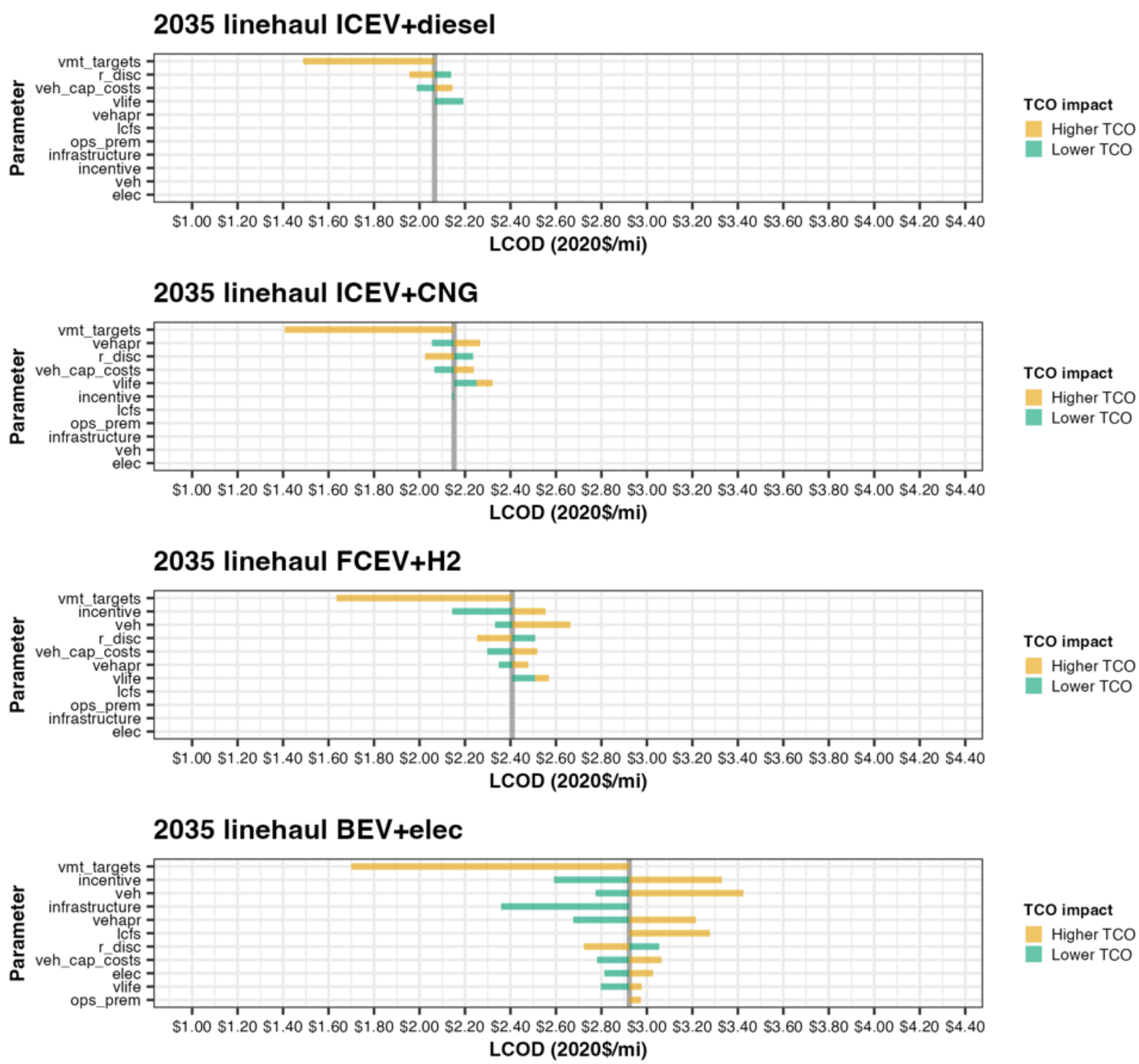


Figure 84. Tornado charts of LCOD for linehaul trucks in 2035

Note: The vertical gray line in each subplot shows the LCOD for the base case. The red and green bars show the impact of setting the associated parameter to the hi and lo variations summarized in Table 43. These are ordered from top to bottom descending from the parameter that has the largest absolute difference between the low and high cases to the parameter that has the lowest absolute difference. Colors reflect the impact on overall TCO, with red being an increase in overall TCO and green being a decrease. Impact on LCOD can go in the reverse direction.

Figure 85 shows how TCOs vary across the different regions in California using a histogram to display the frequency of TCOs that fall in different cost ranges. These demonstrate the general cost competitiveness of ZEV alternatives for drayage, at least through 2035 when the incentive supports are fully removed in this baseline scenario. After that the relative increase in electricity costs to other fuel projects degrades BEV+elec as an option. However, at that point, the regulatory requirements remove the diesel and CNG ICEV options from the choice set leaving BEV+elec and FCEV+H2 in relative parity in the market.

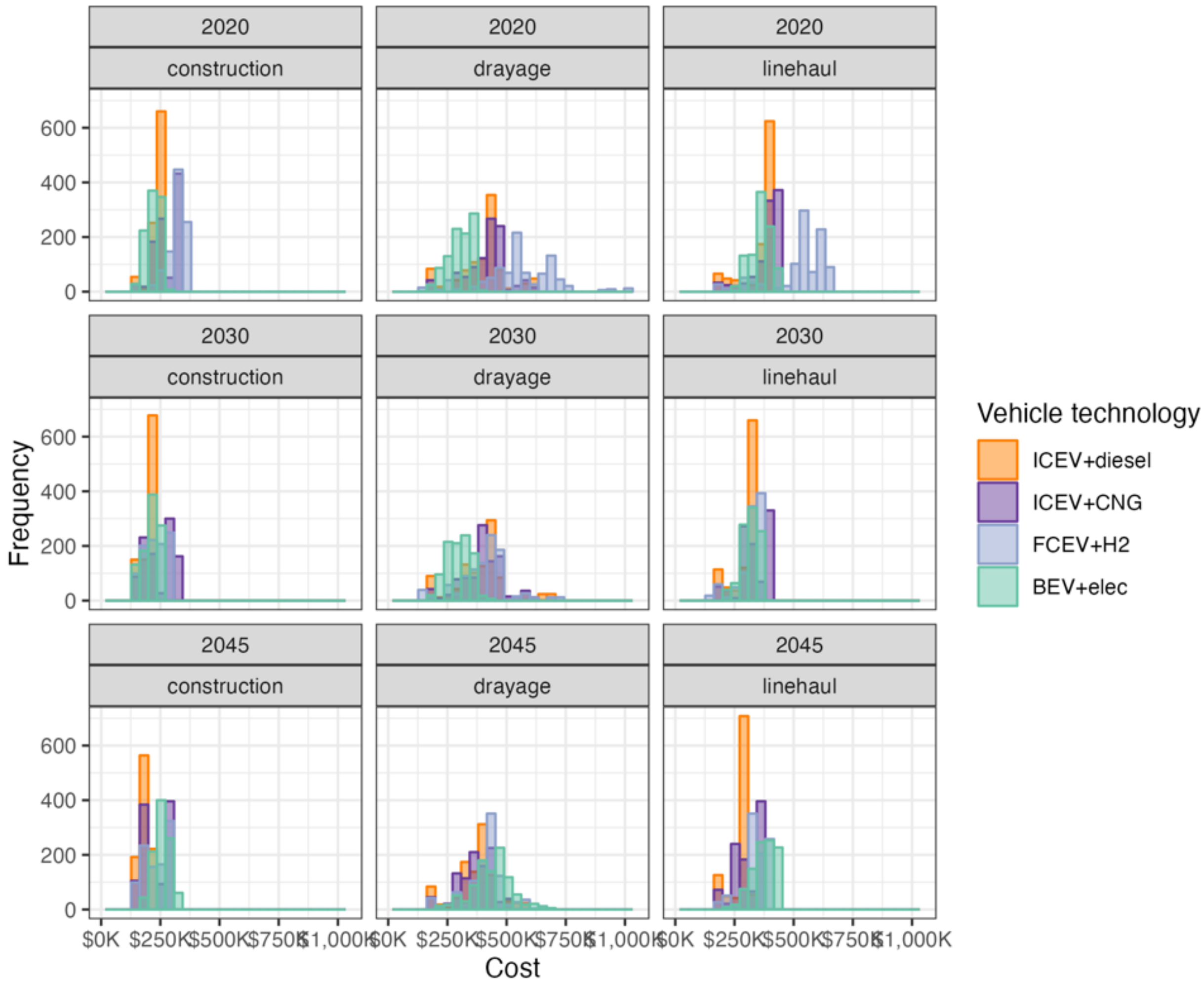
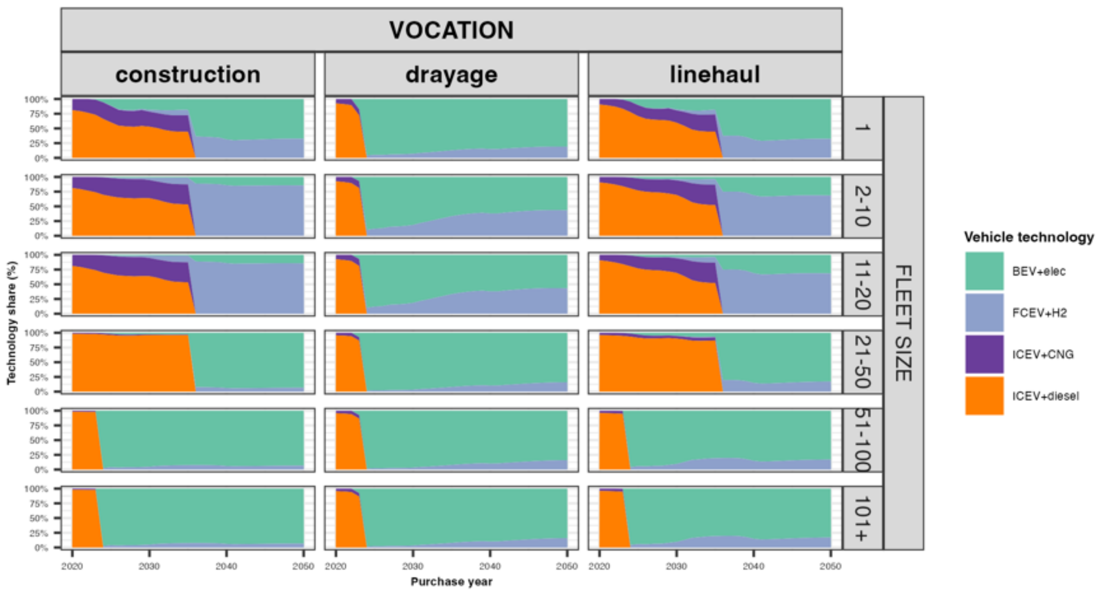


Figure 85. Histogram of TCOs across different regions for specific acquisition years and vocations

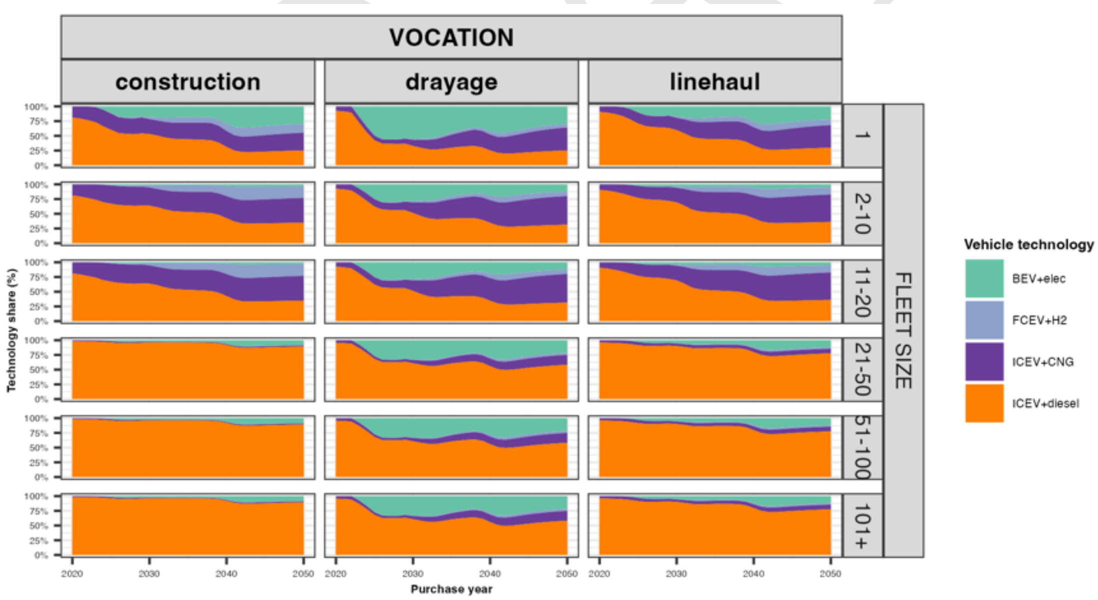
Notes: The histogram shows the distribution of costs across regions and fleet sizes for the baseline MM scenario and the baseline parameters from Table 43. These frequencies are not weighted by population.

5.1.3 Impacts of regulations

By default, all scenarios model the impacts of Truck and Bus and Advanced Clean Fleets regulations. As previously noted, the Advanced Clean Trucks regulation is not explicitly modeled as outlined in Section 4.1.5. Because the Advanced Clean Fleets regulation limits the choice set available to fleet categories (vocations, sizes, etc.), it can mask the impact of preferences based exclusively upon TCO in the model. We ran the PET with and without the ACF regulation to understand its impacts. In these runs, all baseline parameters were used along with current HVIP incentivization levels designed to taper to zero by 2035. There are no TCO differences with and without the ACF regulation because it targets turnover rather than cost. However, Figure 86 shows the removal of the restricted choice sets required by ACF have a dramatic impact on the technology shares preferred by fleets. The baseline case with ACF regulations in panel (a) shows the regulation's removal of CNG and diesel options for all drayage trucks starting in 2024 and for all vocations for fleets larger than 50 vehicles. The result is that BEVs are generally preferred in drayage and FCEV in construction and linehaul applications. Without the regulation, however, ZEVs lose much of their competitiveness in the market, indicating that incentivization alone isn't sufficient to move the fleet to ZEVs under the MM scenario.



(a) Technology shares with ACF regulation

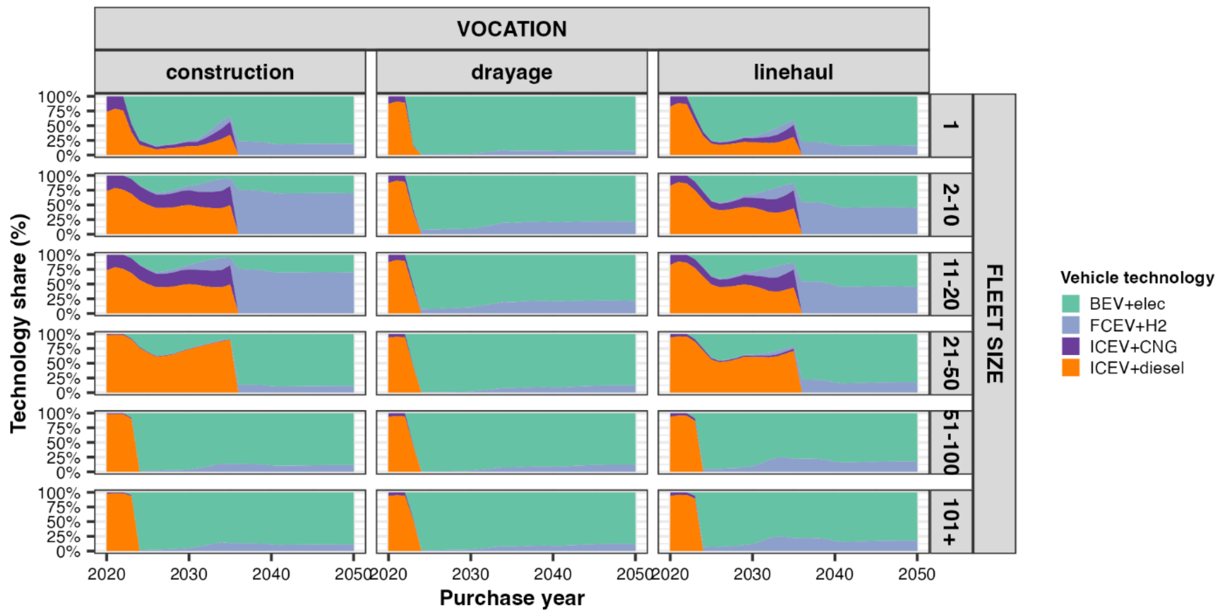


(b) Technology shares without ACF regulation

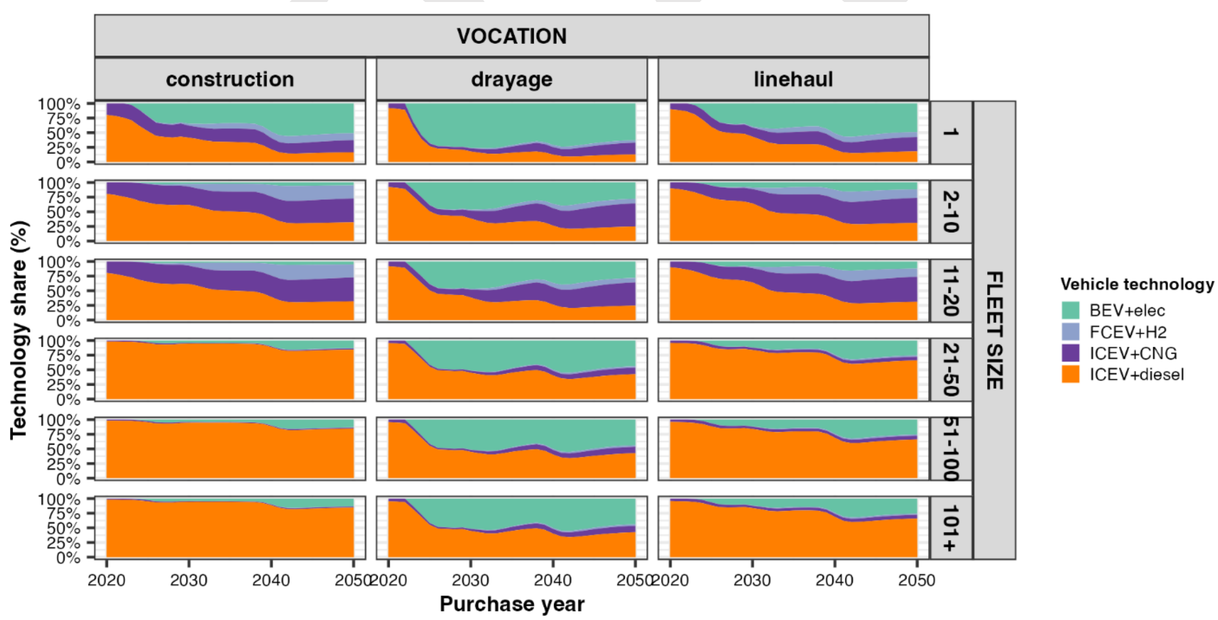
Figure 86. Technology shares over time under MM with and without ACF regulations

Notes: Model runs used the MM scenario and the baseline parameters from Table 43 except regulations varied between (a) the baseline with ACF and (b) without ACF.

To see if a more optimistic scenario could induce a more significant ZEV shift outside of any regulatory pressure, we re-ran the no regulations case using the OH case corresponding to better electricity prices and lower capital costs. When compared with Figure 86, the results in Figure 87 show that ZEVs become marginally more competitive. The primary implications being that regulations such as ACF is necessary to drive the transition to ZEVs and our ongoing analysis of incentive designs will assume the ACF regulation is active.



(a) Technology shares with ACF regulation



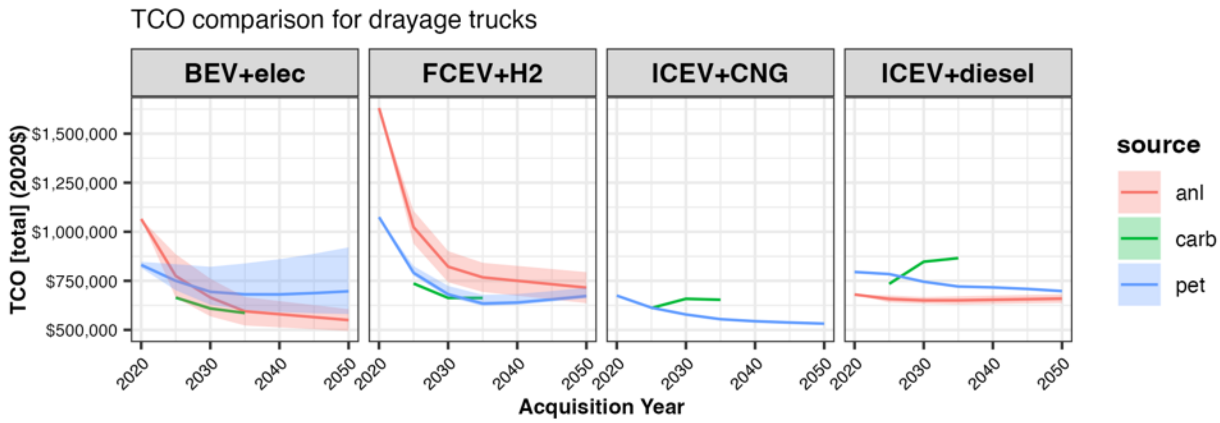
(b) Technology shares without ACF regulation

Figure 87. Technology shares over time under OH with and without ACF regulation

Notes: Model run used the OH scenario and the baseline parameters from Table 43 except ACF regulations were excluded.

5.2 Comparison of PET TCOs to the literature

Figure 88 shows TCO estimates for drayage trucks from the PET compared to estimates for class 8 day cab tractors from CARB (CARB, 2021d) and ANL (Burnham et al., 2021), which are the most directly comparable and recent results available in the literature. PET TCOs shown are the statewide means of TCOs computed for all regions weighted by base year truck stock. Three PET scenarios are included to reflect the extremes of the scenarios considered. The lower cost case corresponds to the AH scenario representing the high-demand, optimistic production scenario represents the lowest costs. The higher cost case corresponds to the CL case representing the low-demand, conservative production scenario associated with the highest costs. The mid case corresponds to the MM scenario representing the mid-demand, moderate production scenario lying between the extremes. Because the PET's annual VMTs are lower than the CARB (599,280 mi) and ANL (573,288 mi) estimates, the PET's EMFAC-derived VMT is scaled to match the CARB's total VMT. These comparisons omit costs for infrastructure, labor costs, and payload/operations penalties as not all sources include them in their TCO estimates. Also excluded are any fleet-redeemed LCFS credits, which the PET computes for BEVs and CARB computes for BEVs and FCEVs. We do not exclude LCFS impacts that are embedded in retail fuel cost—all fuels except electricity in the PET and all fuels except electricity and hydrogen for CARB.



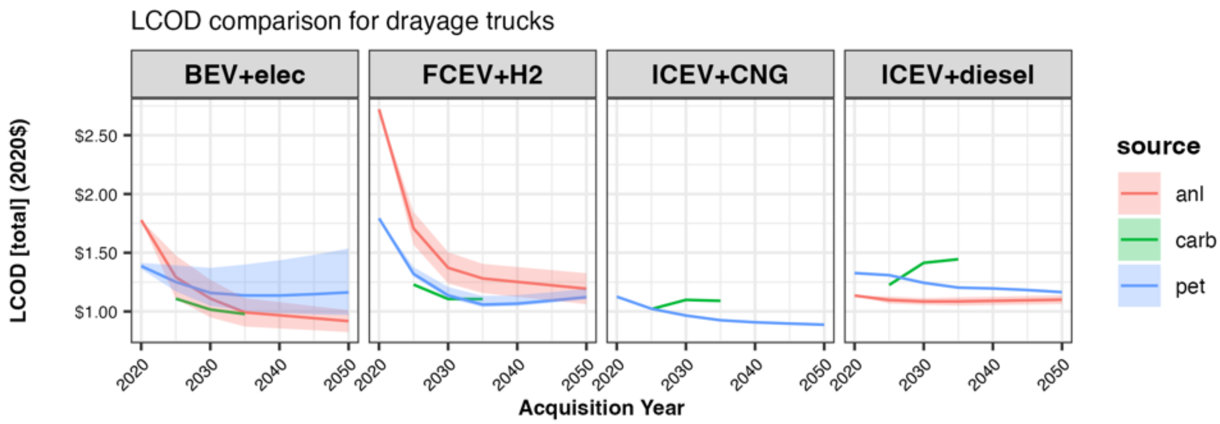


Figure 88. TCO and LCOD comparison between the PET and other estimates

Notes: The 'pet' data show the statewide mean TCO and LCOD estimates (using a 12 year vehicle life) generated by the PET model for the MM (mid) case with low and high bounds shown for the AH and CL cases respectively. The 'carb' data show TCO estimates from CARB's Draft Advanced Clean Fleets Total Cost of Ownership Discussion Document (CARB, 2021d), which has single estimates for 2025, 2030, and 2035, so no ranges are shown. The 'anl' data show TCO estimates from ANL's recent comprehensive TCO document (Burnham et al., 2021), which has estimates for 2020, 2025, 2030, 2035, and 2050 for high and low cases. The midpoint line for ANL's data is a simple average of the high and low cases. To align the comparisons, infrastructure costs and incentives have been stripped out of the PET and CARB estimates while payload and labor costs have been removed from ANL's estimates. These analyses use a 0% discount rate.

The comparison shows that the PET's estimates for ZEV vehicles tend to correspond well with CARB's estimates for 2025 through 2035, though the PET's middle estimates for BEV+elec are slightly higher than both with the optimistic cost scenario generally tracking ANL's mid-range estimate. The PET's TCOs for FCEV+H2 track CARB's estimates for 2025 through 2035 very well, with ANL's estimates consistently higher. ANL did not estimate ICEV+CNG cost, the PET and CARB's estimates are in good alignment in 2025 with the PET being more optimistic about costs in future years. Finally, for ICEV+diesel, the PET matches CARB's estimate in 2025 and then splits the estimates between the higher costs of CARB and lower costs of ANL's estimate. Figure 89 breaks down the specific component costs of the TCOs to explain the variation, which primarily lies in fuel cost estimates for both electricity and hydrogen. The PET's electricity rates are heavily influenced by the utilities with the largest truck populations associated with them.

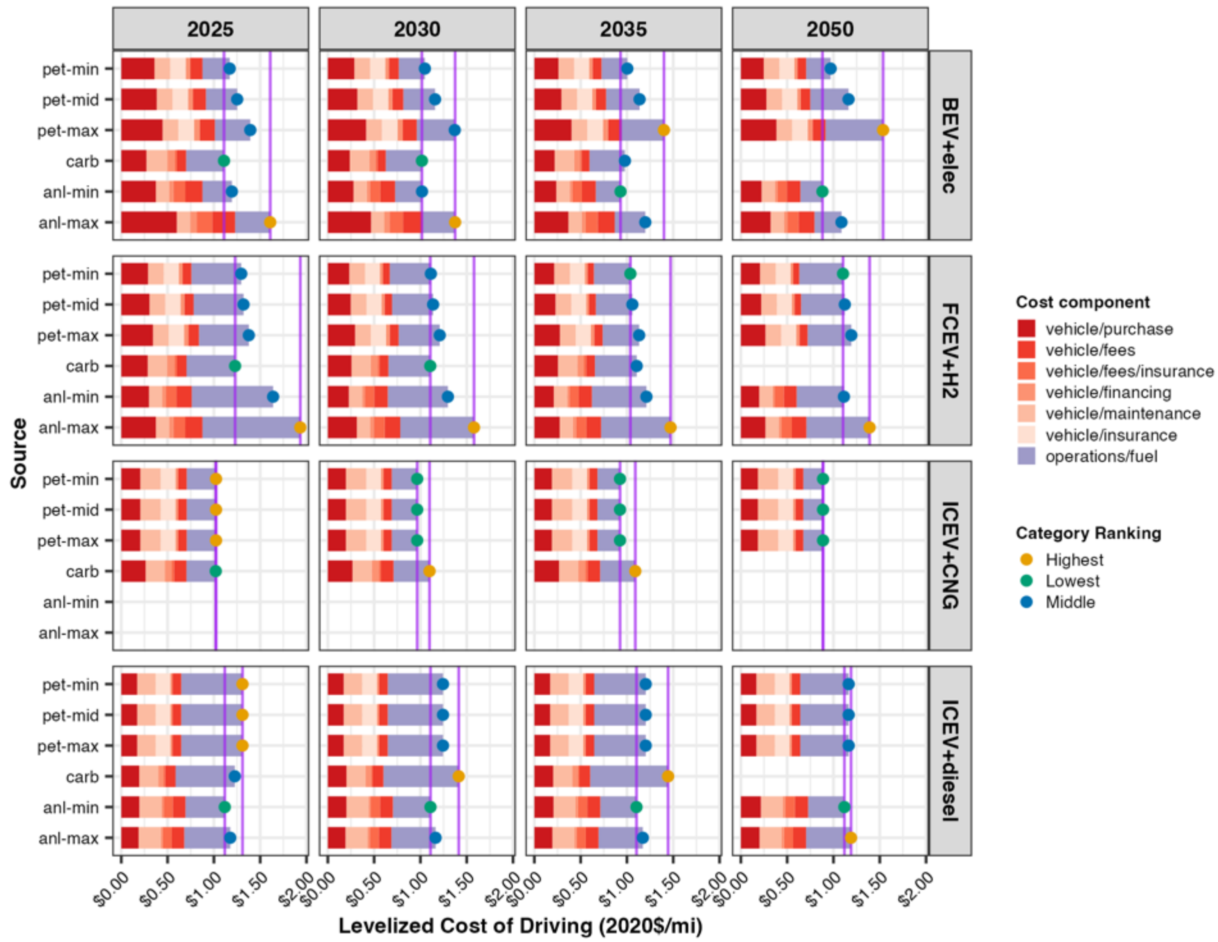
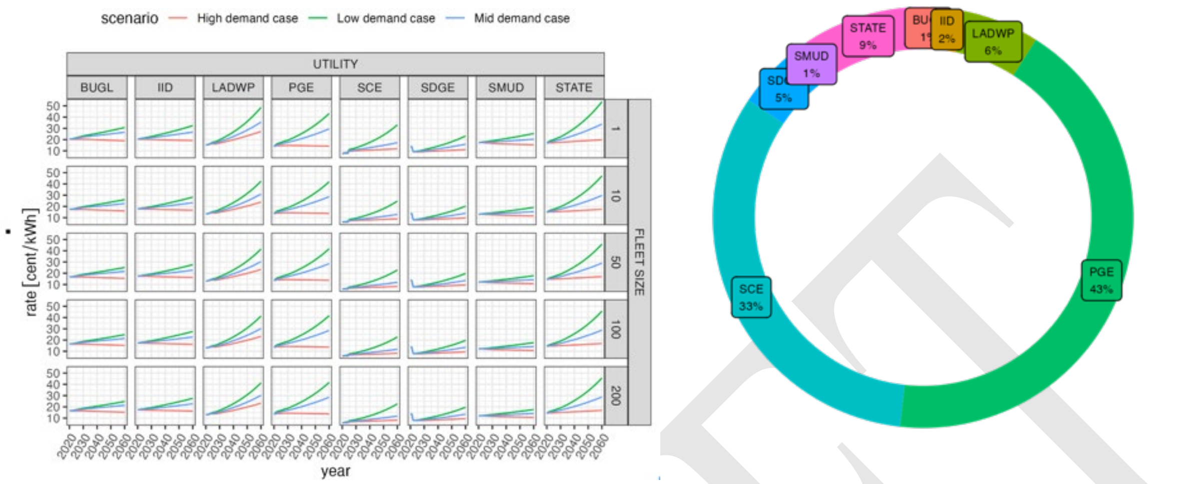


Figure 89. Component cost comparison between the PET and other estimates for drayage (day cab) trucks

Source: The 'pet' rows show statewide mean LCOD component cost estimates generated by the PET model (using a 12-year vehicle life). The 'carb' rows show LCOD estimates from CARB's Draft Advanced Clean Fleets Total Cost of Ownership Discussion Document (CARB, 2021d), which has estimates for 2025, 2030, and 2035. The 'anl' rows show TCO estimates from ANL's recent comprehensive TCO document (Burnham et al., 2021), which has estimates for 2020, 2025, 2030, 2035, and 2050. The vertical lines show the lowest and highest LCOD in each group to facilitate visual comparison and the highest and lowest LCOD's in each subplot are color coded.

Figure 90 shows the fraction of total trucks in the PET's 2020 base year that are within each utility's boundaries. We see here that PGE and SCE account for more than three quarters of the total truck fleet across all vocations. Recalling from Figure 44 the electricity rates by utility, we note that PGE (43% of the total) is forecast to have among the highest rates in the state, with rates even in the Mid-demand case approaching $0.30/kWh versus the $0.21/kWh in the CARB forecast.[55] This means that BEV trucks lose some of their operations benefit in a statewide average as time proceeds.



(a) Electricity rates by utility and fleet size (b) Share of vehicles associated with each Utility

Figure 90. Electricity rates and California utility market share

Source: Panel (a) is a reproduction of Figure 44 from Section 4.1.3.3. Panel (b) is computed from the PET's 2020 (base year) truck stock estimates, derived from EMFAC.

Figure 88 and Figure 89 also highlight the divergent costs of hydrogen in the models, with the PET and CARB tracking closely while ANL's model estimates significantly higher costs.

From this comparison we conclude that the PET's estimates provide a reasonable range of costs for the day cab/drayage vocation. It is important to note that some costs are not included in this comparison, most specifically infrastructure costs that the PET models for all BEV+elec trucks and for large FCEV+H2 trucks. Nonetheless, the general alignment with the literature qualitatively validates the PET.

5.3 Baseline scenario selection

Based upon the sensitivity analysis, we selected the three market scenarios summarized in Table 44 as a baseline for comparing different incentive designs. The mid-market case is the same as the baseline in the sensitivity analysis except we have adopted a 2:1 EVSE instead of the 1:1 used in the sensitivity baseline. Whether to scale VMTs to higher levels was a challenging question. On the one hand, the sensitivity analysis showed that higher VMT assumptions will make BEVs more TCO and LCOD competitive. This isn't a justification by itself, but fleets may factor this in during purchase decisions and commit to running BEVs longer and for more miles to achieve TCO benefits. On the other hand, the range issues associated with BEVs make higher mileage operations more challenging and possibly infeasible, particularly in non-depot vocations

[55] See Figure 12: Electricity Price Forecasts in (CARB, 2021d).

such as linehaul and construction, where access to charging may prove to be challenging. We ultimately decided to stay conservative with these estimates and used the unscaled EMFAC-derived VMT totals. We also dismissed the option of using the higher VMTs for the optimistic scenario because these scenarios are intended to represent technical and market conditions and not operational choices.

Table 44. Market scenarios for evaluating incentive designs

Parameter	Optimistic market	Mid-market	Conservative market
Electricity Scenario (Figure 44)	High demand case	Mid demand case	Low demand case
Vehicle Production Scenario (Section 2.4.2)	Optimistic	Moderate	Conservative
Retail markup	35% for ICEV 40% for ZEV until 2030, then 35%, Source: the ICCT (Sharpe & Basma, 2022)	35% for ICEV 40% for ZEV until 2030, then 35%, Source: the ICCT (Sharpe & Basma, 2022)	35% for ICEV 40% for ZEV until 2030, then 35%, Source: the ICCT (Sharpe & Basma, 2022)
Operations premium	10% BEV penalty diminishing	10% BEV penalty diminishing	20% BEV penalty diminishing
Infrastructure	2:1 EVSE:Truck	2:1 EVSE:Truck	1:1 EVSE:Truck
Vehicle lifetime	10	10	15
Vehicle financing APR	4%	4%	4%
Discount rate	3%	3%	3%
VMT	EMFAC VMT (Section 4.1.3.3)	EMFAC VMT (Section 4.1.3.3)	EMFAC VMT (Section 4.1.3.3)

5.4 Policy designs

The PET assumes that all available vehicle incentives will be used by fleets to reduce their capital expenses. The primary design characteristic in this context is therefore the availability of incentive funds over time along with any restrictions on the use of those funds. Possible design considerations identified as part of prior incentive program designs in Section 1.1, include the following features described below.

- **Funding available per vocation and fuel type:** vehicle incentives typically have cost values associated with specific fuel types, for example, in the FY 2022/2023 funding for HVIP (CARB, 2023a), the baseline incentive for a class 8 vehicle is $120,000, but this can be increased through a number of modifiers, including a 100% bonus for fuel cell trucks (making the total incentive $240,000 for these vehicles).

- **Fleet size restrictions or bonuses**: for instance, smaller fleets may be eligible for more funding than larger fleets. Starting in 2023, larger fleets (101+) have their voucher amounts reduced by 20% to 50% based upon size, while smaller fleets (10 or fewer vehicles) receive a 15% bonus.

Additional incentive design characteristics that currently cannot be modeled by the PET include:

- **Geographical restrictions or bonuses**: specific regions, such as those classified as disadvantaged communities, may receive additional funding. At this time, the PET is not capable of modeling this feature as its spatial resolution is designed around the intersection of County, Air basin, Air District, and utility regions. This is a feasible modification for future work on the tool.

- **Total funding available to all vehicles (or within categories)**: the total amount of available funding each year may be restricted by budgetary constraints. At this time, the PET does not model this type of restriction and it is left for future work.

Though we also need to consider the impacts of other (non-CARB) incentives—infrastructure incentives are particularly important if we're modeling infrastructure purchase and financing—we hold them steady for this analysis so we can explore the impacts of vehicle incentive designs. Modeled infrastructure incentives include utility-specific incentives (1.2.2) as well as CEC EnergIIZE incentives (1.2.1).

As a first pass to consider specific incentive designs, we explored the impacts of two general design characteristics. The first characteristic structures funding availability per truck for specific vocations and fleet sizes over time. We start with historical HVIP incentives for the years 2020-2022 and model 2023 incentives as shown in Table 45. The designs vary based upon how these incentives are modeled going forward. Four incentive designs are considered:

- The *tapering 2035 design* gradually reduces them to zero gradually between 2025 and 2035, at which point the ACF regulation requires only new ZEV purchases in the state.

- The *tapering 2050 design* tapers to 2050 rather than 2035, keeping funding available for longer.

- The *flat design* holds the incentives stable indefinitely (through 2050). Note that this design only makes sense in the context incremental caps, which we discuss next.

- Finally, the *no incentives* design assumes no incentives are available and acts as a base case for comparison.

Table 45. HVIP FY2022/2023 PET incentive design

Vocation	Fuel type	Fleet Size	Note	Multiplier	Incentive
drayage	electricity	1	+25%=[drayage] +15%=[small]	143.75%	$172,500
drayage	electricity	2-10	+25%=[drayage] +15%=[small]	143.75%	$172,500
drayage	electricity	11-20	+25%=[drayage]	125.00%	$150,000
drayage	electricity	21-50	+25%=[drayage]	125.00%	$150,000
drayage	electricity	51-100	+25%=[drayage]	125.00%	$150,000
drayage	electricity	101+	+25%=[drayage] -20%=[large]	100.00%	$120,000
construction	electricity	1	+15%=[small]	115.00%	$120,000
construction	electricity	2-10	+15%=[small]	115.00%	$138,000
construction	electricity	11-20		100.00%	$120,000
construction	electricity	21-50		100.00%	$120,000
construction	electricity	51-100		100.00%	$120,000
construction	electricity	101+	-20%=[large]	80.00%	$96,000
linehaul	electricity	1	+15%=[small]	115.00%	$138,000
linehaul	electricity	2-10	+15%=[small]	115.00%	$138,000
linehaul	electricity	11-20		100.00%	$120,000
linehaul	electricity	21-50		100.00%	$120,000
linehaul	electricity	51-100		100.00%	$120,000
linehaul	electricity	101+	-20%=[large]	80.00%	$96,000
drayage	hydrogen	1	+100%=[H2] +25%=[drayage] +15%=[small]	287.50%	$345,000
drayage	hydrogen	2-10	+100%=[H2] +25%=[drayage] +15%=[small]	287.50%	$345,000
drayage	hydrogen	11-20	+100%=[H2] +25%=[drayage]	250.00%	$300,000
drayage	hydrogen	21-50	+100%=[H2] +25%=[drayage]	250.00%	$300,000
drayage	hydrogen	51-100	+100%=[H2] +25%=[drayage]	250.00%	$300,000
drayage	hydrogen	101+	+100%=[H2] +25%=[drayage] -20%=[large]	200.00%	$240,000
construction	hydrogen	1	+100%=[H2] +15%=[small]	230.00%	$276,000
construction	hydrogen	2-10	+100%=[H2] +15%=[small]	230.00%	$276,000
construction	hydrogen	11-20	+100%=[H2]	200.00%	$240,000
construction	hydrogen	21-50	+100%=[H2]	200.00%	$240,000
construction	hydrogen	51-100	+100%=[H2]	200.00%	$240,000
construction	hydrogen	101+	+100%=[H2] -20%=[large]	160.00%	$192,000
linehaul	hydrogen	1	+100%=[H2] +15%=[small]	230.00%	$276,000
linehaul	hydrogen	2-10	+100%=[H2] +15%=[small]	230.00%	$276,000
linehaul	hydrogen	11-20	+100%=[H2]	200.00%	$240,000
linehaul	hydrogen	21-50	+100%=[H2]	200.00%	$240,000
linehaul	hydrogen	51-100	+100%=[H2]	200.00%	$240,000
linehaul	hydrogen	101+	+100%=[H2] -20%=[large]	160.00%	$192,000

Source: HVIP implementation manual.(CARB, 2023a). Baseline incentive for class 8 ZEVs is $120,000. Hydrogen vehicles receive a 100% increase vs the baseline, small fleets (1-10 HDVs) receive a 15% escalation, drayage trucks receive a 25% escalation, large fleets (101+) have a 20% reduction. Factors are multiplicative (a small drayage fleet receives 1.15*1.25 = 1.4375 = 43.75% increase.

The second design characteristic considered is whether incremental caps should be used. It is a regular feature of vehicle incentive programs to limit the incentive amount based upon the differential cost of the ZEV technology and the conventional diesel counterpart. However, recent implementations of HVIP do allow total incentives to exceed the incremental cost, as long as they don't exceed the full value of the vehicle (CARB, 2023a). Specific rules regarding limits to incremental costs and the stacking of incentives are complex and beyond the current resolution of the PET. As such, we model two simplified designs:

- The *capped incentives* design limits the value of the vehicle incentives for the vocational trucks modeled to the incremental capital cost between the ZEV and the diesel counterpart.
- The *uncapped incentives* design limits the value of the vehicle incentives for the vocational trucks modeled to be no more than the full value of the ZEV vehicle.

These two design domains, funding availability and incentive caps, can be combined into eight distinct incentive designs. To evaluate these, we developed three representative market condition scenarios based upon the results of the sensitivity analysis in Section 5.1:

- The *mid-market scenario* uses the moderate vehicle market conditions and mid-demand electricity case summarized in Table 41. All parameters follow the baseline case described in the sensitivity analysis. It uses the default technology adjustment factor (Section 5.1.1.3), baseline retail markup, and a 2-to-1 EVSE to truck assumption. All regulations are modeled (the Truck and Bus rule and ACF).
- The *conservative market scenario* uses the same parameters as the mid-market scenario except the low-demand (higher cost) electricity case is used, the conservative vehicle production case is used, the severe technology adjustment factors is adopted, and a 1-to-1 EVSE to truck assumption is made.
- The *optimistic market scenario* is the same as the mid-market scenario except the high-demand (lower cost) electricity case is used, the optimistic vehicle production case is used, and the low retail markup case is assumed.

Combining the 8 incentive designs with these three market scenarios produces 24 design-scenario combinations. To these, we added three additional design-scenario cases that use the *no incentives* design with the three market scenarios but do not model the ACF regulation. The mid-market, no-regulation case serves as a baseline BAU scenario to consider the impact of incentive policies. This resulted in 27 distinct design-scenario cases to consider.

5.5 Recommended incentive strategies

We ran the PET TCO, fleet turnover, and impact models for each of the 27 design-scenario cases to explore the policy space and recommend the best designs.

5.5.1 Policy design comparison

To compare the eight policy designs, we used several results from the impact module to assess incentive performance. We first considered how expenditures in the market varied across the design-scenario combinations. To illustrate the outputs we used, we show results for the *tapering design 2035 with incentive caps* under the *mid-market scenario*. Figure 91 shows the total expenditures of nearly $180B generated by fleet purchases of vehicle and infrastructure, associated maintenance, and fuel consumption. The impact of the ACF regulation is apparent in the spike in purchases in 2035.

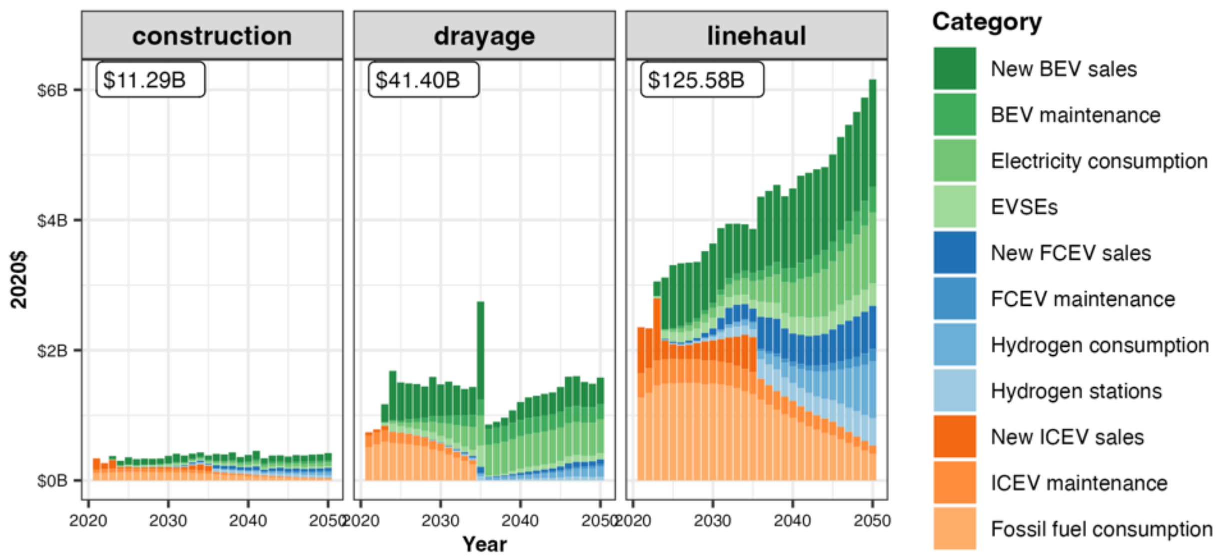


Figure 91. Total expenditures for the tapering 2035 design with incentive caps under the mid-market scenario.

We are also interested in the total incentivization required under this design so we plotted the total incentives over time by fleet size and vocation in Figure 92. The tapering design that removes incentives in 2035 is readily apparent. This figure highlights the relative importance of very large (101+) fleets across the board and of small fleets (<10) in linehaul. Overall, large fleets claim about 40% (1.875/4.682) of the incentives. We can also see that in this design-scenario combination, BEVs claim most of the incentives.

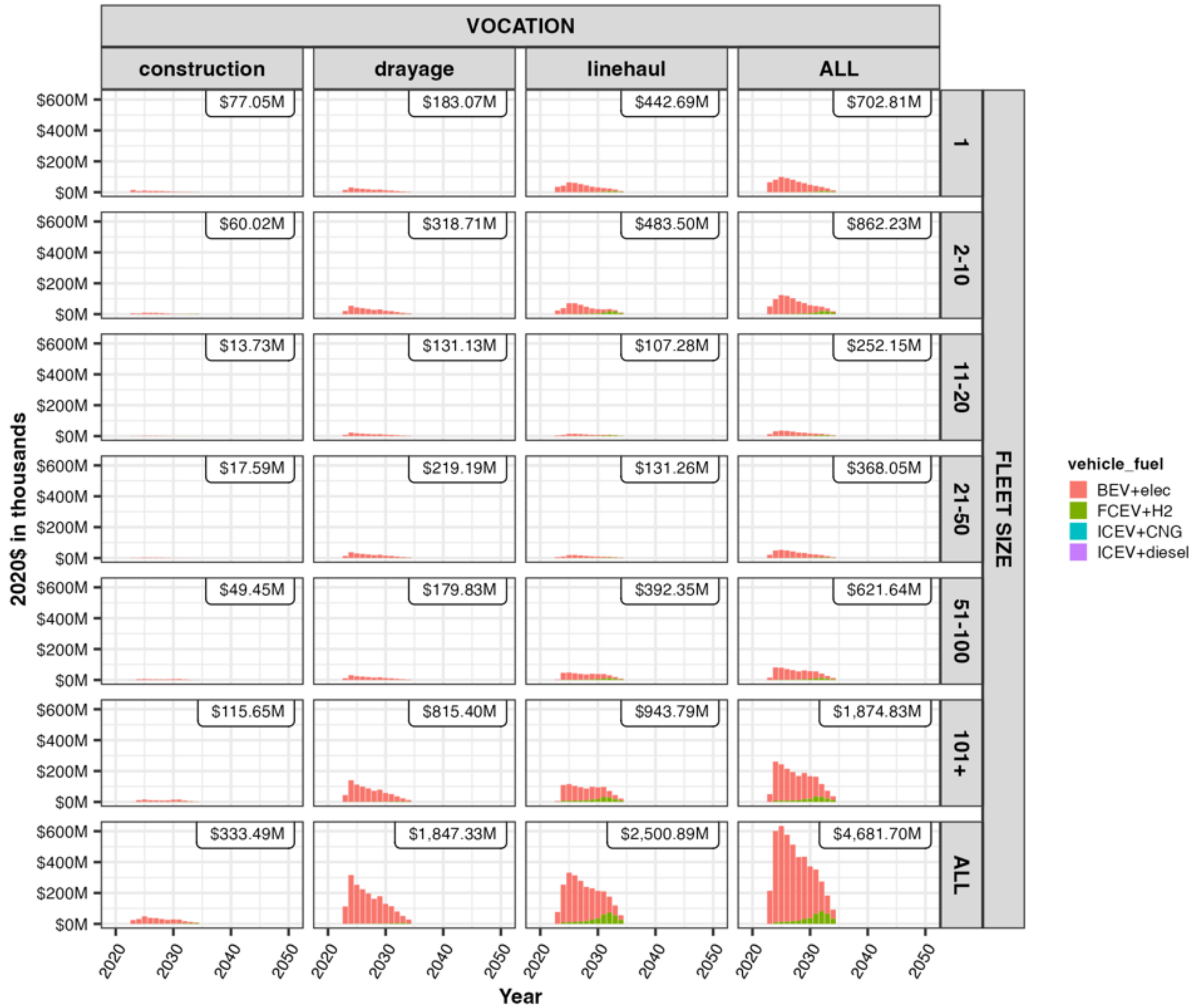


Figure 92. Total incentives over time for the tapering 2035 design with incentive caps under the mid-market scenario.

To systematically assess the various designs, we plotted total incentives versus various indicators. Figure 93 plots the total incentives versus the total economic expenditures resulting from fleet behaviors including capital expenses on vehicles, infrastructure, maintenance, and fuel shown in Figure 91. Clear patterns emerge in this plot. Unsurprisingly, the conservative scenarios generate more expenditures than the optimistic scenarios. This is consistent with how the model is designed and highlights a limitation. Because growth is assumed to be fixed, increasing costs will increase expenditures and there is no mechanism in the model for those cost pressures to reduce demand other than shifting purchases from one technology to other. In our market scenarios, the primary cost changes are in zero-emission options, meaning that fleets could elect internal combustion alternatives if they are cheaper and, critically, if regulations allow.

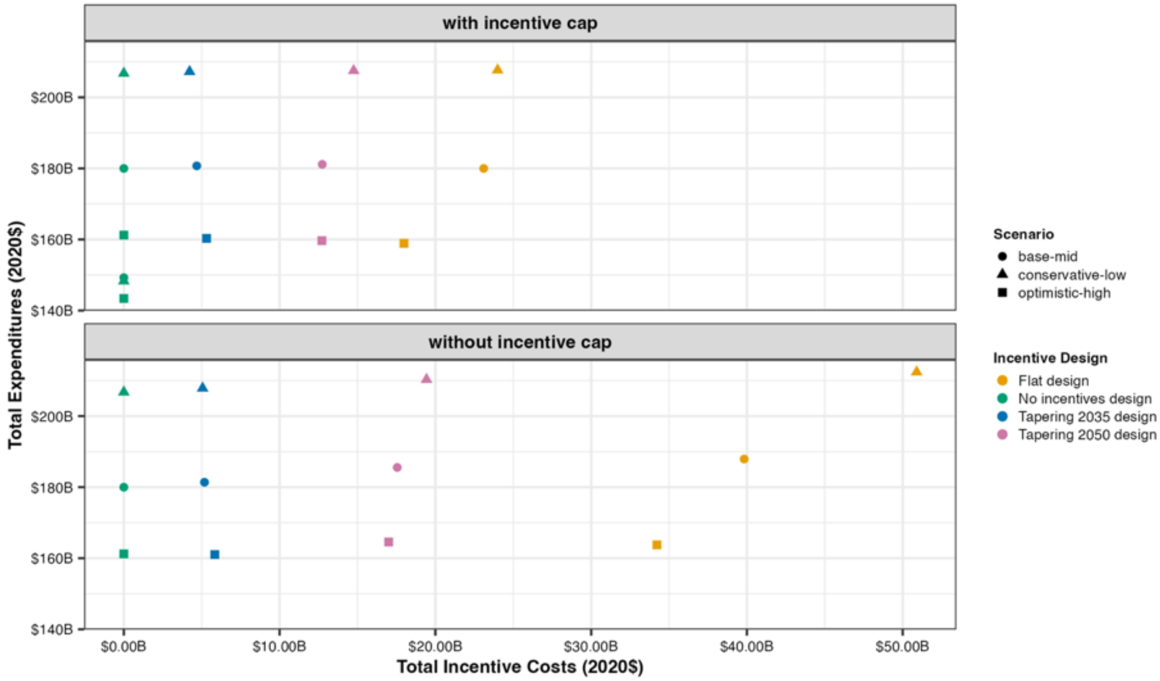


Figure 93. Total incentives versus generated expenditures for all policy designs

Notes: Totals are for the years 2020 to 2050. Incentive totals are for all regions, vocations, and fleets. Expenditures are for capital expenses on vehicles, infrastructure, maintenance, and fuel.

Other patterns are apparent as well. Generally, except for the non-incentivized design, increasing incentives increases expenditures, particularly in the flat incentive design, but this relationship weakens under the tapering designs. In fact, in the *tapering 2035 design under incentive caps* incentives decrease as market scenario gets more conservative creating higher costs for ZEVs compared to conventional alternatives. This is due to fleets delaying purchases until they are forced to under regulations because TCOs favor non-ZEV options.

Finally, and most importantly, we computed cost-effectiveness (C/E) ratios following the CMAQ methodology discussed in Section 1.7.1 using Eq. 2. To obtain emissions for each design-scenario combination we used the estimated annualized emissions from the impact module. We then subtracted the emissions from the *no incentives design* under the same scenario to compute project reductions. Total incentive dollars from 2020 to 2050 provided the project cost. The resulting C/E ratios are shown in Table 46. Since lower C/Es ratio are preferred as they indicate fewer dollars spent per ton of emissions reduction, the table is sorted in ascending order by C/E ratio.

Table 46. Cost effectiveness results

Incentive Design	Market Scenario	Total Emission Reductions (metric tons)	Total Incentives (millions of $)	C/E ratio ($/short ton)
Tapering 2035 design w/cap	HIOPT	9,821	5,310	490,465
Tapering 2035 design no cap	HIOPT	10,419	5,839	508,403
Tapering 2035 design w/cap	MIDBASE	6,684	4,682	635,448
Tapering 2035 design no cap	MIDBASE	7,278	5,177	645,367
Tapering 2050 design w/cap	HIOPT	12,237	12,711	942,348
Tapering 2050 design no cap	HIOPT	14,077	17,003	1,095,736
Tapering 2050 design w/cap	MIDBASE	9,213	12,738	1,254,336
Flat design w/cap	HIOPT	12,419	17,982	1,313,609
Tapering 2050 design no cap	MIDBASE	11,914	17,552	1,336,459
Flat design w/cap	MIDBASE	10,717	23,101	1,955,497
Flat design no cap	HIOPT	15,019	34,225	2,067,264
Flat design no cap	MIDBASE	13,780	39,825	2,621,898
Tapering 2035 design no cap	LOWCONS	1,441	5,058	3,184,650
Tapering 2050 design no cap	LOWCONS	4,657	19,431	3,785,074
Tapering 2035 design w/cap	LOWCONS	891	4,223	4,301,408
Flat design no cap	LOWCONS	8,502	50,896	5,430,907
Tapering 2050 design w/cap	LOWCONS	1,770	14,757	7,561,300
Flat design w/cap	LOWCONS	1,893	23,994	11,500,272
No incentives design	HIOPT	-40,301	0	NA
No incentives design	MIDBASE	-46,770	0	NA
No incentives design	LOWCONS	-58,467	0	NA

Note: The performance of different incentive designs is sorted from best C/E ratio to worst C/E ratio. Designs that increased emissions were not scored for C/E were placed at the bottom and assigned NA for C/E ratio. Rows are color coded by market scenario to more easily allow designs to be compared within each scenario.

To better understand the implications for the incentive design, these values are also summarized in Figure 94 with C/E ratio plotted against total incentives. The horizontal dashed lines show the thresholds identified by Pildes et al. (2020) as the boundaries for strong, moderate, and weak cost effectiveness. Projects below $2.8M/ton of emissions meet the strong criteria. All incentive designs meet this threshold except when they're evaluated under the *conservative market scenario*. The general trend is that there are diminishing returns to incentive investments as increasing dollars does not actually result in additional emissions reductions to improve the C/E ratio. This isn't to say that incentives are not needed. Though the *none design* here shows a zero C/E, that is only because it has zero investment and in fact has increased emissions associated with it. In fact, these incentive designs have been evaluated in the presence of regulations that require a large part of the fleet to transition to ZEVs by between 2024 and 2035. Since the PET is modeling the ACF regulation in these cases, it also is representing the diminishing returns on additional investments since in the later years after 2035, those fleets will be making the ZEV transition anyway so adding additional funding doesn't improve the outcome.

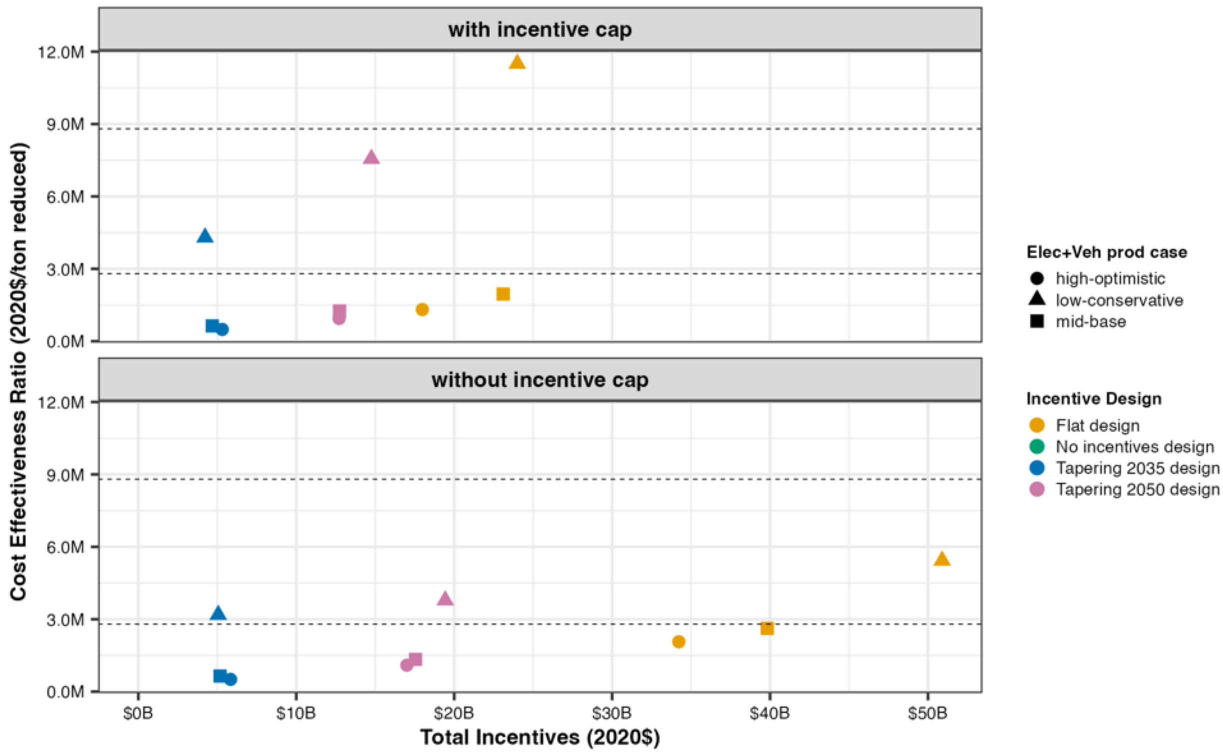


Figure 94. Cost effectiveness metrics for incentive designs

Notes: Lower C/E is better. Project life is assumed to be 30 years: 2020 to 2050. The dashed horizontal lines show the thresholds identified by Pildes et al. (2020) separating strong, moderate, and weak project quality as C/E increases.

As indicated in the table, the *tapering 2035 design* with incentive caps is the best design overall using the C/E metric. It consistently performs better than other options, with its mid-market scenario even ranking higher than the optimistic market scenario performance of other designs. The capped variant of the *tapering 2035 design* in the optimistic scenario at $490,465/ton performs somewhat better than the uncapped variant at $508,403/ton. A similar advantage of $635,448/ton versus $645,367/ton exists in the *mid-market scenario*. Given these findings our recommendation is that, in the presence of the Advanced Clean Fleets regulation, an incentive design that is tailored to drop away when regulations take over is the best approach. From a purely emissions-reduction perspective, a tapering designed to coincide with the onset of broad fuel choice restrictions in 2035 is the better option so we recommend a *tapering 2035 design* with incentive caps be considered by policymakers.

5.5.2 Recommended incentive design and its performance

Having chosen the *tapering 2035 design with incentive caps* we now turn to analyzing how the fleet performance under our three market scenarios and discussing the implications.

5.5.2.1 TCO analysis

Figure 95 shows how the statewide weighted average of TCOs evolve over time for each of the vocations and three market condition scenarios (optimistic=HIOPT, mid-market=MIDBASE, LOWCONS=conservative) for our selected design as well as a last row corresponding to the *flat incentive design* under the conservative market conditions (LOWCONS-FLAT). This figure shows the zero emission options being generally cost competitive with non-ZEV options under the incentive policy in 2025. For BEVs, this true for all vocations in both the mid- and optimistic market scenarios. In these scenarios, though their early advantage diminishes by 2035 when the regulatory rules become binding for most fleets, BEVs remain cost competitive with non-ZEVs in these scenarios out to 2050. These results support the conclusion that BEVs will achieve market parity with non-ZEV options by 2035.

FCEV also achieve a measure of market parity under some vocation-scenario combinations. Though FCEV TCOs are broadly higher in the early years, they generally perform as well as non-ZEVs by 2030. The removal of incentive supports in 2035 can be seen in the slight discontinuity in those years where the unincentivized trend connects to the modeled TCO. By 2035, FCEV generally show unincentivized parity with non-ZEVs and, in some cases particularly in linehaul and under the conservative market conditions, outperform BEVs on TCO, and maintain competitiveness with non-ZEVs for construction even under the conservative conditions.

Still, the lack of parity under the conservative market scenario is a concern that policymakers should track. If the costs of ZEV components and ZEV fuels fail to achieve at least the moderate cost reductions forecast as part of the mid-market scenario here, it may be necessary to maintain policy supports beyond 2035 even though our C/E analysis suggested this was less desirable. The LOWCONS-FLAT case in Figure 95 shows the extreme case of maintaining the full 2023 HVIP design out to 2050 *without* incentive caps, such that the entire incentive can be used unless it exceeds the cost of the vehicle itself. We see here that this helps FCEV find competitiveness in this market case, but cannot make BEVs cost competitive. This is in part due to BEVs receiving LCFS credits directly by operating their own EVSE, but the modeled LCFS credits diminish to zero by 2050, leaving the BEVs uncompetitive due to the higher fuel costs in the conservative scenario.

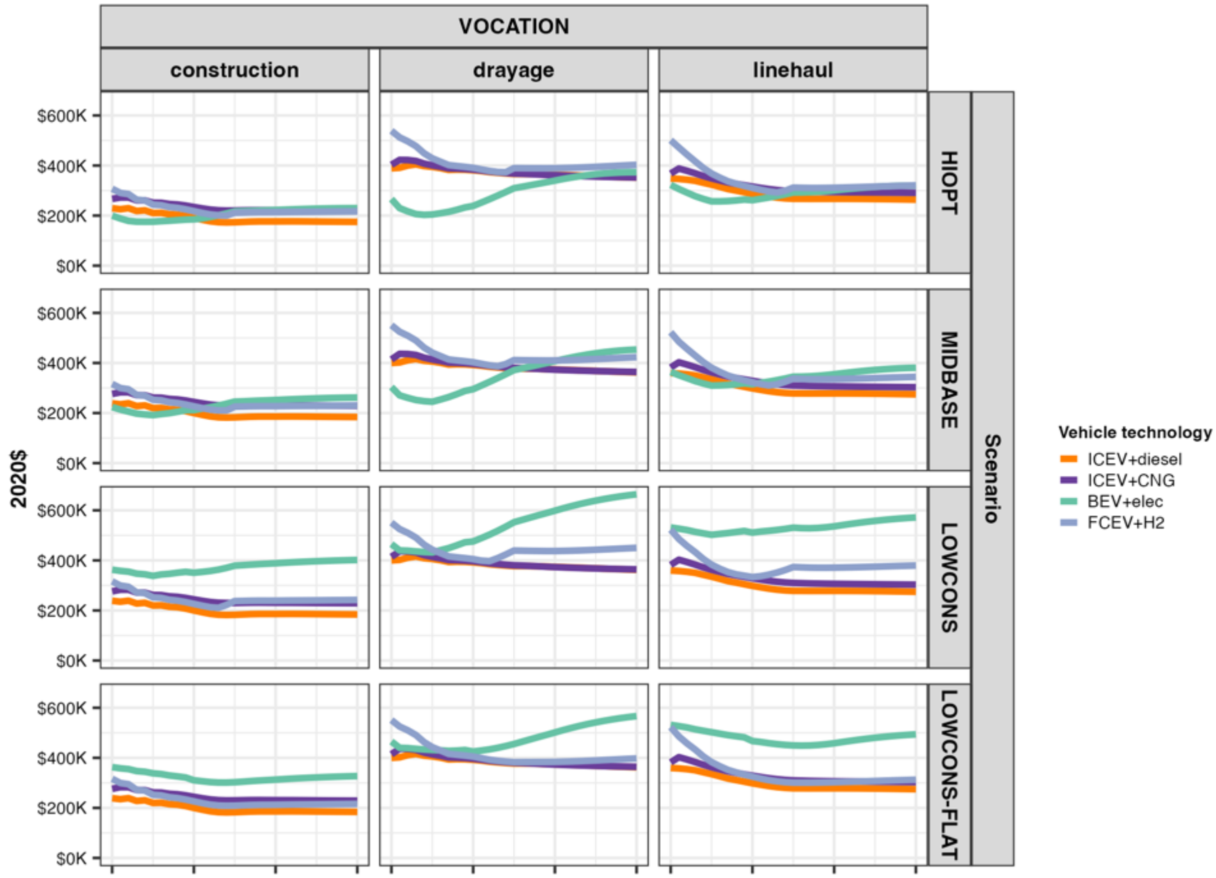


Figure 95. Statewide TCOs of final design recommendation under three market scenarios

Note: HIOPT is the optimistic market scenario, MIDBASE is the mid-market scenario, and LOWCONS is the conservative market scenario. LOWCONS-FLAT is included for comparison purposes to show how the *flat incentive design* only achieves modest gains over the selected *tapering design*.

Figure 96 illustrates the average annualized costs for individual vocation and vehicle fuel combinations in 2025. Here we can see how the substantial incentives provided under this design for BEV and FCEV offset the significantly higher capital expenses of these vehicles in this model year that are offset by incentives.

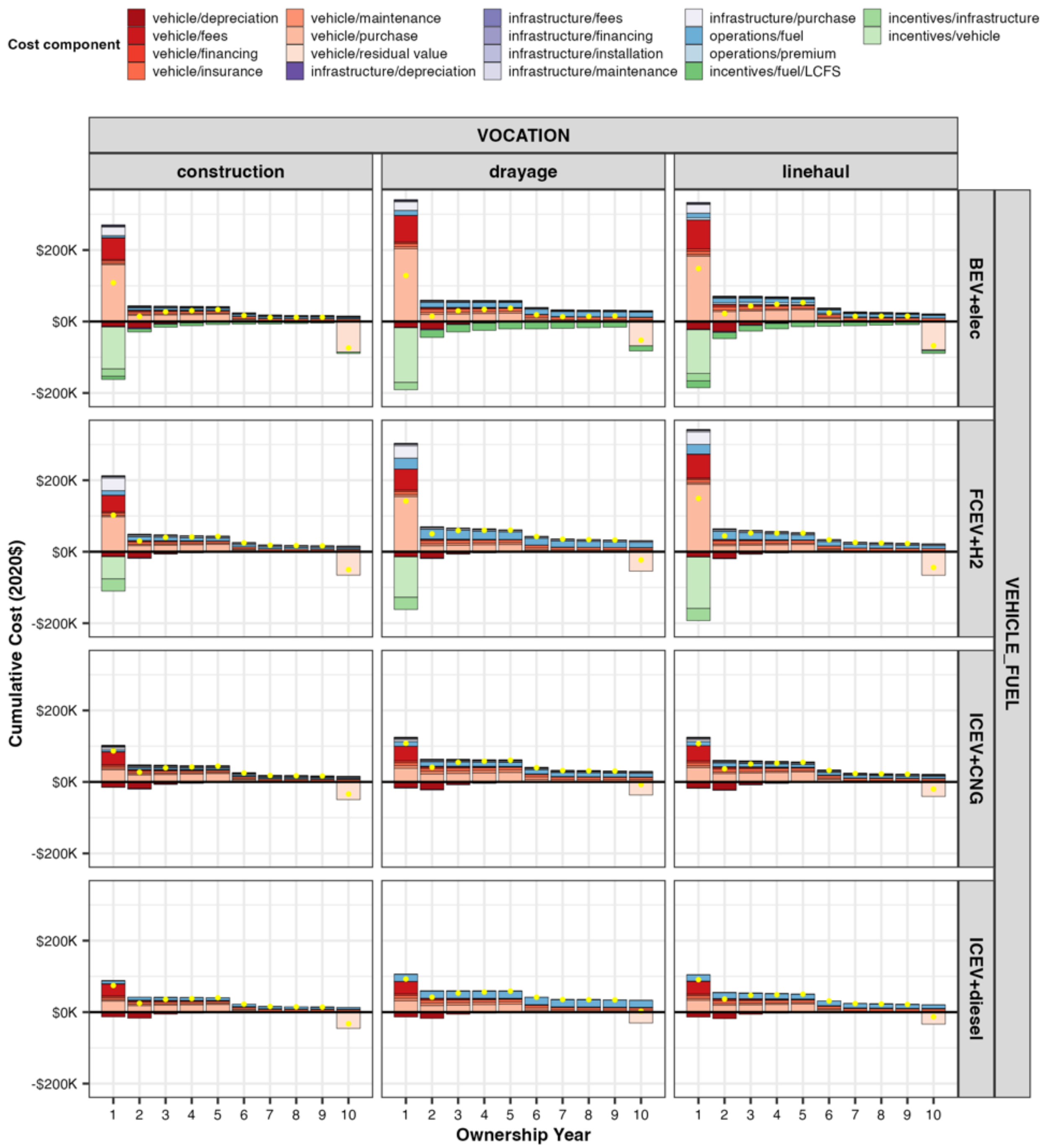


Figure 96. Representative annualized costs in year 2025 under the mid-market scenario

Figure 97 shows cumulative cash flow for the assumed 10-year ownership life in this TCO analysis for the mid-market scenario. This highlights how for drayage there appear to be cash flow advantages early in ownership life for vehicles purchased in 2025 but these dissipate during later acquisition years. These characteristics are likely due to assumed infrastructure costs for the FCEV and BEV options. Solving the infrastructure cost problem could go a long way toward improving ZEV performance in the market. The specific mechanisms for this could be to extend or increase existing incentives for infrastructure provided by utilities and the CEC, or it could be adaptation by fleets to achieve economies of scale through Truck-as-a-Service or Charging-as-a-Service solutions. Nonetheless, as our sensitivity analysis showed, fuel-related expenses (and cost gains) are likely to be a significant driver for uptake.

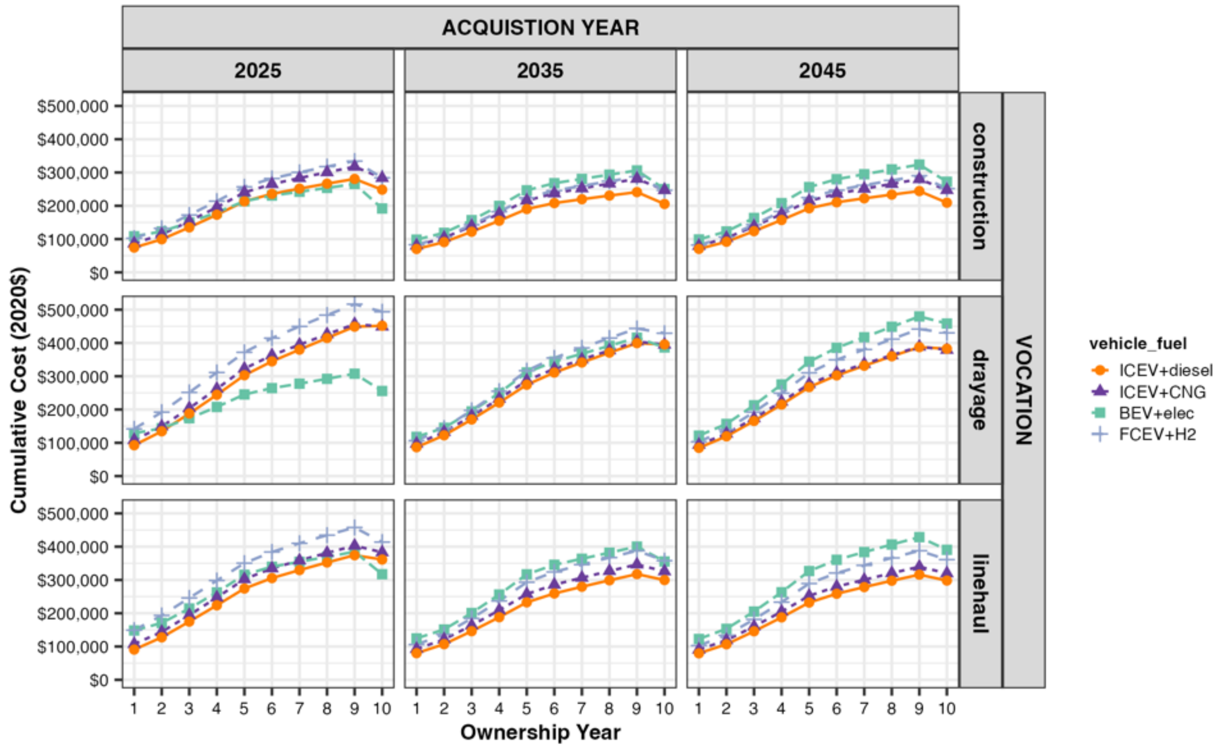


Figure 97. Representative cumulative cash flows for specific milestone years in the mid-market scenario

5.5.2.2 Technology Shares

Figure 98 through Figure 100 show the forecast technology shares over time for new truck purchases for the mid-, optimistic, and conservative market scenarios respectively. As we've discussed previously, the results emphasize the impact of the ACF regulation on vehicle technology choice where drayage fleets and large fleets lose the non-ZEV alternative for new vehicle purchases.

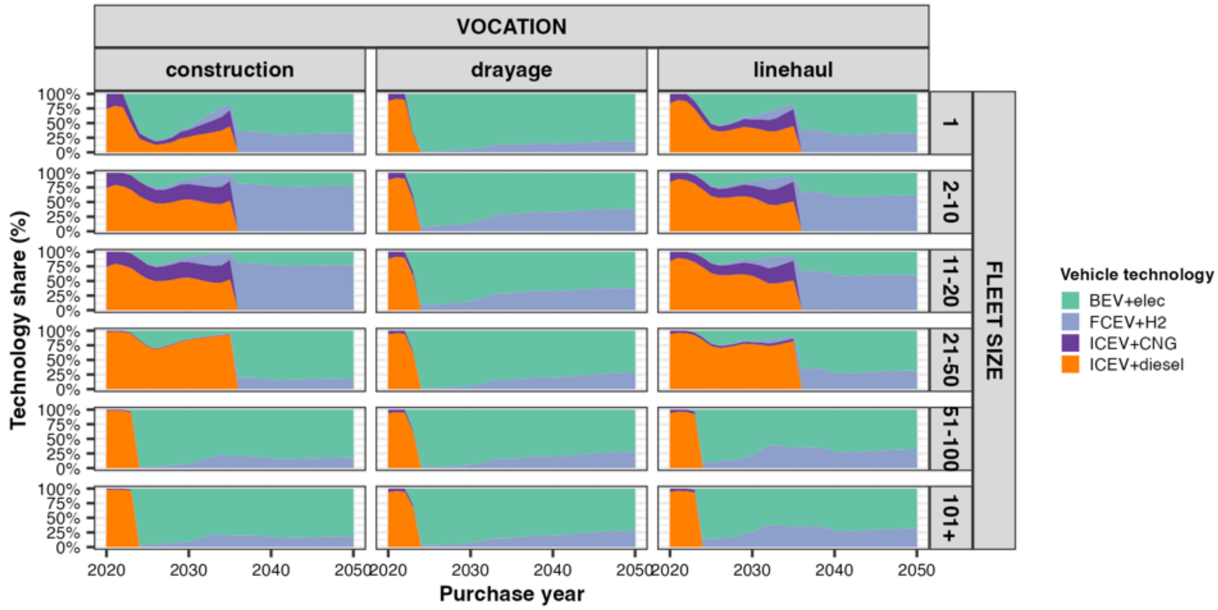


Figure 98. Technology shares for the mid-market scenario

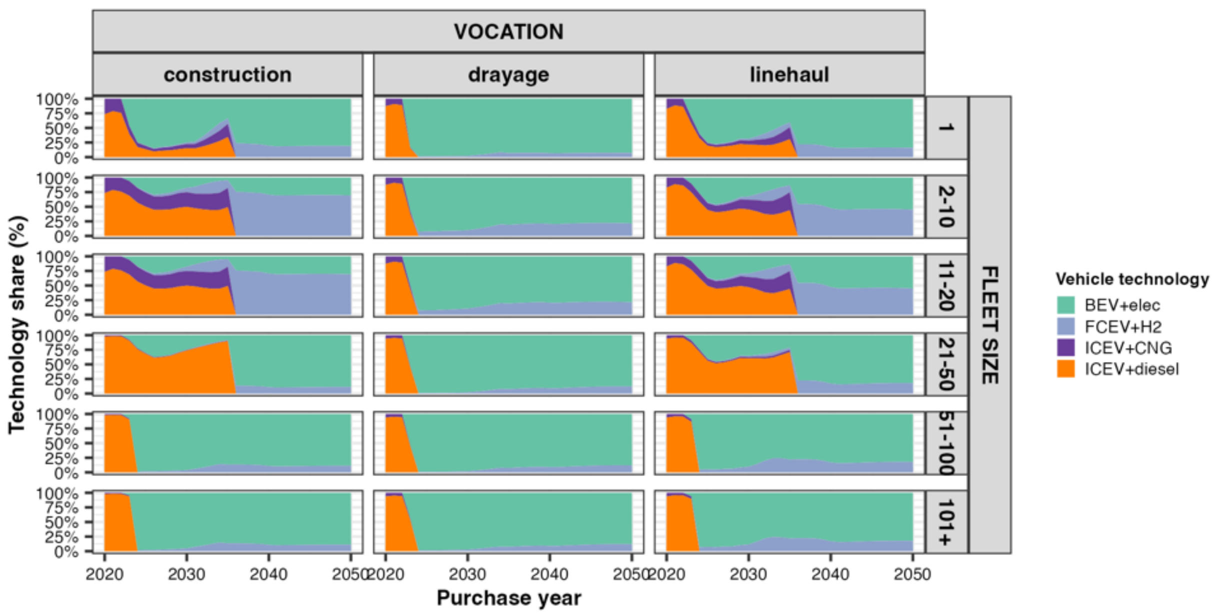


Figure 99. Technology shares for the optimistic market scenario

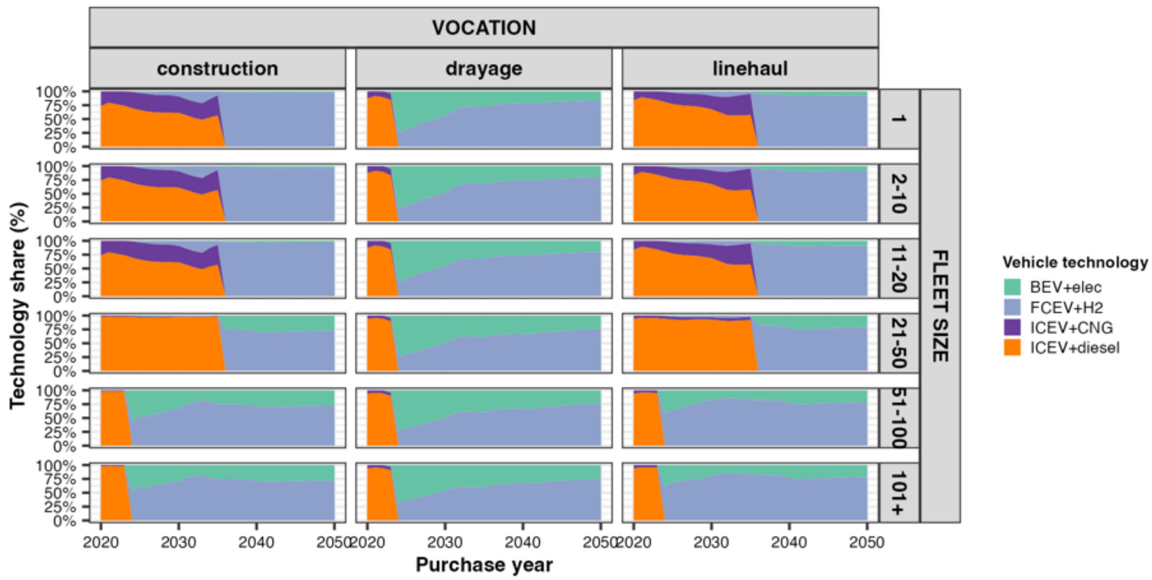


Figure 100. Technology shares for the conservative market scenario

5.5.2.3 New Truck Sales

Figure 101 through Figure 103 show new truck sales over time under the incentive design. The previously discussed spike in new trucks entering the market in 2035 is prominent. The splits between BEV+elec and FCEV+H2 trucks varies with the market scenario, but the fact remains this is a large discontinuity. From a fleet perspective this may be problematic but still feasible in theory. The PET, however, does not model the supply-side of the vehicle market, which may struggle to deliver 6,000 new ZEV trucks in a single year. There are many behavioral features in fleet procurement that may moderate this discontinuity, which we discussed in Section 3.2. Among these are features of decision making in organizations illustrated in Figure 34 that emphasize strategic motives and decision-making. In short, fleets are likely to be aware of an impending supply-side "doomsday" and will plan for it. Further, the OEMS will definitely be aware (or should be made aware) so that they can effectively market to fleets to transition earlier. Bae et al. (2023; 2022) also note the importance of business networks in influencing fleet perspectives on technology. As such, we recommend that policymakers use these results as a worst-case scenario of behavioral near-sightedness and continue to take action to educate fleets about the risks of delaying transition under the ACF regulatory scheme. On the other side, policymakers should be aware that that exceptions provided in the ACF regulations allowing for fleets to forego ZEV purchases could delay compliance if OEMs are unable or unwilling to hit supply targets, though the ACT regulation provides CARB with a mechanism to avoid that. Further work on the PET should be done to model how ACT's OEM requirements could drive cost changes to create more rapid turnover in the years leading up to 2035.

Another notable point in these plots lies in how shifting electricity costs alters the linehaul splits between electric trucks and fuel cell trucks. This apparent sensitivity suggests that continued work on obtaining the best fuel cost estimates will support better policymaking with the PET.

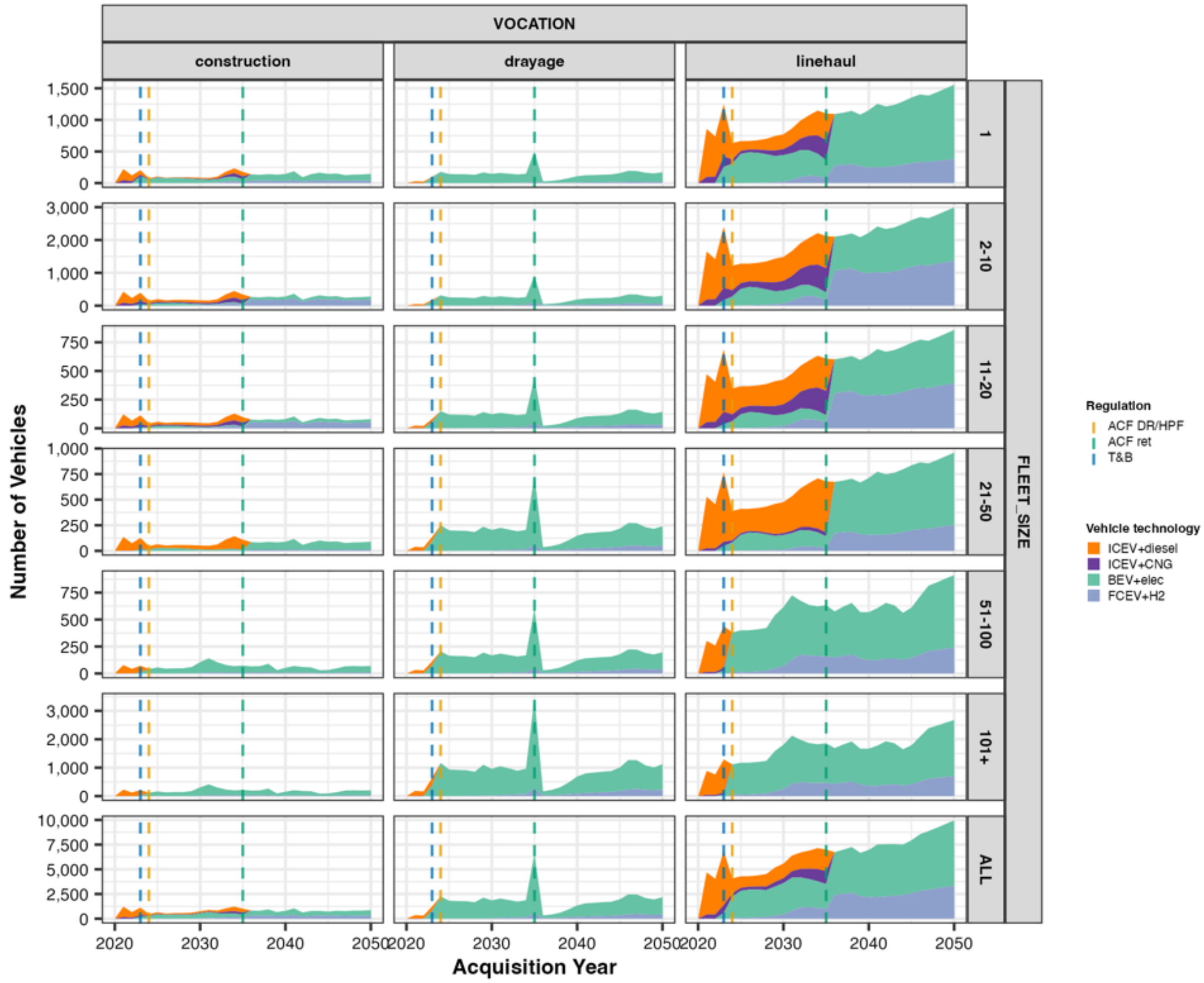


Figure 101. New truck sales under the mid-market scenario

Note: The y-axes in these plots vary vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen. The onset of ACF and T&B regulations are illustrated with vertical dashed lines.

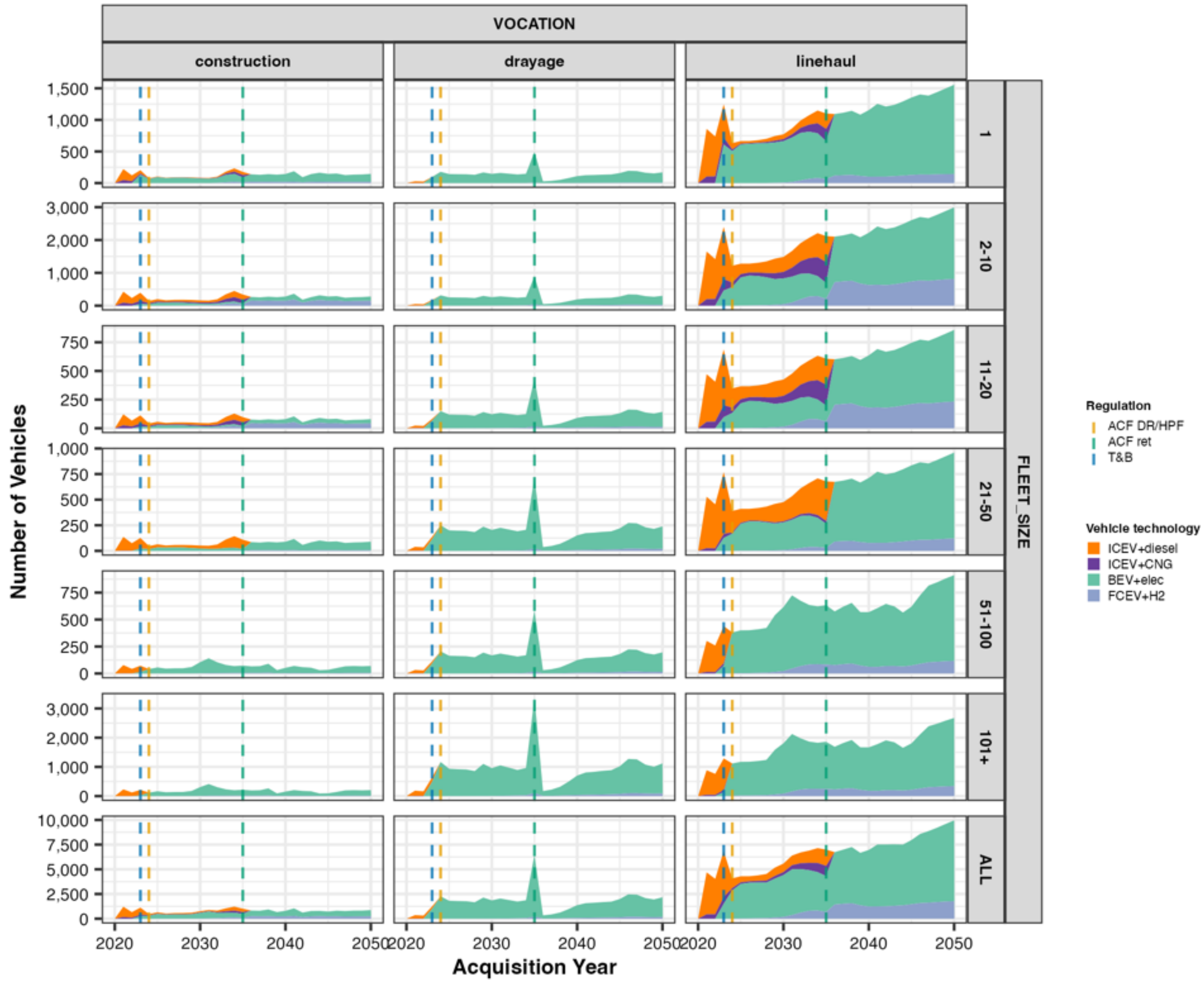


Figure 102. New truck sales under the optimistic market scenario

Note: The y-axes in these plots vary vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen. The onset of ACF and T&B regulations are illustrated with vertical dashed lines.

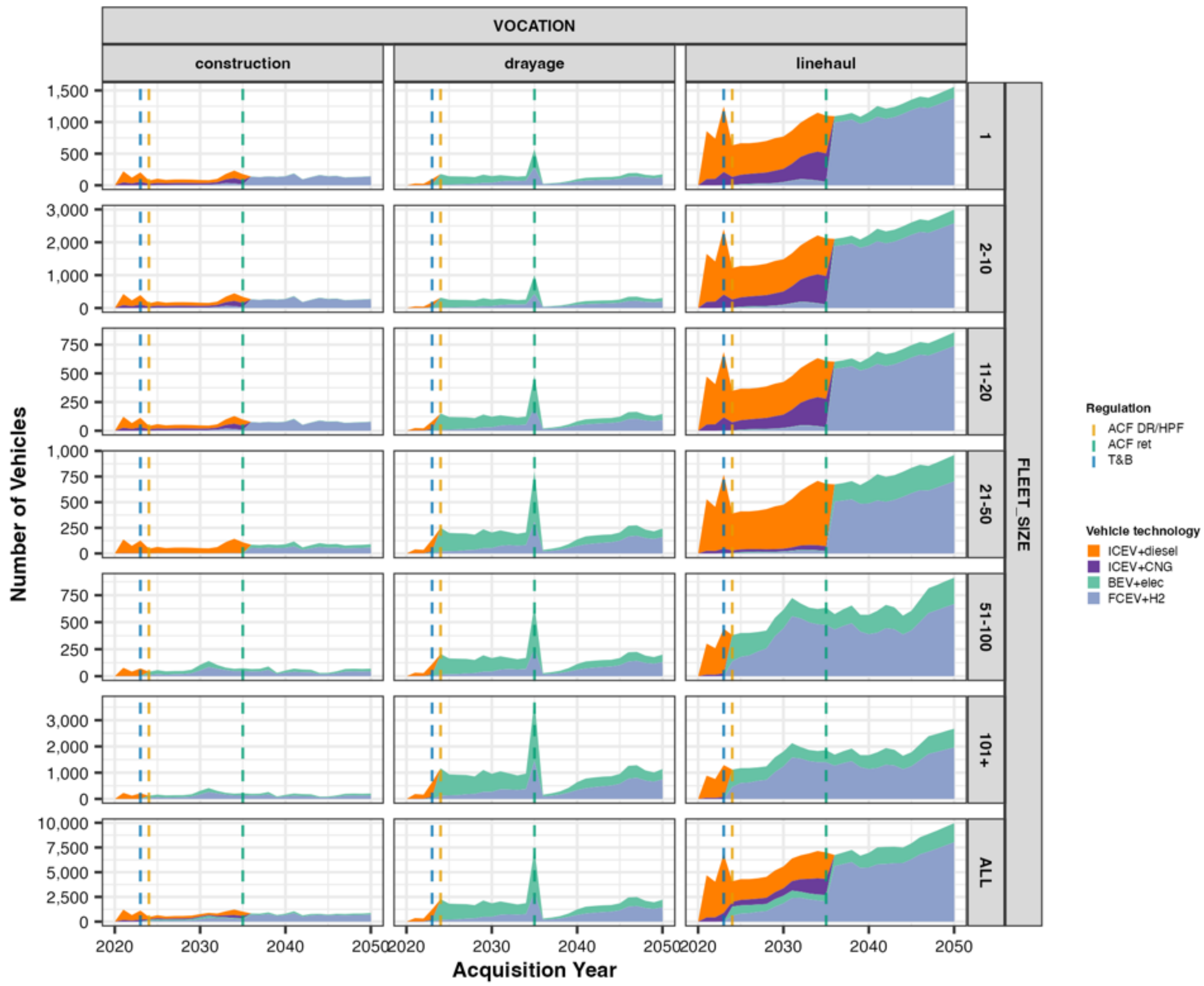


Figure 103. New truck sales under the conservative market scenario

Note: The y-axes in these plots vary vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen. The onset of ACF and T&B regulations are illustrated with vertical dashed lines.

5.5.2.4 Incentive Costs

The new trucks sales summarized above are supported by incentivization that is summarized Figure 104 through Figure 106. The figures show total vehicle incentives for the selected design range from \$4.2B to \$5.3B across the scenarios, with the mid-market estimate at \$4.6B over the 30-year model horizon, though under this design no more incentives are offered after 2035 so it is effectively a 15-year program. It is interesting to note that the optimistic scenario generates more incentive costs as more ZEV vehicles are purchased during periods when incentivization is available under this design. However, as we noted in the policy design comparison (Section 5.5.1), the higher incentive costs under the optimistic scenario support more emissions reductions and have a better cost effectiveness than the mid-market scenario.

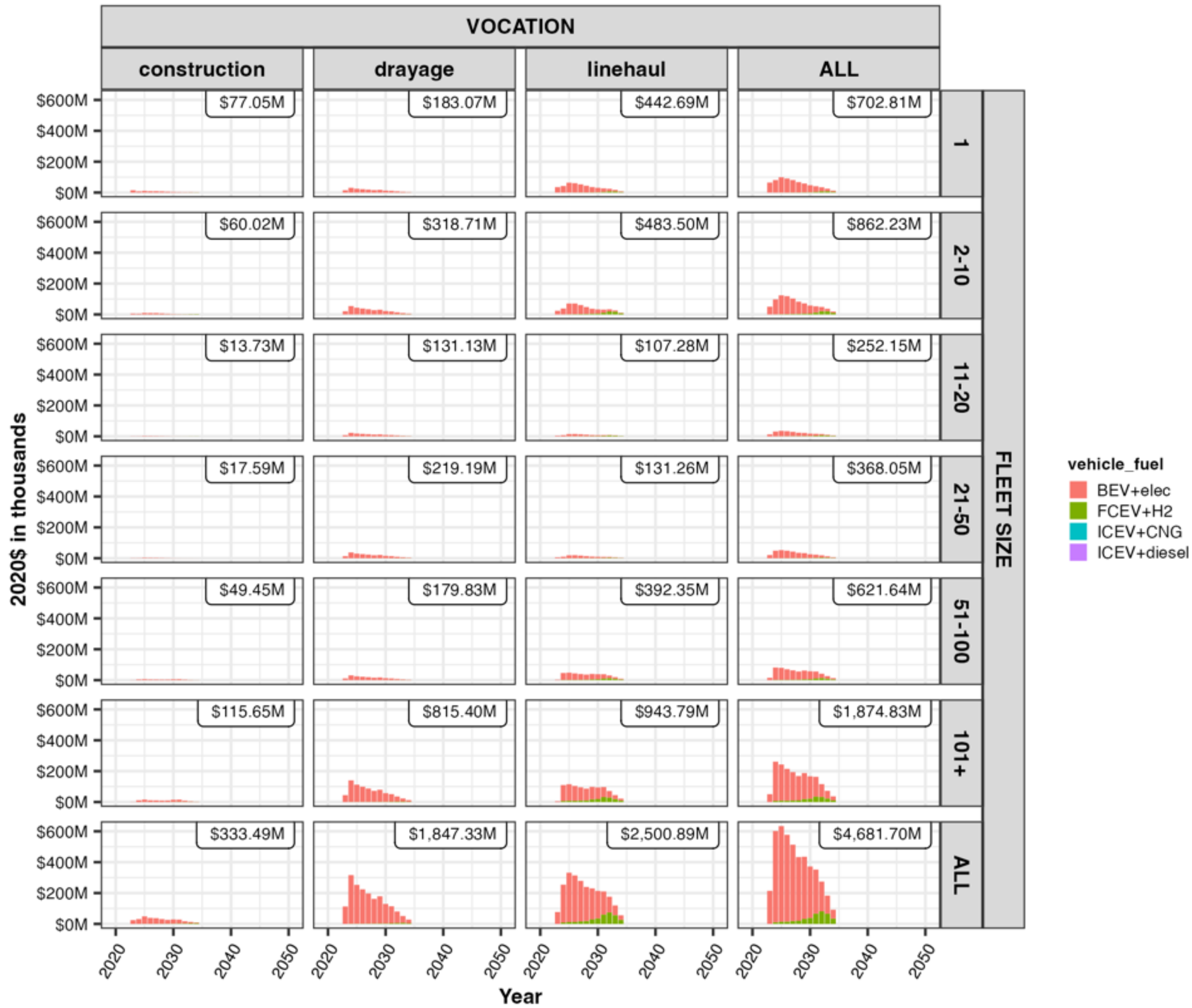


Figure 104. Incentive costs for the mid-market scenario

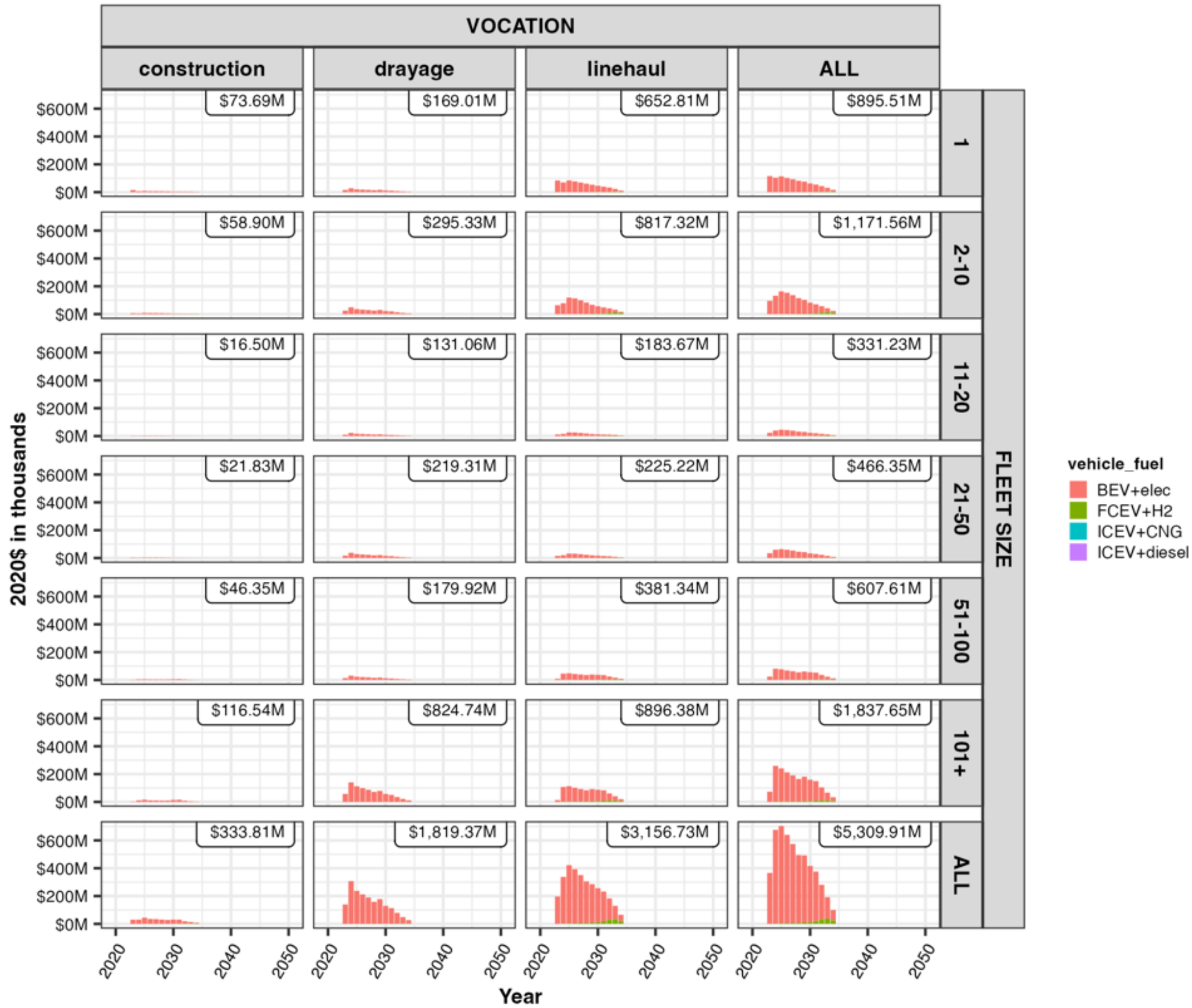


Figure 105. Incentive costs for the optimistic market scenario

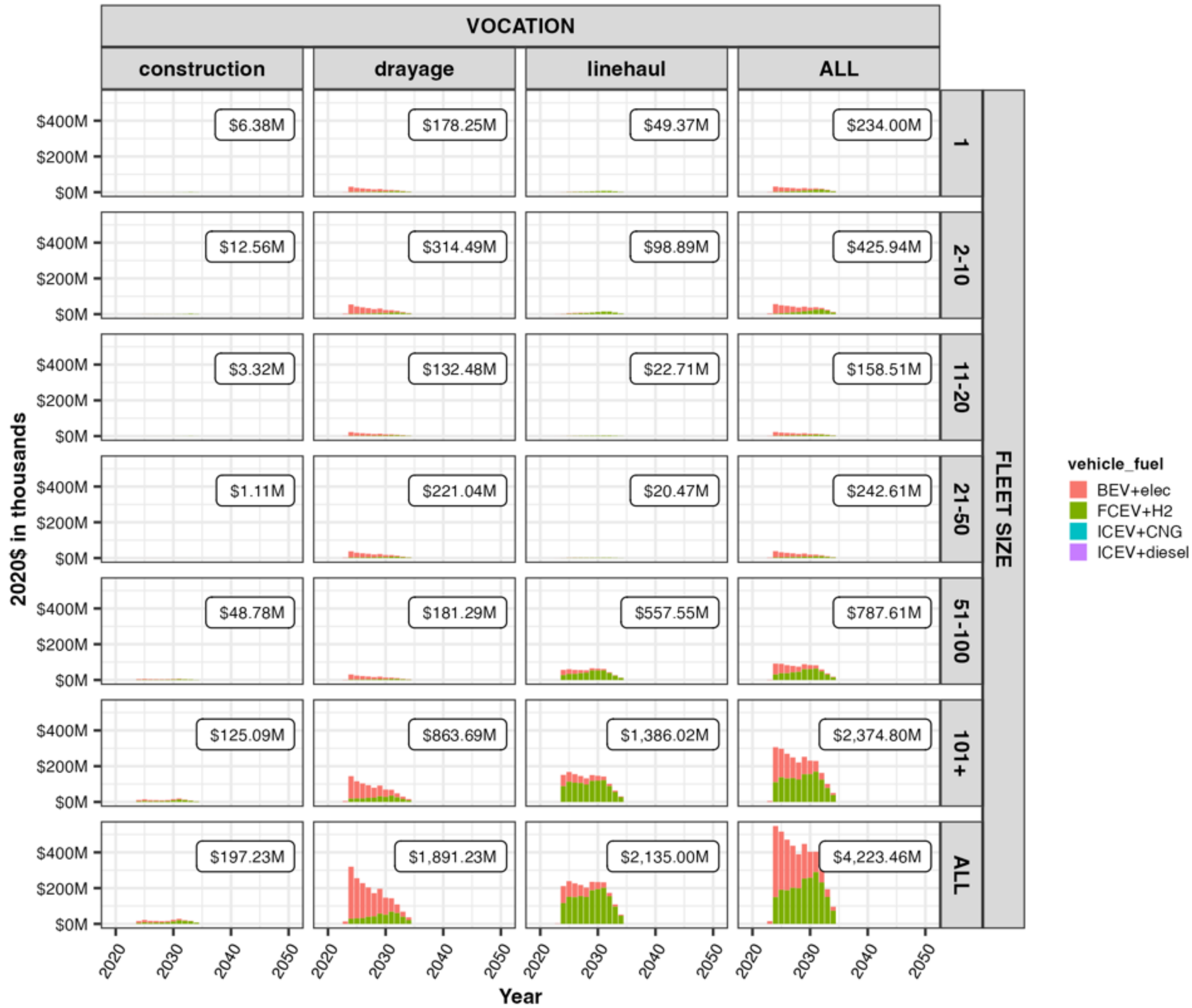


Figure 106. Incentive costs for the conservative market scenario

5.5.2.5 Truck Stocks

The truck stock figures in Figure 107 through Figure 109 highlight how the PET's cost sensitivity leads to significantly different outcomes under different market scenarios, with the splits between BEV+elec and FCEV+H2 tilting toward the latter in the more conservative market scenarios. One factor not currently modeled is the propensity of fleets to commit to specific fuel choices and stick with them, which we noted in our summary of Bae et al.'s work (2023; 2022) in Section 3.2. This is true when infrastructure purchases are necessary and is particularly true when those infrastructure purchases are "chunky" as with a hydrogen station that would support 20 trucks as this model. With a sensitivity to this feature, the outcomes in this model may differ if, for instance, a particular fuel has a cost advantage early that may influence fleet-level TCOs to commit to that fuel.

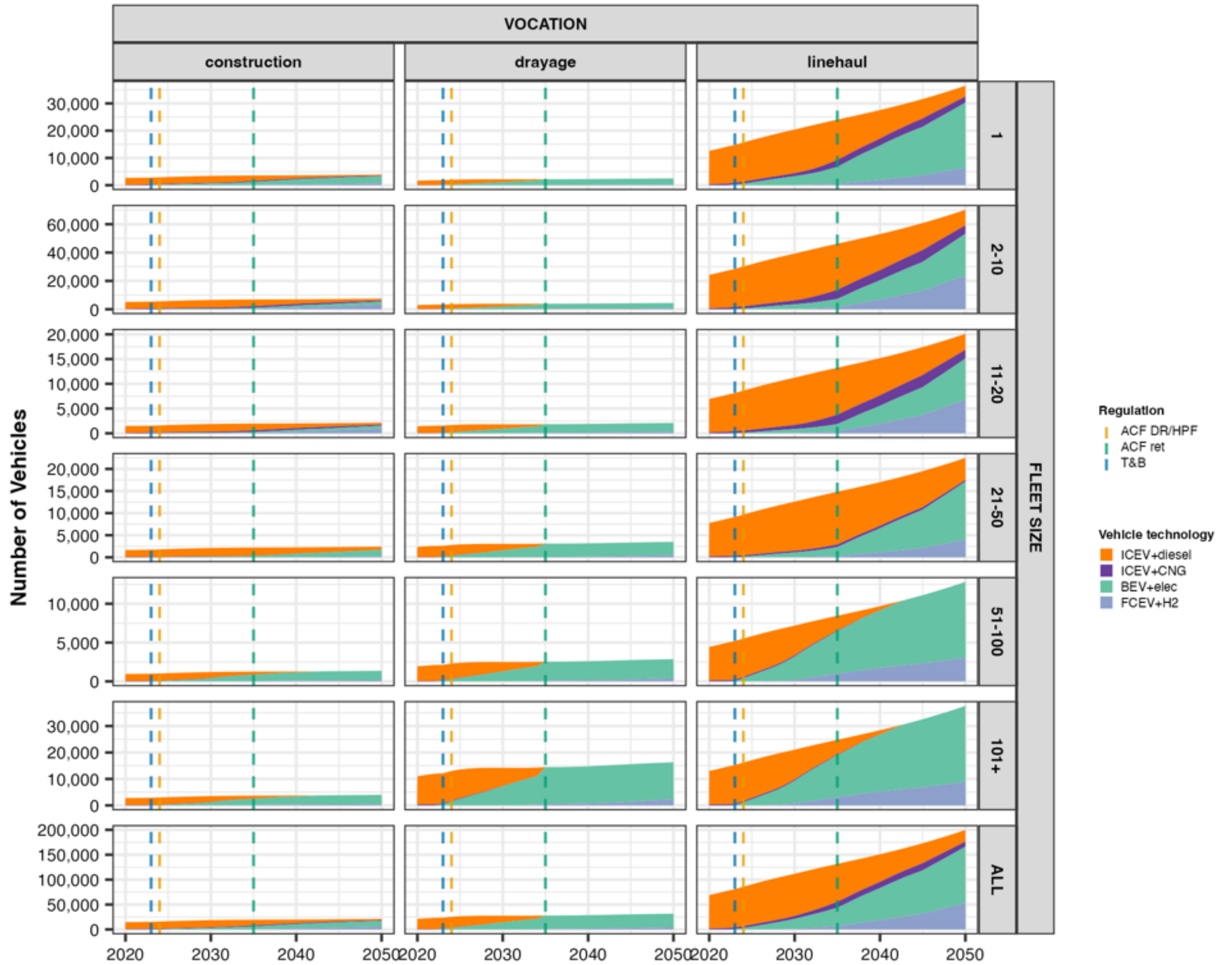


Figure 107. Truck stocks under the mid-market scenario

Note: The y-axes in these plots vary vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen. The onset of ACF and T&B regulations are illustrated with vertical dashed lines.

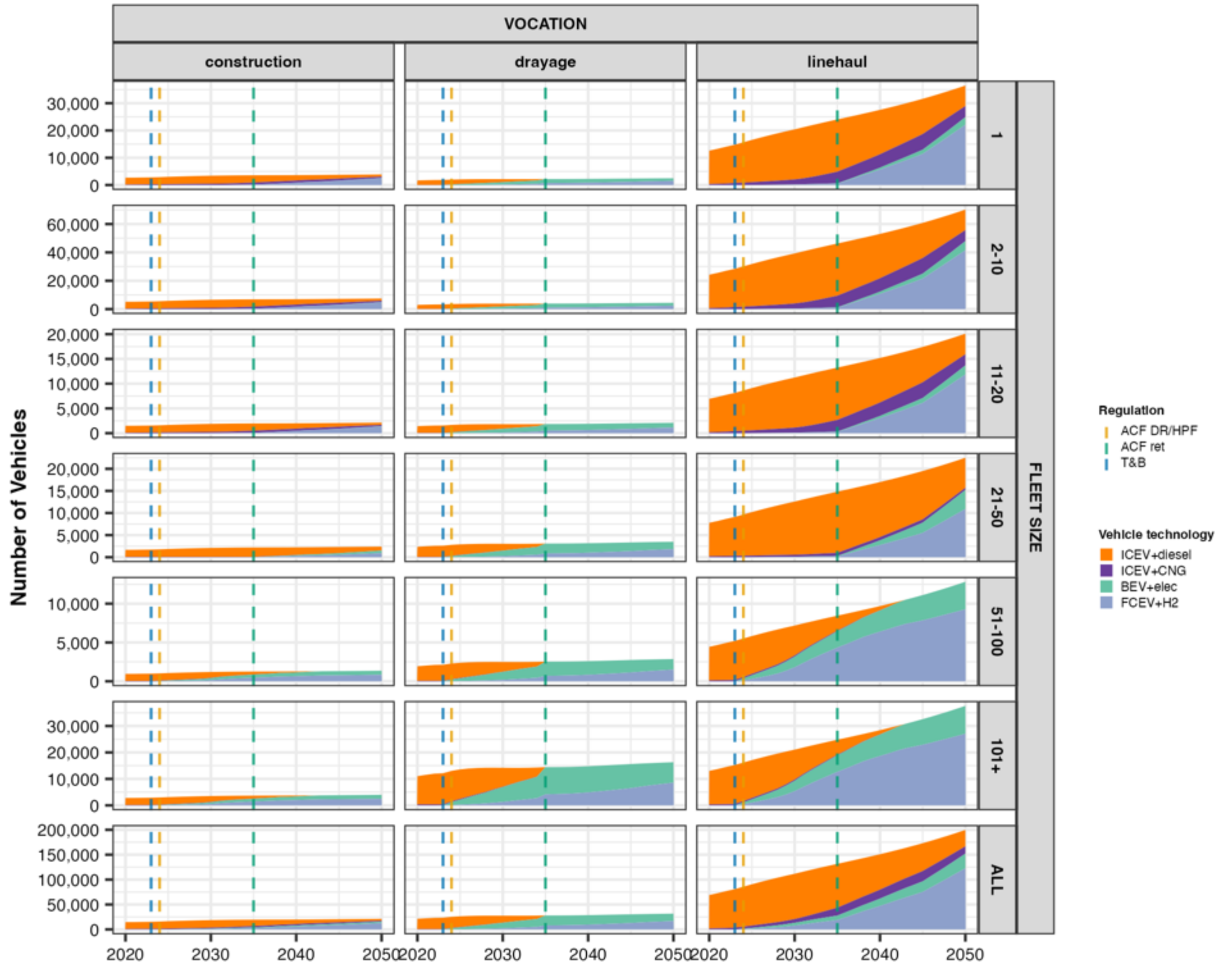


Figure 108. Truck stocks under the conservative market scenario

Note: The y-axes in these plots varies vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen.

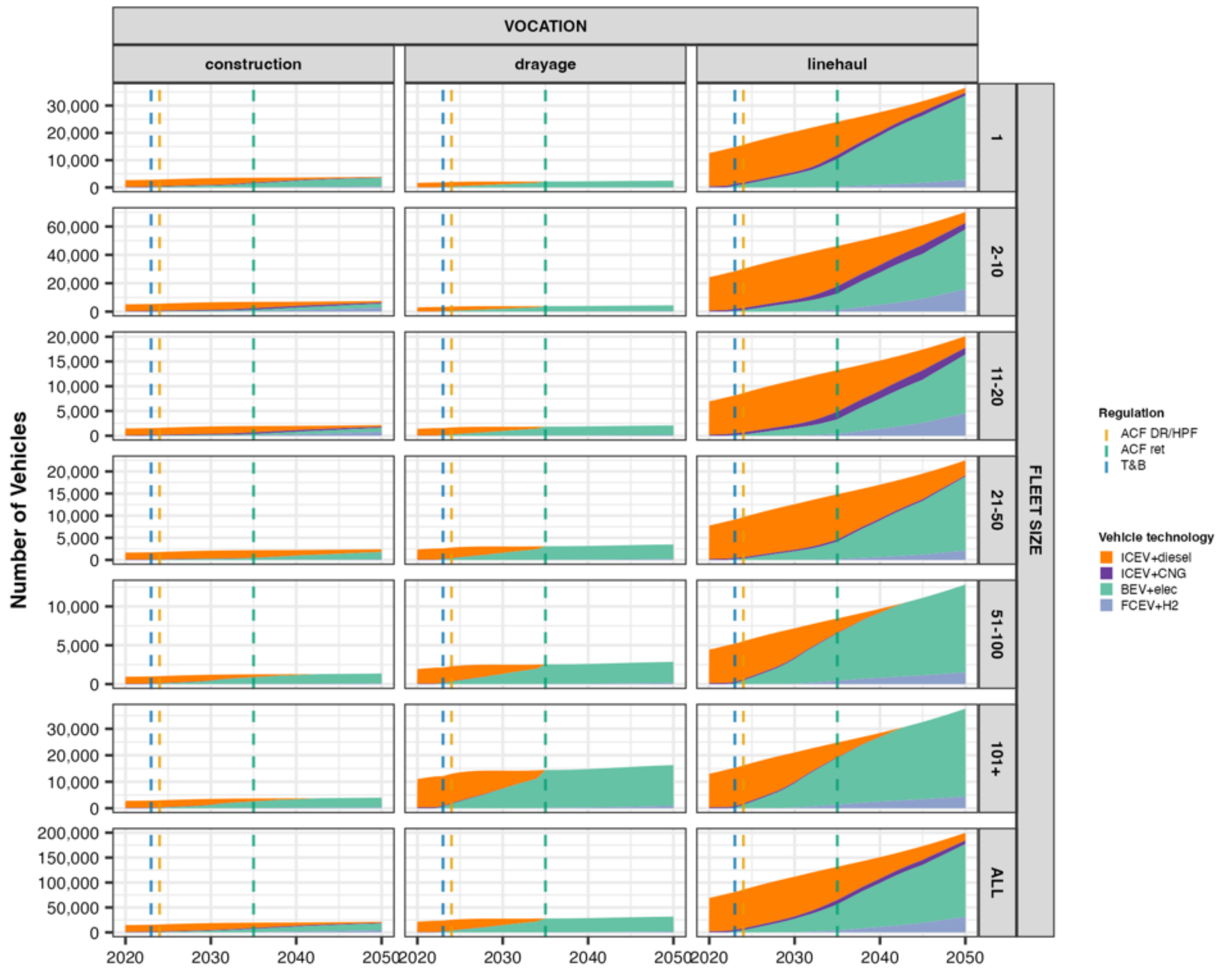


Figure 109. Truck stocks under the optimistic market scenario

Note: The y-axes in these plots varies vertically to allow patterns in lower-volume vocation/fleet-size groupings to been seen.

5.5.2.6 Expenditures

Figure 110 through Figure 112 show the annual induced expenditures under the mid, optimistic, and conservative market scenarios respectively. There is approximately a $46 billion difference in expenditures between the optimistic scenario at the low end and conservative scenario at the high end. This is roughly $1.5 billion per year (though it is weighted to later years), which illustrates the breadth of the market scenarios and their differential impacts. Again the 2035 discontinuity is prominent in the BEV sales and in the termination of ICEV sales.

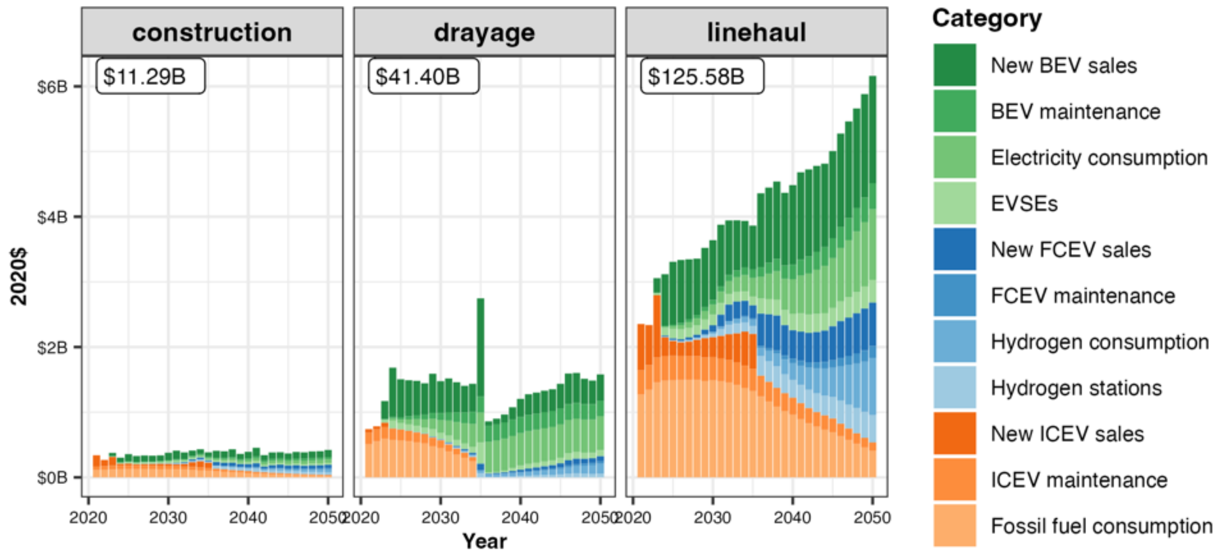


Figure 110. Annual expenditures under the mid-market scenario

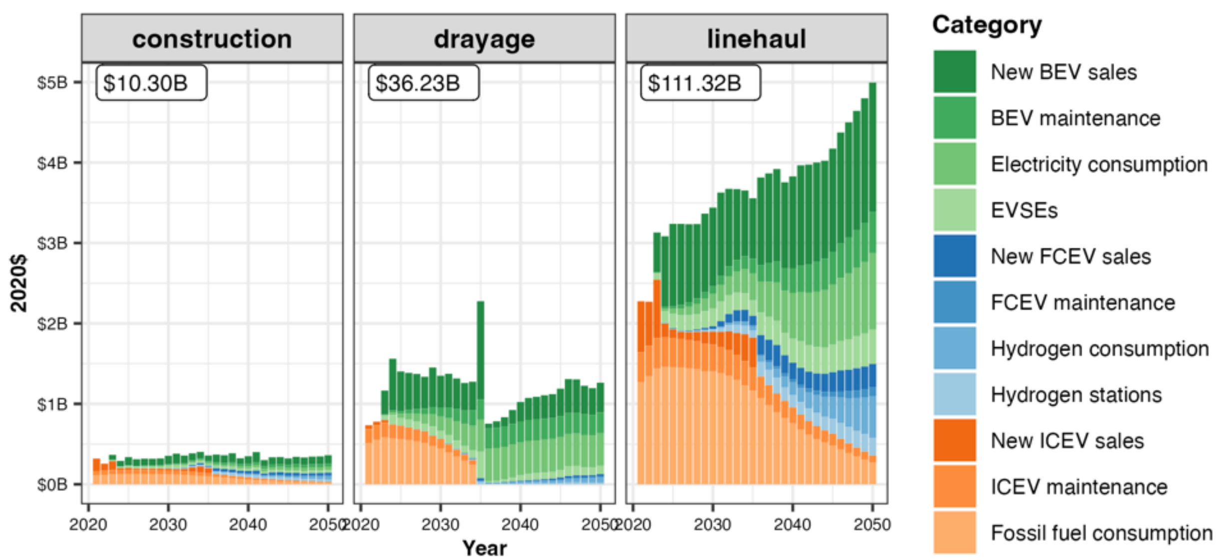


Figure 111. Annual expenditures under the optimistic market scenario

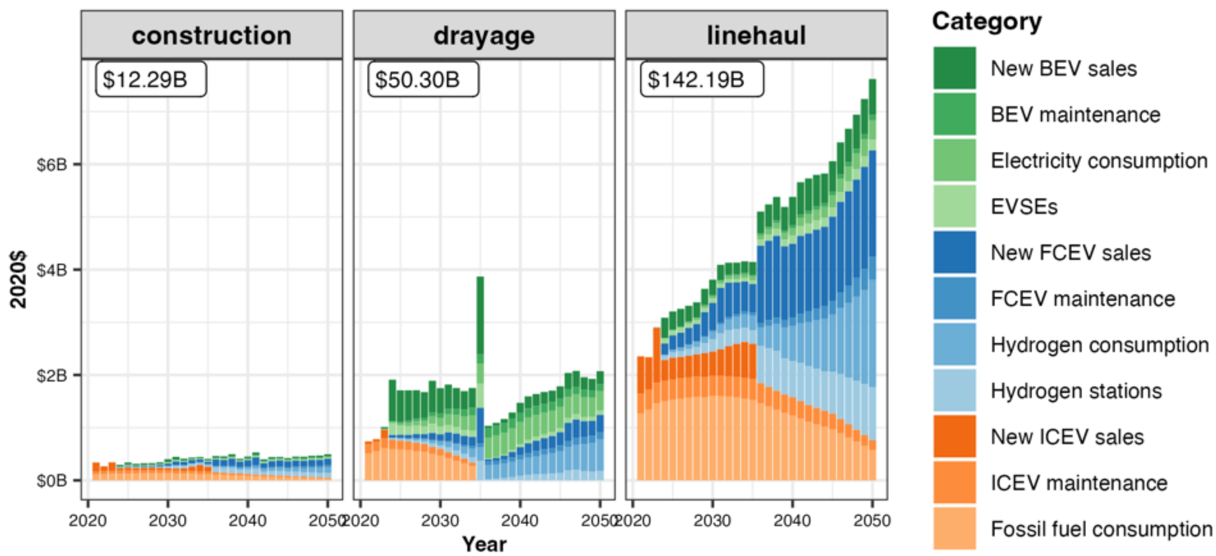


Figure 112. Annual expenditures under the conservative market scenario

5.5.2.7 VMT target comparison

Recall that the PET's vehicle and fuel costs are underpinned by the TRACE model discussed in Section 2.3. The model optimizes the vehicle technology splits of construction, linehaul, drayage trucks to minimize system costs while meeting EMFAC-forecast VMT demands subject to fuel feedstock constraints and the carbon reduction goals set by policymakers. The TRACE scenario underpinning our cost forecasts is based upon the following "80in50" scenario:

- Reach an 80% reduction in GHGs by 2050 with 40% reduction reached in 2030
- Major ZEV requirements modeled:
  - CA Executive Order N-79-20
  - CARB Advanced Clean Trucks regulations
- TRACE's electricity forecasts used the PET's rates
- 2:1 EVSE to truck ratio was assumed

Whereas TRACE is a supply side optimization, it is prescriptive regarding fuel type uptake, its purpose is to provide guidance to the State on what fuel pathways are most promising for on-road heavy-duty transportation. Our focus is to understand how pricing will influence fleet-side decisions to select vehicle technologies consistent with the State's mandates. The presence of regulations in the PET dictate some of those decisions, but generally, relative TCO is the governing dynamic of the choice model. Because the PET's costs are dependent on TRACE's modeling of a Wright's law relationship on vehicle component costs, it is useful to compare the resulting VMT splits forecast by PET to those forecast by TRACE to produce the cost estimates. Significant deviation could indicate that the models are out of balance and making the TRACE cost forecasts, which are derived from market-penetration assumptions, potentially inaccurate.

Figure 113 through Figure 115 show comparisons of the fuel type VMT shares between the PET results and the TRACE 80in50 results at five-year intervals between 2020 and 2050. A few notable points are apparent:

- TRACE models a more significant role for natural gas trucks, particularly in construction and linehaul vocations. This indicates that the system cost advantages targeted by TRACE differ from the cost-focused dynamics of the PET.
- The PET is slower to transition away from diesel in all cases. However, for all three PET market scenarios the share of internal combustion vehicles (diesel plus natural gas) tends to track closely between the models for construction and linehaul trucks through at least 2035, with TRACE tilting much more heavily to natural gas in those vocations. The advantages there likely come from the lower carbon intensity of renewable natural gas that is favored by TRACE for meeting its optimization goals.
- The impact of the ACF regulation on ZEV shares for drayage is clear in the PET but absent from the TRACE results, where ACF wasn't modeled. The lower volumes of ZEV vehicles in drayage modeled by TRACE could explain why the PET's vehicle costs trend higher than comparisons in the literature (see Section 5.2).
- The PET's FCEV splits tend to best align with TRACE under the conservative scenario in which higher electricity costs make hydrogen vehicles more attractive on the basis of operating expenses. The reverse is true as well in the optimistic scenario for the PET that results in near 100% BEV in the drayage vocation by 2035.

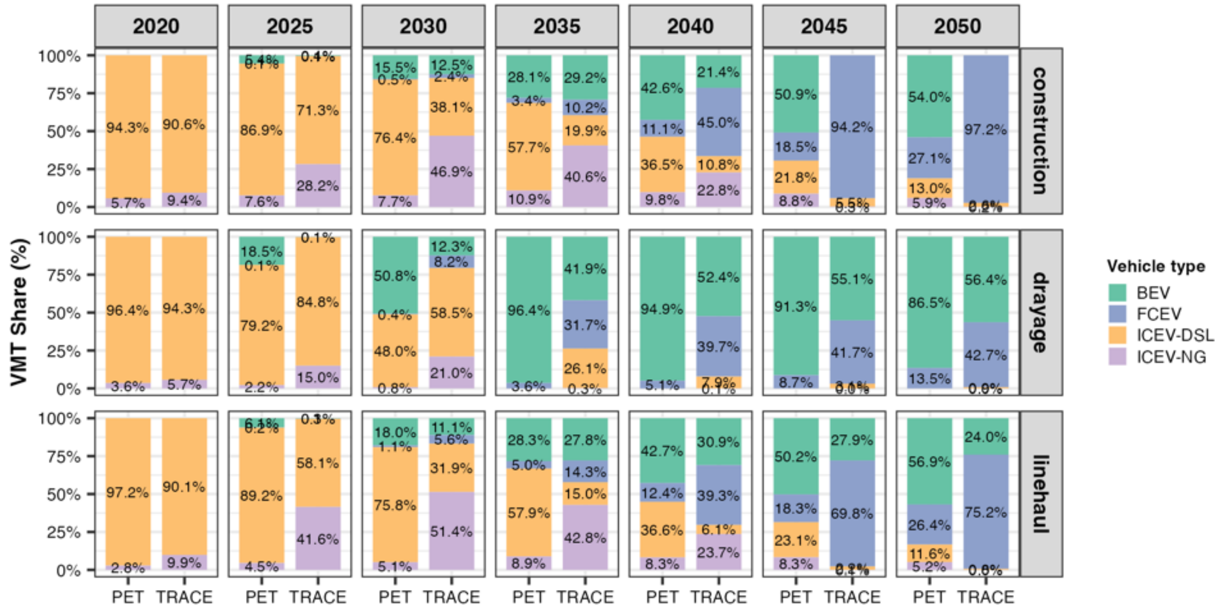


Figure 113. Mid-market scenario VMT technology share comparison to the TRACE 80in50 scenario

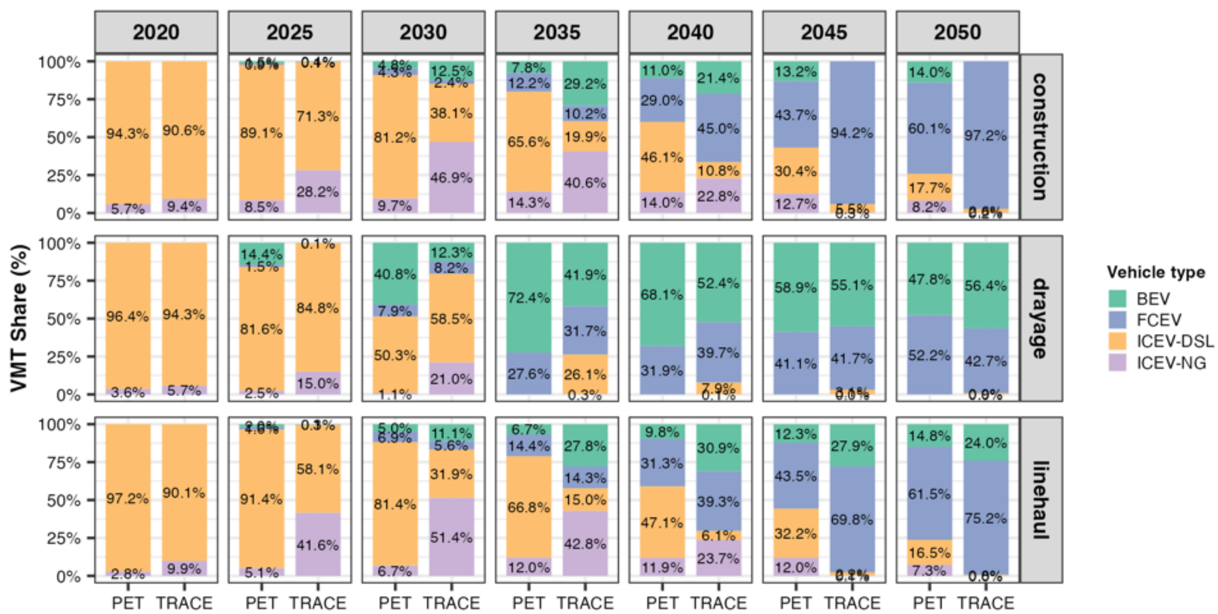


Figure 114. Conservative market scenario VMT technology share comparison to the TRACE 80in50 scenario

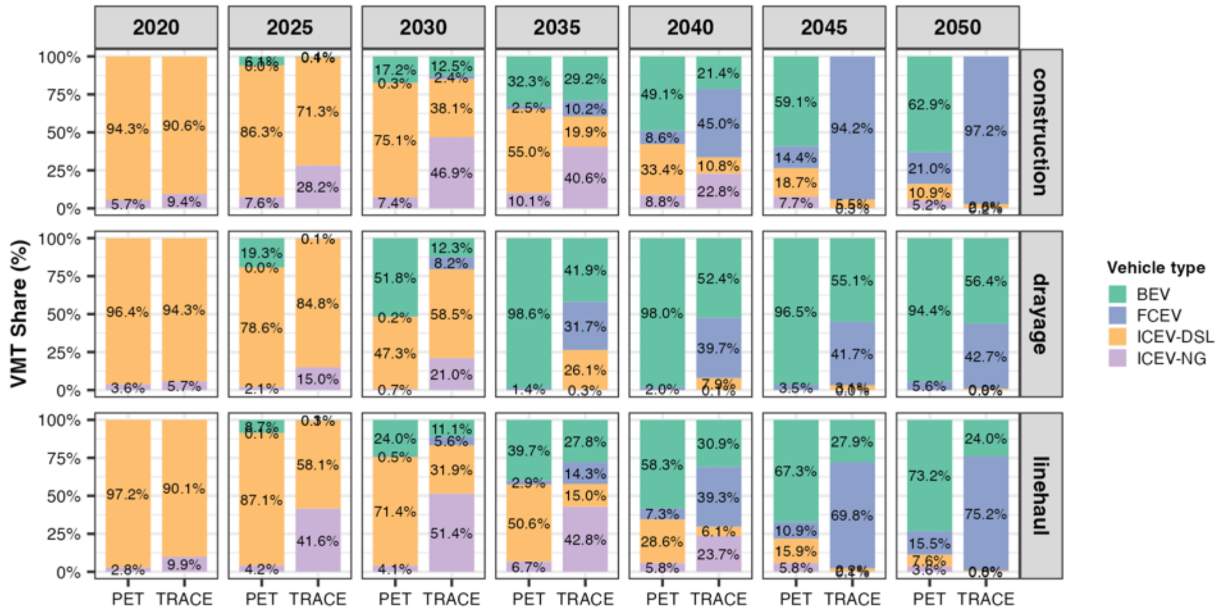


Figure 115. Optimistic market scenario VMT technology share comparison to the TRACE 80in50 scenario

6 Summary, Conclusions, and Recommendations

Through Executive Orders and Legislation, California has committed to an aggressive strategy for reducing GHG and CAP emissions and transitioning to low-carbon transportation is at the center of the State's approach. The success of this transition will hinge on effective deployment of both regulatory and incentive policy over the next decade. The adoption of the Advanced Clean Fleets (ACF) regulation has established a new playing field for HDV fleets operating in the State. Bringing the total cost of ownership of LCT HDV and ORE into parity is central to this successful outcome. Application of the Transportation Rollout Affecting Cost and Emissions (TRACE) model forecast vehicle costs for diesel, natural gas, battery electric, and fuel-cell electric trucks and equipment out to 2050 across conservative, mid-, and aggressive market scenarios using a techno-economic approach that relates production volumes to cost reductions. These scenarios span potential ranges of both capital vehicle and equipment expenses as well as fuel costs that include California's Low Carbon Fuel Standard incentives.

Our findings applying the PET to evaluate for the on-road linehaul, drayage, and construction vocations a range of incentive designs focused on duration of supports and caps tied to conventional technology costs show that cost parity can be reached by 2035, when the bulk of California's heavy-duty fleets will be required under the ACF to only bring zero-emission vehicles into operation. To achieve this, the results recommend an incentive design for CARB's incentive programs that gradually tapers from current (2023) levels down to zero by 2035. Unlike the current CARB incentives, our recommended design institutes caps on incentives to keep them under the incremental cost difference between ZEVs and their conventional counterparts. The costs of the selected design range from $4.2B to $5.3B for incentives through 2035, with the mid-market estimate at $4.6B. This design results in C/E ratios of $490,000, $635,000, and $3,184,000 per short ton of pollutant for our optimistic, mid-, and conservative market scenarios respectively. The optimistic and mid-market results fall within the high-value investment category guidelines under the CMAQ program whereas the conservative scenario ranks as a mixed-quality investment. To improve the likelihood of more favorable market conditions, policymakers should particularly focus on fuel costs as sensitivity results show that they have the most impact on the total cost of ownership driving the transition. Bringing down the cost of electric vehicle supply equipment (EVSE) also shows a notable impact on TCO, particularly if optimized charging to increase the ratio of trucks to EVSE.

The PET developed during this research is a flexible tool that builds on prior CARB-supported work from contract 16RD011 to allow an analyst to represent, within a specific regulatory landscape, detailed incentive designs that are sensitive to a wide range of potential parameters, including location and jurisdiction, fleet characteristics such as vocation and size, as well as the relative costs of low-carbon and conventional fuels. This research demonstrated the PET's use to evaluate candidate incentive designs to support the LCT transition. However, improvements remain that can enhance the tool's effectiveness.

Though we started with the goal of using information on past alternative fuel vehicle incentive programs to develop a causal model of the relationship between incentives and alt-fuel purchases, we found that the available data lacked sufficient variation to support a viable model. Thus, there is a **strong need for better data on fleet uptake of ZEV technology** to develop a data-supported causal choice model. The InfoShed is one step toward this, but because it is targeted at demonstration (pre-commercial TRL 8) projects, the scenario under which fleets participate does not represent market-scale behavior. Since ZEV technology is just transitioning from the pre-commercial stage to early market entry (TRL 9) one candidate alternative approach to developing a fully data-driven technology choice model in the near term is to conduct a choice experiment survey of fleet operators and ask them to select from technology choices with different characteristics. Though such stated preference approaches can give implausible results when used to develop models, they are critical for obtaining information about attributes not available in the marketplace (Brownstone et al., 2000). In the longer term, since the ZEV vehicles will begin entering widespread use in 2024 under ACF, program managers should coordinate with behavioral economists at CARB to implement pilot programs that are designed to identify the causal effects.

With the coming regulations driving evolution in California's transportation sector, it is certain new vehicle and fuel technologies will enter the market and fleet preferences will evolve as experience identifies success. Continued development of the PET should focus on continued **updating and validating the wide range of inputs** used by the model to develop TCO forecasts, including vehicle and fuel costs, vehicle performance characteristics, infrastructure costs, and changing operations that adapt to the technical strengths and weaknesses.

The PET makes numerous assumptions about future trends and behaviors, which can introduce uncertainties into the model's results. As the PET evolves, the **sensitivity analyses should be repeated and expanded** to continually assess how the results might change under different scenarios or assumptions. This is especially true of later year forecasts beyond 2035 when sensitivities can compound in unexpected ways. Additionally, the model could incorporate stochastic methods to better capture the inherent uncertainty in the system.

There are many additional specific enhancements to the PET that were beyond the scope of this project that could increase its ability to model sophisticated and targeted incentive designs. However, the PET is designed to be extended and we recommend the following as achievable next steps to improve the model. The PET's TCO and technology choice model could benefit from the following:

- Add **additional procurement options** including leases and truck- or charging-as-a-service, and allow for differentials depending on fleet characteristics such as size and location.
- Though the PET's technology choice model is strictly driven by TCO, other **alternative choice model formulations should be considered** that may be more robust and behaviorally grounded, such as the TEMPO model's use of marginal cost intensity of travel (essentially LCOD) (Muratori et al., 2021) or approaches that explicitly consider return on investment. Improvements can also build on the theoretical framework of fleet decision-making from Bae et al.'s (2022) work.
- The TCO and technology choice model could be expanded to **include used trucks** (see below).

The policy capabilities of the PET could be expanded with the following enhancements:

- Add capabilities to model **total annual incentive dollar limits** over specific horizons (e.g., fiscal years). The PET currently does not allow for constraints on total incentive amounts and instead models a specific design assuming sufficient funding will be available to meet demand. This can be approximated by manually adjusting incentive designs to remain under specific levels, but this is inefficient.
- The PET could easily be enhanced with a **more detailed treatment of other incentives** (CEC, local, federal, etc.). This report generally assumed that other incentives, whether for vehicles or infrastructure, were held fixed. A better understanding of the incentive policies of other agencies would help improve the representation of the complete policy landscape in the model.

- The ability to **directly model the ACF ZEV milestones option** should be included in order to represent the regulatory flexibility that is built into ACF. This would be trivial if individual fleets are modeled (see below).

- The PET should continue to receive **improvements in its representation of geographical restrictions or bonuses on incentives**. Specific regions, such as those classified as disadvantaged communities, may receive additional funding. At this time, the PET is not capable of modeling this feature as its spatial resolution is designed around the intersection of County, Air basin, Air District, and utility regions. This is a relatively straightforward improvement.

The PET's fleet turnover model could by improved with the following:

- The PET's **treatment of used trucks could be improved** to better represent how new and used purchases are distributed across fleets with different characteristics to capture how specific policy may impact different fleet categories. For instance, how will current and proposed policy impact fleets that are more likely to purchase used trucks?

- Research into the **expected evolution of the used ZE truck and equipment market** would also improve the model's ability to represent how stock ages will change in coming years.

Finally, though the PET represents differential decision making using (fixed) fleet size distributions, this is a difficult assumption to sustain. Even with the types of policy supports modeled by the PET, the ZEV transition is likely to create economic barriers to certain business models in California's trucking fleet, such as small fleets and especially independent owner operators. The PET could be extended to **model individual fleets as a synthetic population**. This enhancement would significantly add complexity to the model but would allow it to better represent strategic decisions that are made at the fleet level related to vehicle and infrastructure procurements. The current fleet size segmentation used in the PET allows for a coarse characterization of some of these effects, but expanding these segmentations will ultimately lead to sparsity in the model that degrades its reliability. By instead creating a synthetic population of fleets and modeling their decision-making regarding the size of their fleet and the associated procurements, the model could represent many complex behaviors that are currently beyond the model's capabilities. Specific capabilities this enhancement would provide include:

- Adding an ability to model the growth or shrinkages of specific fleet classes and the total number of trucks.

- Better modeling of how regulatory exceptions related to OEM capacity restrictions will allow for fleets to forego ZEV purchases in a way that could delay compliance.

- Explicit representation of fleets' propensity to commit to specific fuel choices and stick with them.

References

Ajanovic, A., & Haas, R. (2020). Prospects and impediments for hydrogen and fuel cell vehicles in the transport sector. *International Journal of Hydrogen Energy*. https://doi.org/10.1016/j.ijhydene.2020.03.122

Anderhofstadt, B., & Spinler, S. (2019). Factors affecting the purchasing decision and operation of alternative fuel-powered heavy-duty trucks in Germany – A Delphi study. *Transportation Research Part D: Transport and Environment*, *73*(November 2018), 87–107. https://doi.org/10.1016/j.trd.2019.06.003

ANL. (2021, August 5). *Autonomie*. Vehicle & Mobility Systems Department - Argonne National Laboratory. https://vms.taps.anl.gov/tools/autonomie/

Arons, S. M., Brandt, A. R., Delucchi, M., Eggert, A., Farrell, A. E., Haya, B. K., Hughes, J., Jenkins, B. M., Jones, A. D., Kammen, D. M., Kaffka, S. R., Knittel, C. R., Lemoine, D. M., Martin, E. W., Melaina, M. W., Ogden, J. M., Plevin, R. J., Sperling, D., Turner, B. T., … Yang, C. (2007). A Low-Carbon Fuel Standard for California Part 1: Technical Analysis. In *UC Berkeley Recent Work* (Issue 1, pp. 1–181). https://doi.org/10.11436/mssj.15.250

Bae, Y., Mitra, S. K., Rindt, C. R., & Ritchie, S. G. (2022). Factors influencing alternative fuel adoption decisions in heavy-duty vehicle fleets. *Transportation Research Part D: Transport and Environment*, *102*. https://doi.org/10.1016/j.trd.2021.103150

Bae, Y., Mitra, S. K., Rindt, C. R., & Ritchie, S. G. (2020). Factors Influencing Alternative Fuel Adoption Decisions in Heavy-duty Vehicle Fleets in California. *Presented at 99th Annual Meeting of the Transportation Research Board*.

Bae, Y., Rindt, C., Mitra, S., & Ritchie, S. G. (2023). Fleet Operator Perspectives on Heavy-duty Vehicle Alternative Fueling Infrastructure. *Transportation Research Record*. https://doi.org/10.1177/03611981231171150

Bae, Y., Rindt, C. R., Mitra, S., & Ritchie, S. G. (2022). *Fleet Operator Perspectives on Alternative Fuels for Heavy-Duty Vehicles* (SSRN Scholarly Paper 4253440). https://papers.ssrn.com/abstract=4253440

Baker, R. (2008). *Characterization of the off-road equipment population*. https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/04-315.pdf

Bayzid, S. M. (2014). *Modeling maintenance cost for road construction equipment*.

Beaty, K. (2021). *Commercial Vehicle Battery Cost Assessment: Strategic Sourcing Challenges for North American Truck and Bus OEMs and Tier 1 Suppliers*. YUNEV. https://calstart.org/wp-content/uploads/2021/12/Commercial-Vehicle-Battery-Costs-Industry-Report-Final_12.22.21.pdf

Birky, A. K., Laughlin, M., Tartaglia, K., Price, R., Lim, B., & Lin, Z. (2017). *Electrification Beyond Light Duty: Class 2b-3 Commercial Vehicles*.

Birky, A. K., Laughlin, M., Tartaglia, K., Price, R., & Lin, Z. (2017). *Transportation Electrification Beyond Light Duty: Technology and Market Assessment*.

Bjerkan, K. Y., Nørbech, T. E., & Nordtømme, M. E. (2016). Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway. *Transportation Research Part D: Transport and Environment*, *43*. https://doi.org/10.1016/j.trd.2015.12.002

Blynn, K., & Attanucci, J. (2019). Accelerating Bus Electrification: A Mixed Methods Analysis of Barriers and Drivers to Scaling Transit Fleet Electrification. *Transportation Research Record*. https://doi.org/10.1177/0361198119842117

Boer, E. den, Aarnink, S., Kleiner, F., & Pagenkopf, J. (2013). *Zero-Emission Trucks: An Overview of State-of-the-Art Technologies and Their Potential*.

Bond-Lamberty, B. (2022). *Economic Choice in GCAM*. https://github.com/JGCRI/gcam-doc/blob/gh-pages/choice.md

Bond-Lamberty, B., Patel, P., Lurz, J., Smith, S., abigailsnyder, Dorheim, K. R., russellhz, mbins, Link, R., skim301, nealtg, Narayan, K., Turner, S. W. D., S, A., Feng, L., enlochner, cwroney, Lynch, C., jhoring, … marideeweber. (2022). *JGCRI/gcam-core: GCAM 6.0* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.6619287

Boriboonsomsin, K., Un-Noor, F., Scora, G., & Wu, G. (2022). *Hybridization and Full Electrification Potential in Off-Road Applications* [Technical Report]. https://ww2.arb.ca.gov/sites/default/files/2022-07/18RD016%20revised%20072722.pdf

Brandt, A. R., Eggert, A., Farrell, A. E., Haya, B. K., Hughes, J., Jenkins, B. M., Jones, A. D., Kammen, D. M., Knittel, C. R., Melaina, M. W., O'Hare, M., Plevin, R. J., & Sperling, D. (2007). A Low-Carbon Fuel Standard for California Part 2: Policy Analysis. In *UC Berkeley Recent Work* (Issue 2, pp. 1–98). https://doi.org/10.11436/mssj.15.250

Breetz, H. L., & Salon, D. (2018). Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 U.S. cities. *Energy Policy*, *120*, 238–249. https://doi.org/10.1016/j.enpol.2018.05.038

Brito, J. (2022). *No fleet left behind: Barriers and opportunities for small fleet zero-emission trucking* (WORKING PAPER 2022-31). the ICCT. https://theicct.org/wp-content/uploads/2022/10/small-fleet-ze-trucking-oct22.pdf

Brotherton, T., Gilde, A., & Tomic, J. (2016). 2015 E-Truck Task Force: Key Barriers Affecting E-Truck Adoption, Industry and Policy Implications, and Recommendations to Move the Market Forward. *World Electric Vehicle Journal*, *8*(3), 657–665. https://doi.org/10.3390/wevj8030657

Brown, A. L., Sperling, D., Austin, B., DeShazo, J. R., Fulton, L., Lipman, T., Murphy, C., Saphores, J. D., Tal, G., Abrams, C., Chakraborty, D., Coffee, D., Dabag, S., Davis, A., Delucchi, M. A., Fleming, K. L., Forest, K., Garcia Sanchez, J. C., Handy, S., … Yang, A. (2021). *Driving California's Transportation Emissions to Zero*. https://doi.org/10.7922/G2MC8X9X

Bubeck, S., Tomaschek, J., & Fahl, U. (2016). Perspectives of electric mobility: Total cost of ownership of electric vehicles in Germany. *Transport Policy*, *50*, 63–77. https://doi.org/10.1016/j.tranpol.2016.05.012

Burke, A., & Miller, M. (2020). *Zero-Emission Medium- and Heavy-duty Truck Technology, Markets, and Policy Assessments for California*. https://escholarship.org/uc/item/7n68r0q8

Burke, A., & Sinha, A. K. (2020). *Technology, Sustainability, and Marketing of Battery Electric and Hydrogen Fuel Cell Medium-Duty and Heavy-Duty Trucks and Buses in 2020-2040*. https://doi.org/10.7922/G2H993FJ

Burmich, P. (2005). *Methods to Find the Cost-Effectiveness of Funding Air Quality Projects*. California Air Resources Board.

Burnham, A., Gohlke, D., Rush, L., Stephens, T., Zhou, Y., Delucchi, M. A., Birky, A., Hunter, C., Lin, Z., Ou, S., Xie, F., Proctor, C., Wiryadinata, S., Liu, N., & Boloor, M. (2021). *Comprehensive Total Cost of Ownership Quantification for Vehicles with Different Size Classes and Powertrains* (ANL/ESD-21/4). Argonne National Lab. (ANL), Argonne, IL (United States). https://doi.org/10.2172/1780970

Çabukoglu, E., Georges, G., Küng, L., Pareschi, G., & Boulouchos, K. (2018). Battery electric propulsion: An option for heavy-duty vehicles? Results from a Swiss case-study. *Transportation Research Part C: Emerging Technologies*, *88*, 107–123. https://doi.org/10.1016/J.TRC.2018.01.013

Çabukoglu, E., Georges, G., Küng, L., Pareschi, G., & Boulouchos, K. (2019). Fuel cell electric vehicles: An option to decarbonize heavy-duty transport? Results from a Swiss case-study. *Transportation Research Part D: Transport and Environment*, *70*, 35–48. https://doi.org/10.1016/j.trd.2019.03.004

California DMV. (2023). *Vehicle Registration Fee Calculator*. https://www.dmv.ca.gov/wasapp/FeeCalculatorWeb/newVehicleForm.do

Calstart. (2022). *Global ZET Median Range Growing to Cover Majority of Urban Duty Cycles*. https://globaldrivetozero.org/site/wp-content/uploads/2022/09/image2.png

CARB. (2008a). *Climate Change Scoping Plan:a Framework for change*. https://ww2.arb.ca.gov/sites/default/files/classic/cc/scopingplan/document/adopted_scoping_plan.pdf

CARB. (2017a). *THE CARL MOYER PROGRAM GUIDELINES 2017 Revisions, VOLUME I: PROGRAM OVERVIEW, PROGRAM ADMINISTRATION AND PROJECT CRITERIA*. California Air Resources Board.

CARB. (2019a). *Advanced Clean Trucks Regulation: Final Regulation Order*. https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2019/act2019/fro2.pdf

CARB. (2019b). *Advanced Clean Trucks Total Cost of Ownership Discussion Document—Preliminary Draft for Comment*. https://ww2.arb.ca.gov/sites/default/files/2020-06/190225tco_ADA.pdf

CARB. (2019c). *Proposed Fiscal Year 2019-20 Funding Plan for Clean Transportation Incentives—Appendix D: Heavy Duty Investment Strategy*. California Air Resources Board.

CARB. (2019d). *roposed Fiscal Year 2019-20 Funding Plan for Clean Transportation Incentives—Appendix B: SB 1204 REQUIREMENTS AND PERFORMANCE CRITERIA EVALUATION FOR HEAVY-DUTY PROJECTS*.

CARB. (2020a). *Advanced Clean Fleets Regulation: Initial Statement of Reasons*. https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2022/acf22/isor2.pdf

CARB. (2020b). *California Air Resources Board, Advanced Clean Fleets – Cost Workgroup Cost Data and Methodology Discussion Draft.* https://ww2.arb.ca.gov/sites/default/files/2020- 12/201207costdisc_ADA.pdf

CARB. (2020c). *Proposed Fiscal Year 2020-21 Funding Plan on Clean Transportation Incentives—Appendix D: Heavy-Duty Investment Strategy*. California Air Resources Board.

CARB. (2021a). *EMFAC2021 Volume III Technical Document*. https://ww2.arb.ca.gov/sites/default/files/2021-08/emfac2021_technical_documentation_april2021.pdf

CARB. (2021b). *Heavy-Duty Engine and Vehicle Omnibus Regulation (Omnibus Regulation)*. https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2020/hdomnibuslownox/froa-1.pdf

CARB. (2021c). *Proposed Fiscal Year 2021-22 Funding Plan on Clean Transportation Incentives—Appendix D: Heavy-Duty Investment Strategy*. California Air Resources Board. https://ww2.arb.ca.gov/sites/default/files/2021-10/fy21-22_fundingplan_appendix_d.pdf

CARB. (2022a). *California Greenhouse Gas Emissions for 2000 to 2020: Trends of Emissions and Other Indicators*. https://ww2.arb.ca.gov/sites/default/files/classic/cc/inventory/2000_2020_ghg_inventory_trends.pdf

CARB. (2023a). *IMPLEMENTATION MANUAL FOR THE HYBRID AND ZERO-EMISSION TRUCK AND BUS VOUCHER INCENTIVE PROJECT (HVIP)*. https://californiahvip.org/wp-content/uploads/2023/08/HVIP-FY22-23-Implementation-Manual.pdf

CARB. (2008b). *Statewide Truck and Bus Regulations*. https://www.arb.ca.gov/regact/2008/truckbus08/truckbus08.htm

CARB. (2008c). *Truck and Bus Regulation*. https://ww2.arb.ca.gov/our-work/programs/truck-and-bus-regulation

CARB. (2017b). *Vision Scenario Planning*.

CARB. (2017c). *Vision Scenario Planning. Vision 2.1*.

CARB. (2017d, July 24). *Low Carbon Fuel Standard 2018 Amendments: Pre-Rulemaking Concept Paper*. https://ww2.arb.ca.gov/sites/default/files/classic/fuels/lcfs/lcfs_meetings/080717conceptpaper.pdf

CARB. (2017e, November). *California's 2017 Climate Change Scoping Plan*. https://ww2.arb.ca.gov/sites/default/files/2022-12/2022-sp.pdf

CARB. (2019e). *EMFAC2017 Web Database*.

CARB. (2021d, September 9). *Draft Advanced Clean Fleets Total Cost of Ownership Discussion Document*. https://ww2.arb.ca.gov/sites/default/files/2021-08/210909costdoc_ADA.pdf

CARB. (2022b). *Hybrid And Zero-Emission Truck and Bus Voucher Incentive Project*. https://californiahvip.org/

CARB. (2022c, November). *2022 SCOPING PLAN FOR ACHIEVING CARBON NEUTRALITY*. https://ww2.arb.ca.gov/sites/default/files/classic/cc/scopingplan/scoping_plan_2017.pdf

CARB. (2023b). *Advanced Clean Fleets Regulation Summary | California Air Resources Board*. https://ww2.arb.ca.gov/resources/fact-sheets/advanced-clean-fleets-regulation-summary

CARB. (2023c). *Air Resources Board Equipment Registration (ARBER) System | California Air Resources Board*. https://ww2.arb.ca.gov/our-work/programs/air-resources-board-equipment-registration-arber-system

Carer Forklifts, Inc. (2023). *Electric Intermodal Port Forklifts*. https://www.carerforklifts.com/electric-intermodal-port-forklifts/

Carley, K. (1993). Coding Choices for Textual Analysis: A Comparison of Content Analysis and Map Analysis. *Sociological Methodology*, *23*, 75–126. https://doi.org/10.2307/271007

CASECE, Inc. (2023). *CASE 580 EV - The Industry's First Fully Electric Backhoe Loader | CASE Construction Equipment*. https://www.casece.com/northamerica/en-us/products/backhoe-loaders/580ev-project-zeus

CDTFA. (2023). *California City & County Sales & Use Tax Rates*. https://www.cdtfa.ca.gov/taxes-and-fees/sales-use-tax-rates.htm

CEC. (2020a). *2020-2023 Investment Plan Update for the Clean Transportation Program*.

CEC. (2020b). *California Energy Demand 2020-2030 Revised Forecast*. https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2019-integrated-energy-policy-report/2019-iepr

CEC. (2022). *Implementation Manual for Energy Infrastructure Incentives for Zero-Emission Commercial Vehicles Project (EnergIIZE)*. https://energiize.org/implementationmanual/EnergIIZE_Implementation+Manual_+Q3+2022+vFinal.pdf

Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, *20*(1), 37–46. https://doi.org/10.1177/001316446002000104

CPUC. (2020). *Zero-Emission Vehicles*.

Di Filippo, J., Callahan, C., & Golestani, N. (2019). *Zero-Emission Drayage Trucks: Challenges and Opportunities for the San Pedro Bay Ports*. UCLA Luskin Center for Innovation. https://innovation.luskin.ucla.edu/wp-content/uploads/2019/10/Zero_Emission_Drayage_Trucks.pdf

DieselNet. (2023a). *Emission Standards: USA: Heavy-Duty Onroad Engines*. https://dieselnet.com/standards/us/hd.php

DieselNet. (2023b). *Emission Standards: USA: Nonroad Diesel Engines*. https://dieselnet.com/standards/us/nonroad.php

Dominković, D. F., Bačeković, I., Pedersen, A. S., & Krajačić, G. (2018). The future of transportation in sustainable energy systems: Opportunities and barriers in a clean energy transition. *Renewable and Sustainable Energy Reviews*, *82*, 1823–1838. https://doi.org/10.1016/j.rser.2017.06.117

Dumortier, J., Siddiki, S., Carley, S., Cisney, J., Krause, R. M., Lane, B. W., Rupp, J. A., & Graham, J. D. (2015). Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle. *Transportation Research Part A: Policy and Practice*, *72*, 71–86. https://doi.org/10.1016/j.tra.2014.12.005

Electric Intermodal Port Forklifts. (n.d.). Retrieved February 2, 2023, from https://www.carerforklifts.com/electric-intermodal-port-forklifts/

Energy and Environmental Economics. (2016). *Summary of the California State Agencies' PATHWAYS Project: Long-Term GHG Reduction Scenarios*.

Feldman, D., Ramasamy, V., Fu, R., Ramdas, A., Desai, J., & Margolis, R. (2021). *U.S. Solar Photovoltaic System and Energy Storage Cost Benchmark: Q1 2020*.

Figenbaum, E. (2022). Retrospective Total cost of ownership analysis of battery electric vehicles in Norway. *Transportation Research Part D: Transport and Environment*, *105*, 103246. https://doi.org/10.1016/j.trd.2022.103246

Forrest, K., Mac Kinnon, M., Tarroja, B., & Samuelsen, S. (2020). Estimating the technical feasibility of fuel cell and battery electric vehicles for the medium and heavy duty sectors in California. *Applied Energy*, *276*, 115439. https://doi.org/10.1016/j.apenergy.2020.115439

Frambach, R. T., & Schillewaert, N. (2002). Organizational innovation adoption: A multi-level framework of determinants and opportunities for future research. *Journal of Business Research*, *55*(2), 163–176. https://doi.org/10.1016/S0148-2963(00)00152-1

Frederickson, C., Durbin, T., Li, C., Ma, T., Scora, G., Jung, H., Johnson, K., & Huang, E. (2022). Performance and Activity Characteristics of Zero Emission Battery-Electric Cargo Handling Equipment at a Port Terminal. *SAE International Journal of Advances and Current Practices in Mobility*, *4*(2022-01–0576), 2412–2425.

Fulton, L., & Miller, M. (2015). *Strategies for transitioning to low-carbon emission trucks in the United States.* Sustainable Transportation Energy Pathways Program at UC Davis and the National Center for Sustainable Transportation.

Globisch, J., Dütschke, E., & Wietschel, M. (2017). Adoption of electric vehicles in commercial fleets: Why do car pool managers campaign for BEV procurement? *Transportation Research Part D: Transport and Environment*, *October*. https://doi.org/10.1016/j.trd.2017.10.010

Hall, D., Pavlenko, N., & Lutsey, N. (2018). *Beyond road vehicles: Survey of zero-emission technology options across the transport sector* (Working Paper 2018–11). ICCT. https://theicct.org/publication/beyond-road-vehicles-survey-of-zero-emission-technology-options-across-the-transport-sector/

Hardman, S., Chandan, A., Tal, G., & Turrentine, T. (2017). The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. *Renewable and Sustainable Energy Reviews*, *80*. https://doi.org/10.1016/j.rser.2017.05.255

Henze, V. (2022, December 6). Lithium-ion Battery Pack Prices Rise for First Time to an Average of $151/kWh. *BloombergNEF*. https://about.bnef.com/blog/lithium-ion-battery-pack-prices-rise-for-first-time-to-an-average-of-151-kwh/

Holland, S. P., Hughes, J. E., & Knittel, C. R. (2009). Greenhouse Gas Reductions under Low Carbon Fuel Standards? *American Economic Journal: Economic Policy*, *1*(1), 106–146. https://doi.org/10.1257/pol.1.1.106

Huang, H., Khanna, M., Önal, H., & Chen, X. (2013). Stacking low carbon policies on the renewable fuels standard: Economic and greenhouse gas implications. *Energy Policy*, *56*(2013), 5–15. https://doi.org/10.1016/j.enpol.2012.06.002

Hunter, C., Penev, M., Reznicek, E., Lustbader, J., Birky, A., & Zhang, C. (2021). *Spatial and Temporal Analysis of the Total Cost of Ownership for Class 8 Tractors and Class 4 Parcel Delivery Trucks* (NREL/TP-5400-71796, 1821615, MainId:6232; p. NREL/TP-5400-71796, 1821615, MainId:6232). https://doi.org/10.2172/1821615

ICF. (2019). *Comparison of Medium- and HeavyDuty Technologies in California*. https://efiling.energy.ca.gov/GetDocument.aspx?tn=236878

Insuranks.com. (2023). *Heavy Equipment Insurance: Cost, Companies & Quotes From $11*. https://www.insuranks.com/heavy-equipment-insurance

Javid, R. J., & Nejat, A. (2017). A comprehensive model of regional electric vehicle adoption and penetration. *Transport Policy*, *54*. https://doi.org/10.1016/j.tranpol.2016.11.003

Jenn, A., Springel, K., & Gopal, A. R. (2018). Effectiveness of electric vehicle incentives in the United States. *Energy Policy*, *119*. https://doi.org/10.1016/j.enpol.2018.04.065

Jin, L., Searle, S., & Lutsey, N. (2014). *Evaluation of state-level U.S. electric vehicle incentives* [Whitepaper]. https://theicct.org/publication/evaluation-of-state-level-u-s-electric-vehicle-incentives/

Johnson, K. (2021). *Volvo Lights Emissions and Activity Results*.

Keen, K. (2020). *As battery costs plummet, lithium-ion innovation hits limits, experts say*. S&P Global Market Intelligence.

Krippendorff, K. (1989). Content Analysis. *International Encyclopedia of Communication*, 403–407. https://repository.upenn.edu/asc_papers/226

Kuhn, M., Anculle, E., & Bubna, P. (2021). *E-Truck Virtual Teardown Study*. https://theicct.org/wp-content/uploads/2022/01/Final-Report-eTruck-Virtual-Teardown-Public-Version.pdf

Lade, G. E., & Lin Lawell, C. Y. C. (2015). The design and economics of low carbon fuel standards. *Transportation Economicsr*, *52*, 91–99. https://doi.org/10.1016/j.retrec.2015.10.009

Lane, B., Kinnon, M. M., Shaffer, B., & Samuelsen, S. (2022). Deployment planning tool for environmentally sensitive heavy-duty vehicles and fueling infrastructure. *Energy Policy*, *171*, 113289. https://doi.org/10.1016/j.enpol.2022.113289

Lane, B., Reed, J., Shaffer, B., & Samuelsen, S. (2021). Forecasting Renewable Hydrogen Production Technology Shares Under Cost Uncertainty. *International Journal of Hydrogen Energy*.

Langholtz, B. M. H. J., Stokes, L. M., & Eaton. (2016). 2016 BILLION-TON REPORT Advancing Domestic Resources for a Thriving Bioeconomy. *Oak Ridge National Laboratory*, *1160*(July), 448–2172. https://doi.org/ORNL/TM-2016/160

LBLN. (2021, April 16). New Electric Container Cranes at The Port of Long Beach. *Long Beach Local News*. https://www.longbeachlocalnews.com/2021/04/16/new-electric-container-cranes-at-the-port-of-long-beach/

Lebeau, K., Lebeau, P., Macharis, C., & Van Mierlo, J. (2013). How expensive are electric vehicles? A total cost of ownership analysis. *2013 World Electric Vehicle Symposium and Exhibition (EVS27)*, 1–12. https://doi.org/10.1109/EVS.2013.6914972

Leyland, A. (2020). *LITHIUM ION BATTERY CELL PRICES FALL TO $110/KWH, BUT RAW MATERIAL RISK LOOMS LARGE*. Benchmark Mineral Intelligence.

Liu, Z., Song, J., Kubal, J., Susarla, N., Knehr, K. W., Islam, E., Nelson, P., & Ahmed, S. (2021). Comparing total cost of ownership of battery electric vehicles and internal combustion engine vehicles. *Energy Policy*, *158*, 112564. https://doi.org/10.1016/j.enpol.2021.112564

Mac Kinnon, M., Forrest, K., Lane, B., Rindt, C., Ritchie, S., & Samuelsen, G. S. (2020). *Pathways Towards a Near-Zero Heavy Duty Sector—Final Report 16RD011*.

McCullough, M. P., Hamilton, L. L., & Walters, C. G. (Eds.). (2021). *Cost Effectiveness of California's Clean Air Act Agricultural Equipment Incentives*. https://doi.org/10.22004/ag.econ.312800

Middlebrooks, G. (2022, March 9). New data tracks 26% growth of zero-emission truck and bus model availability globally in midst of economic, supply chain challenges | March 9, 2022. *CALSTART*. https://calstart.org/new-data-tracks-growth-of-zero-emission-truck-and-bus-model-availability-globally-in-midst-of-economic-supply-chain-challenges/

Moreda, G. P., Muñoz-García, M. A., & Barreiro, P. (2016). High voltage electrification of tractor and agricultural machinery—A review. *Energy Conversion and Management*, *115*, 117–131. https://doi.org/10.1016/j.enconman.2016.02.018

Moultak, M., Lutsey, N., & Hall, D. (2017a). *Transitioning to zero-emission heavy-duty freight vehicles*. The International Council on Clean Transportation (ICCT). https://theicct.org/publications/transitioning-zero-emission-heavy-duty-freight-vehicles

Moultak, M., Lutsey, N., & Hall, D. (2017b). *Transitioning to zero-emission heavy-duty freight vehicles*.

Muratori, M., Borlaug, B., Ledna, C., Jadun, P., & Kailas, A. (2023). Road to zero: Research and industry perspectives on zero-emission commercial vehicles. *iScience*, *26*(5), 106751. https://doi.org/10.1016/j.isci.2023.106751

Muratori, M., Jadun, P., Bush, B., Hoehne, C., Vimmerstedt, L., Yip, A., Gonder, J., Winkler, E., Gearhart, C., & Arent, D. (2021). Exploring the future energy-mobility nexus: The transportation energy & mobility pathway options (TEMPO) model. *Transportation Research Part D: Transport and Environment*, *98*, 102967. https://doi.org/10.1016/j.trd.2021.102967

Murdoch, B., Marcon, A. R., Downie, D., & Caulfield, T. (2019). Media portrayal of illness-related medical crowdfunding: A content analysis of newspaper articles in the United States and Canada. *PLOS ONE*, *14*(4), e0215805. https://doi.org/10.1371/journal.pone.0215805

Nagy, B., Farmer, J. D., Bui, Q. M., & Trancik, J. E. (2012). *Statistical Basis for Predicting Technological Progress*.

Narassimhan, E., & Johnson, C. (2018). The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: Analysis of US States. *Environmental Research Letters*, *13*(7). https://doi.org/10.1088/1748-9326/aad0f8

Neuendorf, K. A., Skalski, P. D., Cajigas, J. A., & Allen, J. C. (2017). *The content analysis guidebook* (Second edition). SAGE. http://www.gbv.de/dms/bowker/toc/9781412979474.pdf

Noll, B., del Val, S., Schmidt, T. S., & Steffen, B. (2022). Analyzing the competitiveness of low-carbon drive-technologies in road-freight: A total cost of ownership analysis in Europe. *Applied Energy*, *306*, 118079. https://doi.org/10.1016/j.apenergy.2021.118079

NREL. (2019). *Commercial EV Inventory*.

Phadke, A., Khandekar, A., Abhyankar, N., Wooley, D., & Rajagopal, D. (2021). *Why Regional and Long-Haul Trucks are Primed for Electrification Now*.

Pildes, R., Mittelman, A., Bucci, G., Foreman, C., & Noel, G. (2020). *CONGESTION MITIGATION AND AIR QUALITY IMPROVEMENT (CMAQ) PROGRAM 2020 Cost-Effectiveness Tables Update*. Volpe National Transportation Systems Center. https://www.fhwa.dot.gov/environment/air_quality/cmaq/reference/cost_effectiveness_tables/

PIN Online. (2023, March 22). JCB Launch New Hydrogen Combustion Engine Petro Online. *PIN Petrochemical Chemical & Energy*. https://www.petro-online.com/news/fuel-for-thought/13/international-environmental-technology/jcb-launch-new-hydrogen-combustion-engine/60013

Prasad, B. D. (2008). Content Analysis A method in Social Science Research. In *Lal Das, D.K and Bhaskaran, V (eds.). (2008) Research methods for Social Work, New Delhi:Rawat, pp.173-193.* http://www.css.ac.in/download/deviprasad/content%20analysis.%20a%20method%20of%20social%20science%20research.pdf

R Core Team. (2022). *R: A language and environment for statistical computing.* [Computer software]. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Ramsden, T. (2013). *An Evaluation of the Total Cost of Ownership of Fuel CellPowered Material Handling Equipment* (Technical Report NREL/TP-5600-56408). https://www.nrel.gov/docs/fy13osti/56408.pdf

Reed, J., Dailey, E., Shaffer, B., Lane, B., Flores, R., Fong, A., & Samuelsen, S. (2020). *Roadmap for the Deployment and Buildout of Renewable Hydrogen Production Plants in California*. California Energy Commission.

Rogers, E. M. (1983). Innovation in Organizations. In *Diffusion of Innovations* (pp. 347–370). The Free Press.

Rubin, J., & Leiby, P. N. (2013). Tradable credits system design and cost savings for a national low carbon fuel standard for road transport. *Energy Policy*, *56*(2013), 16–28. https://doi.org/10.1016/j.enpol.2012.05.031

SAE International. (2014). *J2601/2: Fueling Protocol for Gaseous Hydrogen Powered Heavy Duty Vehicles*.

SAE International. (2020). *J2601B: Fueling Protocols for Light Duty Gaseous Hydrogen Surface Vehicles*.

Saphores, J.-D., Rindt, C., Lane, B., Ramirez-Ibarra, M., Mac Kinnon, M., & Nima, S. (2023). *Full Cost Analysis and Business Case Study of Off-Road Zero-Emission Equipment—Draft Literature Review*. CARB Agreement 21MSC006.

Schreier, M. (2012). *Qualitative Content Analysis in Practice*. SAGE Publications Inc. https://us.sagepub.com/en-us/nam/book/qualitative-content-analysis-practice

Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., & Yu, T. (2008). Use of U.S. Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change. *SCIENCE*, *319*(5867), 1238–1240.

Seitz, C. S., Beuttenmüller, O., & Terzidis, O. (2015). Organizational adoption behavior of CO2-saving power train technologies: An empirical study on the German heavy-duty vehicles market. *Transportation Research Part A: Policy and Practice*, *80*, 247–262. https://doi.org/10.1016/j.tra.2015.08.002

Sharpe, B., & Basma, H. (2022). *A meta-study of purchase costs for zero-emission trucks* (Working Paper 2022–09). https://theicct.org/wp-content/uploads/2022/02/purchase-cost-ze-trucks-feb22-1.pdf

Sierzchula, W. (2014). Factors influencing fleet manager adoption of electric vehicles. *Transportation Research Part D: Transport and Environment*, *31*, 126–134. https://doi.org/10.1016/j.trd.2014.05.022

Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*. https://doi.org/10.1016/j.enpol.2014.01.043

Singh, B. (2014). Novel and ruggedized power electronics for off-highway vehicles. *IEEE Electrification Magazine*, *2*, 31–41.

Smith, D., Graves, R., Ozpineci, B., Jones, P. T., Lustbader, J., Kelly, K., Walkowicz, K., Birky, A., Payne, G., Sigler, C., & Mosbacher, J. (2019). *Medium-and Heavy-Duty Vehicle Electrification An Assessment of Technology and Knowledge Gaps*.

Southern California Edison. (2020). *Charge Ready Transport Program*.

Sperling, D., & Yeh, S. (2009). Low carbon fuel standards. *Issues in Science and Technology*, *25*(2), 57–66.

State of California. (2006). *Assembly Bill 32: California Global Warming Solutions Act of 2006*.

State of California. (2016, September 8). *SB-32 California Global Warming Solutions Act of 2006: Emissions limit.* https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201520160SB32

State of California. (2018, September 10). *SB-100 California Renewables Portfolio Standard Program: Emissions of greenhouse gases.* https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201720180SB100

Stemler, S. (2001). An overview of content analysis. *Practical Assessment, Research, and Evaluation*, *7*. https://doi.org/10.7275/Z6FM-2E34

Stodolsky, F., L. Gaines, & A. Vyas. (2000). *Analysis of Technology Options to Reduce the Fuel Consumption of Idling Trucks* (ANL/ESD-43, 771201; p. ANL/ESD-43, 771201). https://doi.org/10.2172/771201

Tornatzky, L., & Fleischer, M. (1990). *The process of technology innovation*. Lexington Books.

Tran, M., Banister, D., Bishop, J. D. K., & McCulloch, M. D. (2013). Simulating early adoption of alternative fuel vehicles for sustainability. *Technological Forecasting and Social Change*, *80*(5), 865–875. https://doi.org/10.1016/j.techfore.2012.09.009

Trencher, G., Taeihagh, A., & Yarime, M. (2020). Overcoming barriers to developing and diffusing fuel-cell vehicles: Governance strategies and experiences in Japan. *Energy Policy*, *142*, 111533. https://doi.org/10.1016/j.enpol.2020.111533

Un-Noor, F., Boriboonsomsin, K., Scora, G., Wu, G., Karikishan, P., Yoon, S., & Collier, S. (forthcoming). A Review on Off-Road Construction and Agricultural Equipment Electrification: Current State of Technology Development and Future Research Directions. *IEEE Transactions on Transportation Electrification*.

Un-Noor, F., Padmanaban, S., Mihet-Popa, L., Mollah, M., & Hossain, E. (2017). A Comprehensive Study of Key Electric Vehicle (EV) Components, Technologies, Challenges, Impacts, and Future Direction of Development. *Energies*, *10*(8). https://doi.org/10.3390/en10081217

Un-Noor, F., Scora, G., Wu, G., Boriboonsomsin, K., Perugu, H., Collier, S., & Yoon, S. (2021). Operational Feasibility Assessment of Battery Electric Construction Equipment Based on In-Use Activity Data. *Transportation Research Record*, *2675*(9), 809–820. https://doi.org/10.1177/03611981211004581

Un-Noor, F., Scora, G., Wu, G., Yoon, S., & Boriboonsomsin, K. (2023). Cost-Effectiveness of Off-Road Equipment Electrification Incentives: Cost Estimation, Evaluation, and Usage Framework. *Transportation Research Record: Journal of the Transportation Research Board*, 03611981231175892. https://doi.org/10.1177/03611981231175892

Unterlohner, F., Earl, T., Cornelis, S., Frongia, T., & Suzan, S. (2021, April 6). *How to decarbonise long-haul trucking in Germany*. Transport & Environment. https://www.transportenvironment.org/discover/how-decarbonise-long-haul-trucking-germany/

U.S. Department of Energy. (n.d.). *H2A Delivery Analysis*.

US EIA. (2021). *Annual Energy Outlook 2021* [Forecast]. https://www.eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2021&cases=ref2021&sourcekey=0

van Velzen, A., Annema, J. A., van de Kaa, G., & van Wee, B. (2019). Proposing a more comprehensive future total cost of ownership estimation framework for electric vehicles. *Energy Policy*, *129*, 1034–1046. https://doi.org/10.1016/j.enpol.2019.02.071

Wagh, R. V., & Sane, N. (2015). Electrification of heavy-duty and off-road vehicles. *Transportation Electrification Conference (ITEC), 2015 IEEE International*, 1–3.

Walter, S., Ulli-Beer, S., & Wokaun, A. (2012). Assessing customer preferences for hydrogen-powered street sweepers: A choice experiment. *International Journal of Hydrogen Energy*, *37*(16), 12003–12014. https://doi.org/10.1016/j.ijhydene.2012.05.026

Wang, H., Wang, Q., & Hu, B. (2017). A review of developments in energy storage systems for hybrid excavators. *Automation in Construction*, *80*. https://doi.org/10.1016/j.autcon.2017.03.010

Welch, D. (2020). *The Beachhead Model: Catalyzing Mass-Market Opportunities for Zero-Emission Commercial Vehicles*. CALSTART. https://globaldrivetozero.org/publication/the-beachhead-model/

Whyatt, G. A. (2010). *Issues Affecting Adoption of Natural Gas Fuel in Light-and Heavy-Duty Vehicles*.

Winebrake, J. J., Green, E. H., Comer, B., Corbett, J. J., & Froman, S. (2012). Estimating the direct rebound effect for on-road freight transportation. *Energy Policy*, *48*, 252–259. https://doi.org/10.1016/j.enpol.2012.05.018

Witcover, J. (2018). *Status Review of California ' s Low Carbon Fuel Standard , 2011 – 2018 Q1 September 2018 Issue* (Issue September, pp. 1–17).

Xu, C., Wu, Y., & Dai, S. (2020). What are the critical barriers to the development of hydrogen refueling stations in China? A modified fuzzy DEMATEL approach. *Energy Policy*, *142*, 111495. https://doi.org/10.1016/j.enpol.2020.111495

Yang, C. (2013). Fuel electricity and plug-in electric vehicles in a low carbon fuel standard. *Energy Policy*, *56*(2013), 51–62. https://doi.org/10.1016/j.enpol.2012.05.006

Yeh, S., Lutsey, N. P., & Parker, N. C. (2009). Assessment of technologies to meet a low carbon fuel standard. *Environmental Science and Technology*, *43*(18), 6907–6914. https://doi.org/10.1021/es900262w

Yeh, S., & Sperling, D. (2010). Low carbon fuel standards: Implementation scenarios and challenges. *Energy Policy*, *38*(11), 6955–6965. https://doi.org/10.1016/j.enpol.2010.07.012

Yeh, S., & Sperling, D. (2013). Low carbon fuel policy and analysis. *Energy Policy*, *56*, 1–4. https://doi.org/10.1016/j.enpol.2013.01.008

Yeh, S., Sperling, D., Griffin, M., Khanna, M., Leiby, P., Msangi, S., Rhodes, J., & Rubin., J. (2012). *National Low Carbon Fuel Standard: Policy Design Recommendations* (Issue July, p. 1=81).

Yeh, S., Witcover, J., & Kessler, J. (2013). Status Review of California's Low Carbon Fuel Standard. In *Research Report Institute of Transportation Studies ◦ University of California, Davis* (Vol. 2013, pp. 1–12). https://doi.org/10.2139/ssrn.2253502

Zhang, L., Brown, T., & Samuelsen, S. (2013). Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles. *Journal of Power Sources*, *240*, 515–524. https://doi.org/10.1016/j.jpowsour.2013.04.048

Zhang, Y., Jiang, Y., Rui, W., & Thompson, R. G. (2019). Analyzing truck fleets' acceptance of alternative fuel freight vehicles in China. *Renewable Energy*, *134*, 1148–1155. https://doi.org/10.1016/j.renene.2018.09.016

Zhou, Y., Wang, M., Hao, H., Johnson, L., Wang, H., & Hao, H. (2015). Plug-in electric vehicle market penetration and incentives: A global review. *Mitigation and Adaptation Strategies for Global Change*, *20*(5). https://doi.org/10.1007/s11027-014-9611-2

Zong, Y. (2017). *Maintenance cost and residual value prediction of heavy construction equipment*.

Abbreviations, Acronyms, and Units

Abbreviation	Definition
AB	Assembly Bill
ACT	Advanced Clean Trucks
AD	Anaerobic Digestion
AEO	Annual Energy Outlook
ANL	Argonne National Laboratory
APCD	Air Pollution Control District
API	Application Programming Interface
AQIP	Air Quality Improvement Program
AQMD	Air Quality Management District
BAU	Business as Usual
BEA	Bureau of Economic Analysis
BEV	Battery Electric Vehicle
BLS	Bureau of Labor Statistics
BWP	Burbank Water and Power
CAP	Criteria Air Pollutant
CARB	California Air Resources Board
CAT	Cap and Trade
CDTFA	California Department of Tax and Fee Administration
CEC	California Energy Commission
CEQA	California Environmental Quality Act
CHE	Cargo Handling Equipment
CI	Carbon Intensity
CMAQ	Congestion Mitigation and Air Quality Improvement Program
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CORE	Clean Off Road Equipment Voucher Incentive Project
CPCFA	California Pollution Control Financing Authority
CPI	Consumer Price Index
CPUC	California Public Utilities Commission
CRF	Capital Recovery Factor
DAC	Direct Air Capture

DC	Direct Current
DEF	Diesel Exhaust Fluid Filter
DGE	Diesel Gallon Equivalent
DMV	Department of Motor Vehicles
DOE	Department of Energy
EERE	Office of Energy Efficiency and Renewable Energy
EIA	Energy Information Agency
EMFAC	EMissions FACtors model
EPA	Environmental Protection Agency
EPIC	Electric Program Investment Charge Program
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FAME	Fatty Acid Methyl Ester—biodiesel derived from renewable sources
FARMER	Agricultural Replacement Measures for Emission Reductions
FCEV	Fuel Cell Electric Vehicle
FE	Fixed-Effects model
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FTE	Full-Time Equivalemnt
FY	Fiscal Year
GDP	Gross Domestic Product
GGRF	Greenhouse Gas Reduction Fund
GHG	Greenhouse Gas
GJ	Gigajoules
GVWR	Gross Vehicle Weight Rating
GWI	Global Warming Intensity
GWP	Glendale Water and Power
HDT	Heavy-Duty Trucks
HDV	Heavy-Duty Vehicles
HEV	Hybrid Electric Vehicle
HP	horsepower
HVIP	California Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project
HVO	Hydrotreatment of Vegetable Oil, a method for renewable diesel production technologies

ICCT	International Council on Clean Transportation
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
IID	Imperial Irrigation District
IRB	Institutional Review Board
ITS	Institute of Transportation Studies
ITS-Irvine	UC Irvine Institute of Transportation Studies
KW	kilowatts
LADWP	Los Angeles Department of Water and Power
LCA	Life-Cycle Assessment
LCFS	Low-Carbon Fuel Standard
LCT	Low-Carbon Transportation
LDV	Light Duty Vehicle
LNG	Liquified Natural Gas
LPR	Local Purchase Coefficient
MCS	Monte Carlo Simulation
MHD	Medium and Heavy Duty
MHDV	Medium and Heavy Duty Vehicle
MJ	Megajoules
MMT	Million Metric Ton
MT	Metric Ton
M&R	Maintenance and Repair
NGVIP	Natural Gas Vehicle Incentive Project
NO_X	Nitrogen Oxides
NREL	National Renewable Energy Laboratory
OEM	Original Equipment Manufacturer
OLS	Ordinary Least Squares
ORE	Off-Road Equipment
PCC	Post-Combustion Capture
PET	Performance Evaluation Tool
PEV	Plug-in Electric Vehicle
PGE	Pacific Gas and Electric
PHEV	Plug-in Hybrid Electric Vehicle

PM	Particulate Matter
POAK	Port of Oakland
POLA	Port of Los Angeles
PTO	Power Take-Off
PV	Photo Voltaic
PWP	Pasadena Water and Power
RD	Renewable Diesel
RFS	Renewable Fuel Standard
RNG	Renewable Natural Gas
ROG	Reactive Organic Gases
RTFO	Renewable Transport Fuel Obligation
SAE	Society of Automotive Engineers
SAM	Social Accounting Matrices
SB	Senate Bill
SCAQMD	South Coast Air Quality Management District
SCE	Southern California Edison
SDGE	San Diego Gas and Electric
SECAT	Sacramento Emergency Clean Air and Transportation truck replacement program
SEM	Structural Equation Model
SJVAPCD	San Joaquin Air Pollution Control District
SMR	Steam Methane Reformation
SMUD	Sacramento Municipal Utility District
SOON	Surplus Off-Road Opt-In for NO_X Program
TCO	Total Cost of Ownership
TOU	Time-of-Use
TRACE	Transportation Rollout Affecting Cost and Emissions
TRL	Technology Readiness Level
UCI	University of California, Irvine
UCLA	University of California, Los Angeles
UCR	University of California, Riverside
USDOT	United States Department of Transportation
UTV	Utility Vehicle
VMT	Vehicle Miles Travelled

VOC	Volatile Organic Compound
VOH	Vehicle Operating Hours
ZE	Zero-Emission
ZERO	Zero Emission Research Opportunity
ZEV	Zero-Emission Vehicle

Appendix A. Vehicle and equipment component cost specifications

Table 47. Vehicle and equipment component cost specifications

Year	Glider HDV ($)	ICE G ($/kW)	ICE D ($/kW)	ICE CNG ($/kW)	Fuel cell ($/kW)	Battery ($/kWh)	Motor / Inverter ($/kW)	Tank liq ($/GJ)	Tank CNG ($/GJ)
2020	95,539	28	31	290	370	50	79	2,207	4,167
2021	95,313	30	30	251	346	47	78	2,095	3,866
2022	95,092	32	29	218	323	45	78	1,989	3,590
2023	94,875	34	28	190	303	43	77	1,889	3,335
2024	94,663	35	27	165	284	41	76	1,796	3,102
2025	94,456	37	26	144	267	39	75	1,709	2,890
2026	94,253	38	25	126	252	37	74	1,629	2,697
2027	94,055	39	24	111	238	35	74	1,555	2,523
2028	93,862	40	24	99	225	34	73	1,488	2,369
2029	93,673	40	23	88	214	32	72	1,428	2,234
2030	93,489	41	23	80	204	31	72	1,375	2,117
2031	93,310	41	22	73	196	30	71	1,330	2,018
2032	93,135	42	22	67	189	29	71	1,292	1,936
2033	92,965	42	21	63	182	29	70	1,261	1,870
2034	92,800	42	21	60	177	28	70	1,237	1,818
2035	92,639	43	21	57	173	28	69	1,217	1,778
2036	92,483	43	20	55	169	27	69	1,203	1,747
2037	92,331	43	20	54	166	27	68	1,192	1,724
2038	92,184	43	20	53	164	27	68	1,184	1,708
2039	92,041	43	20	52	162	27	68	1,178	1,696
2040	91,902	43	20	52	160	27	67	1,174	1,687
2041	91,768	43	20	51	159	27	67	1,171	1,681
2042	91,638	43	20	51	158	26	67	1,168	1,676
2043	91,512	43	20	51	157	26	66	1,167	1,673
2044	91,390	43	20	51	157	26	66	1,166	1,671
2045	91,272	43	20	51	156	26	66	1,165	1,669
2046	91,158	43	20	51	156	26	66	1,164	1,668
2047	91,048	43	19	51	156	26	65	1,164	1,667
2048	90,942	43	19	51	155	26	65	1,164	1,667
2049	90,839	43	19	50	155	26	65	1,164	1,666
2050	90,741	43	19	50	155	26	65	1,163	1,666

Source: Values based on work from CARB 16RD011 Pathways Towards a Near-Zero Heavy Duty Sector (Mac Kinnon et al., 2020), but updated for this project as described in Section 2.3.