STATE OF CALIFORNIA • DEPARTMENT OF TRANSPORTATION

TECHNICAL REPORT DOCUMENTATION PAGE

TR0003 (REV 10/98)

1. REPORT NUMBER
CA17-3089

2. GOVERNMENT ASSOCIATION NUMBER

3. RECIPIENT'S CATALOG NUMBER

4. TITLE AND SUBTITLE
Truck Choice Modeling: Understanding California's Transition to Zero-Emission Vehicle Trucks Taking into Account Truck Technologies, Costs, and Fleet Decision

5. REPORT DATE
November 2017

6. PERFORMING ORGANIZATION CODE

7. AUTHOR
Marshall Miller; Qian Wang; Lew Fulton

8. PERFORMING ORGANIZATION REPORT NO.

9. PERFORMING ORGANIZATION NAME AND ADDRESS
National Center for Sustainable Transportation (NCST) University of California, Davis West Village, 1605 Tilia, Suite #100 Davis, CA 95616

10. WORK UNIT NUMBER
3762

11. CONTRACT OR GRANT NUMBER
65A0527

12. SPONSORING AGENCY AND ADDRESS
California Department of Transportation Division of Research, Innovation and Systems Information (DRISI) MS-83, 1727 30th St, Sacramento, CA 95816

13. TYPE OF REPORT AND PERIOD COVERED
Final Report

14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES

16. ABSTRACT
Many truck models create new technology market penetration scenarios through minimizing cost or in an ad-hoc manner. This model utilizes a fleet decision choice process based on real world factors identified through discussions with trucking fleets. These factors include capital and operating costs, uncertainty (risk), model availability, refueling inconvenience, green PR (perceived benefit of environmentally beneficial technologies), and various incentives. We have developed a spreadsheet structured as a nested multinomial logit model that monetizes these factors to calculate a generalized cost. We have attempted to estimate the value of these factors to different types of fleets using a series of interviews, initial survey work, a truck choice workshop, and finally expert judgment and "basic logic" on how various factors might be valued now and in the future.

17. KEY WORDS

18. DISTRIBUTION STATEMENT

19. SECURITY CLASSIFICATION *(of this report)*

20. NUMBER OF PAGES
69

21. COST OF REPORT CHARGED
$79,058.95

DISCLAIMER STATEMENT

Truck Choice Modeling: Understanding California's Transition to Zero-Emission Vehicle Trucks Taking into Account Truck Technologies, Costs, and Fleet Decision Behavior

November 2017

A Research Report from the National Center for Sustainable Transportation

Marshall Miller, University of California, Davis
Qian Wang, University of California, Davis
Lew Fulton, University of California, Davis

National Center for Sustainable Transportation

UC DAVIS
SUSTAINABLE TRANSPORTATION ENERGY PATHWAYS
of the Institute of Transportation Studies

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: University of California, Davis; University of California, Riverside; University of Southern California; California State University, Long Beach; Georgia Institute of Technology; and University of Vermont. More information can be found at: ncst.ucdavis.edu.

Disclaimer

Acknowledgments

This study was funded by a grant from the National Center for Sustainable Transportation (NCST), supported by USDOT and Caltrans through the University Transportation Centers program. The authors would like to thank the NCST, USDOT, and Caltrans for their support of university-based research in transportation, and especially for the funding provided in support of this project. In addition, we'd like to thank Jimmy O'Dea and Dawn Fenton for reviewing the paper and giving us feedback.

Truck Choice Modeling: Understanding California's Transition to Zero-Emission Vehicle Trucks Taking into Account Truck Technologies, Costs, and Fleet Decision Behavior

A National Center for Sustainable Transportation Research Report

November 2017

Marshall Miller, Institute of Transportation Studies, University of California, Davis

Qian Wang, Institute of Transportation Studies, University of California, Davis

Lew Fulton, Institute of Transportation Studies, University of California, Davis

[page left intentionally blank]

TABLE OF CONTENTS

List of Tables

List of Figures

Truck Choice Modeling: Understanding California's Transition to Zero-Emission Vehicle Trucks Taking into Account Truck Technologies, Costs, and Fleet Decision Behavior

EXECUTIVE SUMMARY

This report presents the results of a project to develop a truck vehicle/fuel decision choice model for California and to use that model to make initial projections of truck sales by technology out to 2050. The report also describes the linkage of this model to a broader scenarios model of road transportation energy use in California to 2050. A separate report provides our detailed assumptions about truck technologies, fuels, and projections to 2050 that are inputs to this choice modeling effort.

The need for low carbon trucking in California, as in other states and countries of the world, is outlined in IPCC reports and the Paris Agreement. And 80% reduction in energy-related CO_2 emissions worldwide is targeted in that agreement. For trucks to contribute anywhere near this level of reduction, new, zero emissions technologies, such as electric and hydrogen fuel cell trucks, would need to be adopted at a large scale and at a rapid pace, both unprecedented for trucks anywhere in the world to date.

Many truck models create new technology market penetration scenarios through minimizing cost or in an ad-hoc manner. This model utilizes a fleet decision choice process based on real world factors identified through discussions with trucking fleets. These factors include capital and operating costs, uncertainty (risk), model availability, refueling inconvenience, green PR (perceived benefit of environmentally beneficial technologies), and various incentives. We have developed a spreadsheet structured as a nested multinomial logit model that monetizes these factors to calculate a generalized cost. We have attempted to estimate the value of these factors to different types of fleets using a series of interviews, initial survey work, a truck choice workshop, and finally expert judgment and “basic logic” on how various factors might be valued now and in the future.

The factors drive the choice analysis and are highly uncertain and likely highly variant across fleet types and even fleets within a type (early adopter, late adopter, in-between), so we use a scenario approach to explore how this uncertainty could affect our results and projections. We created four scenarios and variants: 1) a business as usual (BAU), 2) a zero-emission vehicle (ZEV) mandate requiring the market share of ZEVs to reach 25% by 2050 (ZEV scenario 1a), 3) the same scenario but with a low penalty assumed for refueling time and (ZEV scenario 1b) 4) a ZEV mandate requiring the market share of ZEVs to reach 50% by 2050 (ZEV scenario 2). We

also look at some policies that could help to spur sales growth among ZEV technologies in order to reach specific targets.

Results in Brief

Table 1 shows the greenhouse gas reductions for the four scenarios.

Table 1. Greenhouse gas emissions reductions from 2010 by 2050 for various scenarios for the entire truck fleet.

Scenario	GHG reductions (%) from 2010 by 2050
BAU	10
ZEV scenario 1	22
ZEV scenario 1 with low refueling inconvenience	45
ZEV scenario 2	46

Figure 1 shows the BAU scenario generalized cost for short haul trucks in the early adopter sub-category for the years 2030 and 2050. As capital cost, refueling inconvenience, and model availability decrease for battery electric and fuel cell trucks, their generalized cost decreases closer to the value for diesel trucks. The values for some of the factors in the other scenarios differ from the values shown below because they are functions of the total number of sales for a given technology.

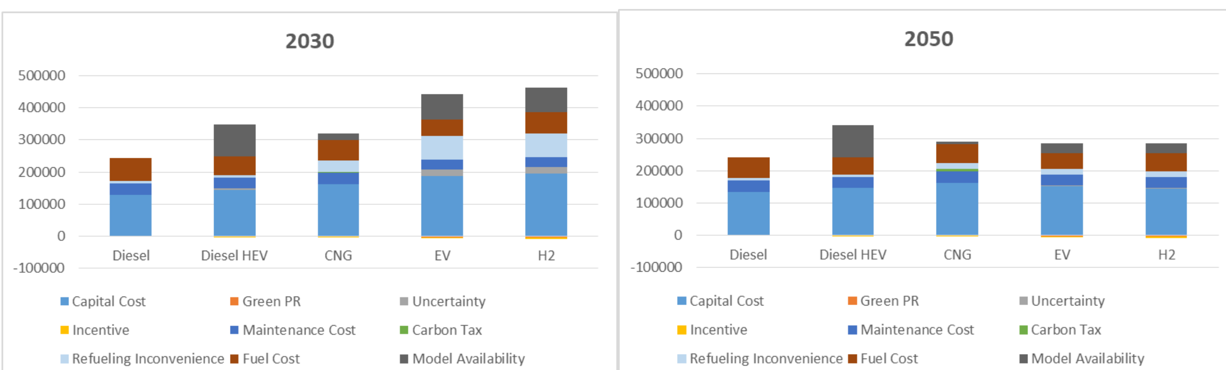


Figure 1. Generalized cost for short haul trucks for the early adopter sub-category for 2030 and 2050.

In general, the BAU scenario market shares change relatively little through 2040 and include only very modest penetrations of new technologies such as battery electric vehicles or fuel cell vehicles, and only toward the end of the timeframe, mostly in the early adopter fleet category. The overall greenhouse gas (GHG) reductions from this scenario are small (10%), mostly due to increased fleet vehicle miles traveled balancing out increases in fuel economy.
The ZEV scenarios were explored to understand the need for incentive funding that might be needed to overcome various disincentives of ZEV technologies, such as the higher capital cost,

perceived uncertainty toward new technologies, refueling inconvenience, and initial low model availability. The results in terms of 2050 market shares in the ZEV scenarios are shown in Figure 2.

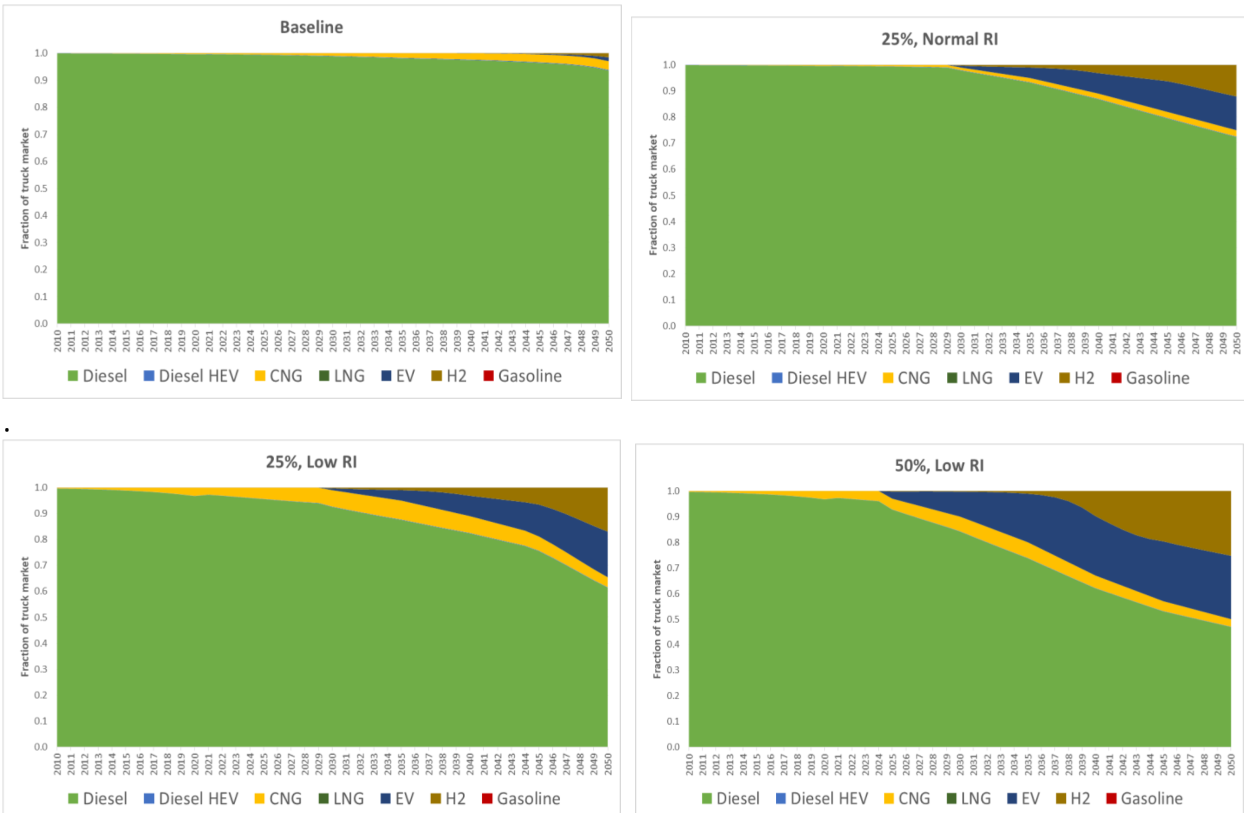


Figure 2. Market shares through 2050 for short haul trucks for all four scenarios. Low RI indicates a low penalty for refuelling time.

Different ZEV technologies were used to meet the mandate for differing truck types. For example, fuel cells met the entire mandate for long haul trucks because our model does not include battery electric trucks in that truck type due to weight considerations. Battery electric and fuel cell trucks reached similar market shares in short haul trucks, but battery electric trucks dominated the ZEV market share in medium-duty vocational and transit buses because the capital costs of battery electric vehicles are lower than the cost of fuel cells in those truck types.

The necessary incentive per vehicle starts as a significant percentage of the capital cost but drops to a small fraction of that cost in most cases, as market shares of ZEV technologies rise toward the target. Short haul trucks and urban buses required no incentives toward 2050 to meet the mandate for scenario 1b (with refueling inconvenience equal to diesel refueling inconvenience).

The total incentives required to meet even the 25% mandate for all truck types are quite high ($7.7 and $9.6 billion for the low refueling inconvenience and normal refueling inconvenience cases, respectively). For certain truck types, the total incentives necessary are much more modest. In scenario 1b transit buses require $53 million, medium-duty vocational trucks require $165 million, and short haul trucks require $116 million from 2030 – 2050.

Conclusions

This study has found that:

- There are a range of factors that truck operators and fleets consider when purchasing new trucks and that may affect their choices involving new drivetrain and fuel technologies
- The high initial cost, low range, and uncertainty of ZEV technologies appear to severely limit their marketability in the near term.
- Over time this situation should improve as these attributes improve, such as through battery cost reduction and better availability of hydrogen for fuel cell trucks.
- The total investment, GHG reductions, and CO_2e cost per tonne of these scenarios are shown in Table 2.

Table 2. Greenhouse gas reductions and cost efficiency for the ZEV scenarios.

ZEV scenario	Investment (billions $)	GHG reductions (ktonne CO_2e)	Cost efficiency ($/tonne)
1a	8.9	13.8	648
1b	6.9	13.8	297
2	42.9	32.0	1.339

These costs could be reduced if vehicle and fuel costs and other attributes are improved faster than we assume in this analysis, and/or if fleets become more amenable to adopting these new technologies than we assume here. The high uncertainty in this regard warrants more work to better understand fleets' concerns and how they may be assuaged. Helping truckers achieve familiarity with the new technologies and fuels in order to lower perceived risk may be one of the most important aspects that policy makers could influence.

Introduction

Significant reductions in greenhouse gas (GHG) emissions are required to mitigate damaging potential impacts associated with climate change (IPCC 2014). In 2014 medium- and heavy-duty trucks and buses contributed roughly 28% of motor vehicle GHG emissions (US EPA 2016). According to the U.S. Energy Information Administration's Annual Energy Outlook (AEO) projections, the trucking sector has by far the largest and the fastest growing energy use of all freight transport modes. Trucking will increase its share of freight energy use from 63% in 2013 to 69% in 2040 (EIA 2014). Reducing trucking sector GHGs through low carbon technologies and fuels will be an important component of climate change goals.

There have been numerous studies that have looked at the potential for California to make significant reductions in GHG emissions and achieve GHG reduction targets (CCST 2011, E3 2015, Greenblatt 2013, Jacobson 2014, McCollum 2012, Roland-Holst 2015). Morrison et al. provides a useful summary of these studies (Morrison 2015). These studies all indicate that meeting these GHG targets is potentially feasible at reasonable costs and that mitigation will come from a variety of strategies (including efficiency, new advanced technologies, and low-carbon energy sources) across a variety of energy supply and end-use sectors. They all point to transportation as a key source of GHG emissions and one of the most important sectors in which to make reductions. These studies, along with studies that looked solely at the transportation sector as a source of GHG reductions (CARB 2009 and 2012, Yang 2009, Yang 2011), focus heavily on the light-duty sector because of its importance in California (nearly 2/3 of fuel use and GHG emissions come from cars and light trucks) and see the importance of vehicle efficiency as well as alternative fuels (biofuels, electricity, and hydrogen) to lowering emissions. These studies represent a variety of modeling methods and approaches, but all suffer from the same lack of data and simplified representation of the non-light-duty transportation sectors.

The trucking sector has historically been poorly represented in models used to characterize energy use and emissions and to analyze scenarios of long-term, low-carbon futures (e.g. to 2050). Heavy- and medium-duty vehicles encompass a diverse set of vehicle and body types and vocational categories that include heavy-duty long-haul, heavy-duty short-haul, utility trucks, medium-duty delivery, buses, and heavy-duty pickups and vans. However, analyses and models that investigate scenarios of future technologies and fuels often aggregate these diverse categories for trucks into heavy-duty and medium-duty only. This simplification ignores significant differences in truck driving distances, efficiencies, suitability for potential advanced technologies, ownership models and other important variables in understanding truck purchase decisions. In addition, these models typically create scenarios either using an idealized economic analysis or through scenario assumptions. They do not attempt to incorporate various policies levers and understand their effect on the real world decision-making process for vehicle purchases.

Some California specific models, such as UC Davis's 80in50 and CA-TIMES models and E3's PATHWAYS model, aggregate categories to include heavy and medium-duty trucks. In some truck analyses, more detailed truck types are incorporated, such as CALHEAT's truck study or UC Davis' TOP-HDV analysis. CALHEAT's study is a technology assessment but does not incorporate detailed costs of advanced and alternative truck technologies. TOP-HDV does include the most detailed representation of truck classes, from smaller class 2 and 3 light- to medium-duty trucks all the way to class 8 long-haul trucks, truck costs and characterization of emissions. CARB's newest VISION model (VISION2) also includes a substantial amount of disaggregation by truck class, vocation and even region. However, none of these models incorporate real world decision making into their scenarios. Scenarios are based on simply minimizing cost or are determined in an ad-hoc manner to meet the study goals. Understanding how trucking fleets actually make purchase decisions is critical to understand the initial transitions to new technologies in California.

In this study, trucks are disaggregated into several truck categories that encompass specific vehicle types and use patterns (such as long-haul tractor trailer trucks, short-haul, delivery trucks, etc.). These truck categories are then segmented into ownership categories that have different factors impacting truck purchases (including risk tolerance, vehicle mileage requirements, fueling models, etc.). The ownership categories are early adopter, late adopter, and in-between. Early adopters are those fleets that may perceive less risk or greater value in new technologies. Late adopters are those fleets who may perceive more risk or less value in new technologies. In-between fleets fall somewhere between the early and late adopters. The decision choice model is applied to each of these truck ownership categories to generate the market shares for vehicle technologies such as fuel cell, battery electric, hybrid, CNG, and LNG. The goal is to provide insight into what factors drive adoption of alternative fuel and drivetrain types for different types of heavy-duty and medium-duty trucks.

The market shares output from the Decision Choice model can be used as an input to a stock turnover trucking model, Transition Scenarios, which calculates GHGs, fuel use, and costs for various scenarios. The Transition Scenarios model is used to understand GHG reductions for the different scenarios created in this study.

This project has focused on defining the decision choice framework, identifying factors that affect fleet purchase decisions, acquiring data relevant to monetary factors, developing reasonable functional forms to define non-monetary factors, creating a spreadsheet model of truck fleet purchase decisions, and using the model to explore the effect of certain policies. We recognize that the present model has limitations and more work is necessary to reduce uncertainties in the model outputs. We describe some of the model limitations and future work to reduce model uncertainties at the end of the paper.

In this report, we first describe the Decision Choice and the Transition Scenarios models. We then discuss scenarios including business as usual (BAU) and two ZEV scenarios which include significant percentages of ZEVs in the trucking fleet by 2050. The section on ZEV scenarios includes examples of potential truck ZEV mandates and estimations of the funding necessary to incentivize fleets to meet the mandates. Finally, we summarize the results and discuss potential future work to improve and extend the models.

Model Descriptions

Truck Decision Choice Model

The truck choice model is structured as a nested multinomial logit model (NMNL) in a Microsoft Excel spreadsheet. The basic structure is similar to consumer choice models created for light duty vehicles, such as LAVE-TRANS (NRC 2013). The model represents a discrete choice formulation that includes a number of important factors that will influence individual decision-makers' preferences among a suite of vehicle technology options. These factors include private economic costs, such as vehicle purchase price, maintenance costs and fuel costs, non-monetary costs, such as aversion to new and uncertain technologies, and lower availability of fuel infrastructure, and incentives or subsidies. The utility of each vehicle type is estimated for different truck purchase decision-makers. Figure 3 shows the nest structure for the NMNL model. These nests represent groups of close substitutes for decision-makers as they consider the utility of various technology alternatives.

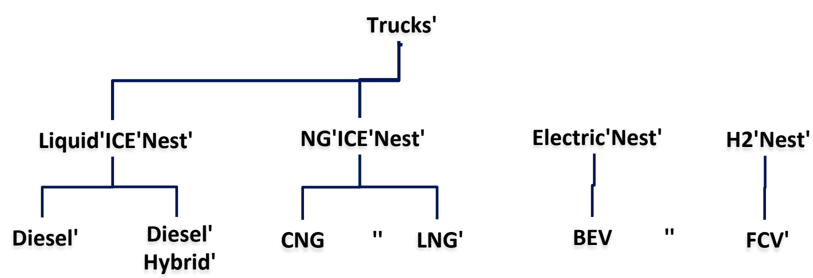


Figure 3. Representative nest structure for the truck choice model.

A set of nests is created for each truck application (short haul, long haul, medium-duty urban, etc.) The nest technologies include diesel, gasoline, hybrid, CNG, LNG, battery electric, and fuel cell. Future versions of the model will likely add new technologies and fuels (e.g. plug-in hybrids). The truck choice model provides the probability of truck purchase for a given set of truck purchasers. These can be translated into market share and then an absolute number of trucks, giving the mix of truck types adopted for each application. Figure 4 shows the inputs to and outputs from the choice model.

These resulting market shares can be combined with a truck stock turnover model. The turnover model then calculates truck fleet numbers related to vehicle survival, total mileage, emissions and fuel consumption for each truck type and from the fleet as a whole.
Trucks are disaggregated into several truck categories that encompass specific vehicle types and use patterns. These truck categories will then be segmented into risk groups that have

different factors impacting truck purchases. The decision choice model is applied to each of these risk groups to generate the market shares for each vehicle technology. The model represents a discrete choice formulation that includes a number of important factors that will influence individual decision-makers' preferences among a suite of vehicle technology options. Nests represent groups of close substitutes for decision-makers as they consider the utility of various technology alternatives. The choice formulation assumes a variation in the utility of trucks for decision makers. The utility of each vehicle type is estimated for different truck purchase decision-makers and then translated to purchase probabilities.

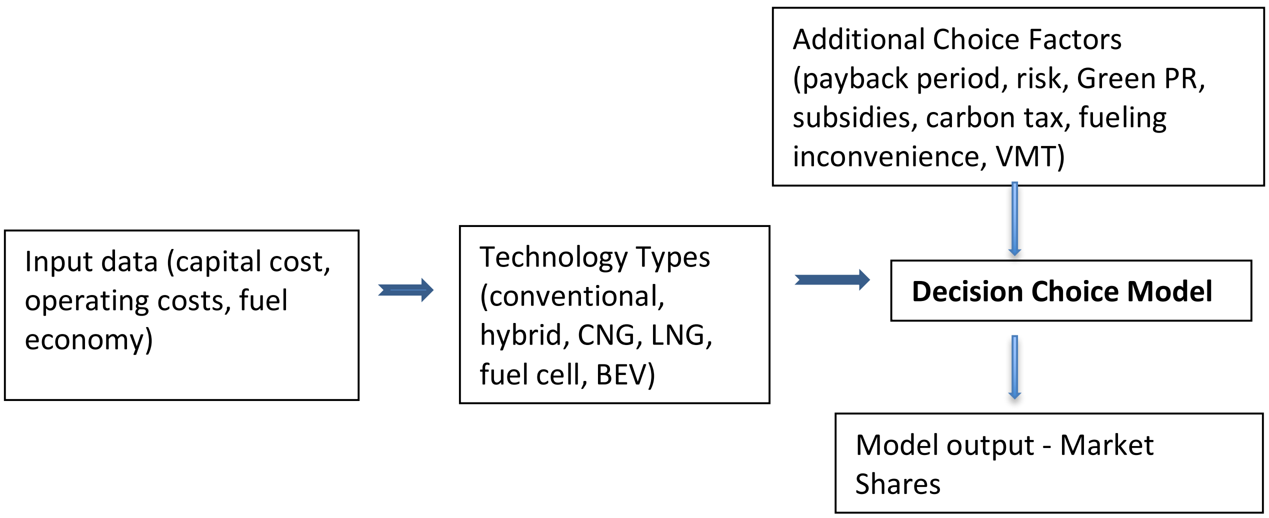


Figure 3. Inputs to and outputs from the Decision Choice Model

Total Generalized Cost

The model calculates a total generalized cost which is the numerical summation of both monetary and non-monetary factors: capital cost, fuel cost, green public relations, uncertainty, incentives, refueling inconvenience, maintenance cost, carbon tax, and model availability cost. For monetary factors, the cost in US dollars is calculated. Non-monetary factors are quantified by certain functions and subsequently expressed in US dollars.

For each truck type (e.g. long haul, short haul, medium-duty urban, transit bus, etc.) the generalized cost is calculated for each technology type (e.g. diesel, natural gas, hybrid, fuel cell, battery electric, gasoline). Using these generalized costs, the model calculates the market shares. The factors are described below along with the formula used to calculate that factor's contribution to the total generalized cost. Appendix A includes the values chosen for constants in the factor formulas.

Capital Cost

Capital cost is the cost of purchasing a vehicle which is the sum of the component costs. The components of a vehicle includes glider, engine, transmission, engine after treatment system (EATS), fuel storage, fuel cell, battery, and motor/controller. These costs for different truck categories were identified from either published sources or from a survey of prices on commercial vehicle sales websites. Beyond 2030, a cost per percent efficiency increase was applied based on the cost of efficiency increase in the 2020-2030 period (Miller 2017).

Fuel Cost

Fuel cost is the lifetime spending on fuel per vehicle. Let FC denote the fuel cost, FC_0 denote the annual fuel cost. The present value (PV) of fuel cost is calculated with the following equation

$$FC = -PV(\rho, n, FC_0)$$

where ρ denotes the discount rate and n denotes the analysis period.

Let m denote the payment per period. The PV function is defined as

$$PV(\rho, n, m) = m \times \frac{1-(1+\rho)^n}{\rho(1+\rho)^{n-1}}$$

All the PV functions in this report follows this definition.

Let M_0 denote annual mileage, FE denote fuel economy, FP denote fuel price. Annual fuel cost is determined by the following equation:

$$FC_0 = \frac{M_0}{FE} \times FP$$

The projection of fuel prices for diesel, gasoline, and electricity is from the U.S. Energy Information Administration. Electricity costs do not include demand or time of use charges. Based on the EIA projections four fuel price scenarios were created, namely, reference fuel price, low fuel price, high fuel price, and user custom input fuel price. Fuel prices for hydrogen and natural gas are calculated from a fuels model which inputs demand generated by various scenarios of market penetration of new technology vehicles (Miller 2017).

Two approaches were used to estimate vehicle fuel economy based on the vehicle type. Diesel, gasoline, and natural gas vehicle fuel economies were estimated using present values from EMFAC 2014 and information from available literature to project future fuel economies. Fuel cell, battery electric, and hybrid vehicle fuel economies were estimated using dynamic vehicle simulations and tying the results to present EMFAC values for diesel vehicles (Miller 2017).

Green Public Relations (Green PR)

Green PR is a sub-category of public relations which communicates a company's environmental awareness and practices to the public. In the context of heavy-duty vehicle sector, customers may prefer one fleet because it runs cleaner trucks. In our model, Green PR is a fleet's benefit of customer preference due to its adoption of cleaner technology. The benefit is high when only a few vehicles of that new technology exist and decreases with cumulative sales. The trend is illustrated by in Figure 5.

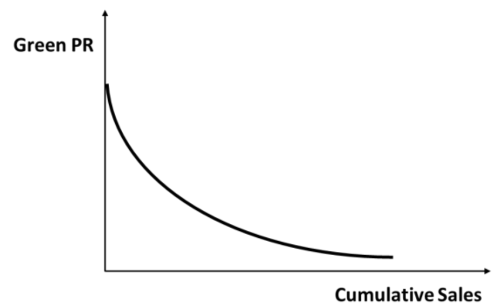


Figure 4. Functional form of the Green PR factor.

Green PR is quantified by an exponential cost function which enters total generalized cost as a negative cost. Each novel technology is assigned a Green PR value in the base year. A slope coefficient for the exponential function is defined by estimating the cumulative sales point at which the green value of the new technology is reduced by half. The slope coefficient is the logarithm of 0.5 divided by the specified cumulative sales.

Let g_j denote the Green PR (in dollars) of a vehicle of novel technology *j*, g_j^0 denote the Green PR (in dollars) of a truck of novel technology *j* in base year, Q_j denote the cumulative sales of technology *j*, *β* denote the slope coefficient, *ρ* denote the discount rate, and n denote the analysis period. Mathematically,

$$g_j = -PV(\rho, n, g_j^0 e^{\beta Q_j})$$

Let $\hat{q}$ denote the cumulative sales point at which the green value of the new technology is reduced by half. Then β is determined by the following equation

$$\beta = \ln(0.5)/\hat{q}$$

Due to the difficulty of quantification, four Green PR scenarios, namely, low Green PR, expected Green PR, high Green PR, and user custom Green PR, were created to allow some flexibility. Note that different Green PR scenarios only vary by g_j^0.

Uncertainty

Uncertainty represents fleets' aversion to the risk of new technology. It incorporates concerns of reliability/vehicle downtime, sales into the secondary market, technology market stability, etc. The aversion is high when only a few vehicles of that new technology exist and decreases with cumulative sales. The trend is illustrated in Figure 6.

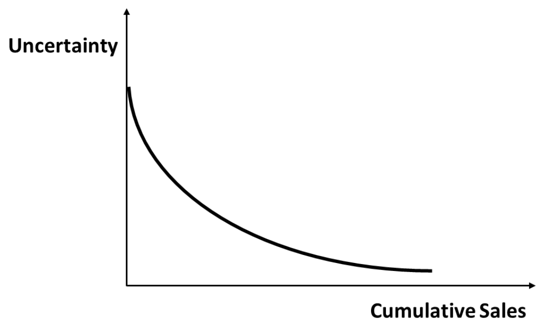


Figure 5. Functional form of the uncertainty factor

Uncertainty is quantified by an exponential cost function which enters total generalized cost as a positive cost. A risk premium is assigned to each risk group reflecting their perceived cost of adopting a vehicle of new technology in each period. The premium is discounted to present value assuming a certain length of lease and annual real interest rate. A risk premium multiplier is assigned to each technology reflecting their different degrees of uncertainty. A slope coefficient for the exponential function is defined by estimating the cumulative sales point at which the uncertainty of new technology is reduced by half. The slope coefficient is the logarithm of 0.5 divided by the specified cumulative sales.

Let v_{ij} denote perceived cost (in dollars) of novel technology *j* to group *i*, δ_j denote risk premium multiplier of technology *j*, V_{ij} denote the dollar quantity for group *i* to avoid or gain the opportunity to purchase a truck with novel technology *j* per period, ρ denote the discount rate, and n denote the analysis period. Mathematically,

$$v_{ij} = \delta_j \times PV(\rho,\ n, V_{ij})$$

Let P_i denote the dollar quantity for group *i* to avoid or gain the opportunity to purchase a truck with novel technology per period in base year, b_i denote the slope coefficient of group *i*, Q_j denote cumulative sales of technology *j*. V_{ij} is determined by the following equation

$$V_{ij} = \ P_i e^{b_i Q_j}$$

Let $\widehat{Q_i}$ denote the cumulative sales point at which the risk or novelty value of the new technology is reduced by half for group *i*. b_i is determined by the following equation

$$b_i = \ln(0.5)/\widehat{Q_i}$$

Incentive

Incentive is the rebate that a fleet receives when purchasing a new technology truck. Information on available incentives is from Alternative Fuel Data Center, U.S Department of Energy (AFDC 2017). Based on the information four incentive scenarios were created, namely, low incentive, expected incentive, high incentive, and user custom input incentive. While these four incentive scenarios are explicitly defined in the model, in general the incentive factor allows us to explore the effect of any incentive for a given truck type and technology for any period of years. This feature is discussed below in Market Scenarios and Results.

Refueling Inconvenience

Refueling inconvenience is the cost of refueling other than the fuel cost itself. It incorporates range, refueling time, and refueling station availability of different technologies. A refueling time multiplier and a station availability multiplier are assigned to each technology reflecting their difference in refueling time and station availability. Annual refueling inconvenience is the annual spending of trucker salary due to refueling. Annual refueling inconvenience is discounted to present value assuming a certain length of lease and annual real interest rate.

Let RI denote refueling inconvenience, RI_0 denote annual refueling inconvenience, ρ denote the discount rate, and n denote the analysis period. Mathematically,

$$RI = -PV(\rho, n, RI_0)$$

Let M_0 denote annual mileage, R denote range, w denote trucker hourly wage, RT denote refueling time multiplier, SA denote station availability multipler. Annual refueling inconvenience is determined by the following equation

$$RI_0 = \frac{M_0}{R} \cdot w \cdot 0.5\ hour \cdot RT \cdot SA$$

Refueling inconvenience for fleets that refuel at truck stops (many heavy-duty vehicles) and light-duty stations (heavy-duty pickups and vans) is mainly a function of station availability. As more stations become available, the inconvenience decreases. Fleets that fuel at private depots have a different issue. For a given fuel such as natural gas, hydrogen, or electricity, these fleets may not have fueling infrastructure. In order to purchase any new technology vehicles that use these fuels, fleets will have to either build the infrastructure at their depot or perhaps use another depot that has the infrastructure. This aspect of refueling inconvenience has not yet been incorporated into the model.

Maintenance Cost

Maintenance cost is the lifetime cost of maintenance of a vehicle. Annual maintenance cost is the product of maintenance cost per mile and annual mileage. Annual maintenance cost is discounted to present value assuming a certain length of lease and annual real interest rate.

Let MC denote maintenance cost, MC_0 denote annual maintenance cost, ρ denote the discount rate, and n denote the analysis period. Mathematically,

$$MC = -PV(\rho, n, MC_0)$$

Let MC_m denote maintenance cost per mile, M_0 denote annual mileage. Annual maintenance cost is determined by the following equation

$$MC_0 = MC_m \cdot M_0$$

Maintenance costs were taken from an analysis by Sharpe (Sharpe 2013).

Carbon Tax

Carbon tax is a tax levied on the carbon content of fossil fuels. Annual carbon tax is the product of annual fuel consumption and carbon tax per gallon of fuel. Annual carbon tax is discounted to present value assuming a certain length of lease and annual real interest rate.

Let CT denote carbon tax, CT_0 denote annual carbon tax, ρ denote the discount rate, and n denote the analysis period. Mathematically,

$$CT = -PV(\rho, n, CT_0)$$

Let FC_0 denote annual fuel consumption, CT_g denote carbon tax per gallon of fuel. Annual carbon tax is determined by the following equation

$$CT_0 = FC_0 \times CT_g$$

Let M_0 denote annual mileage, FE denote fuel economy. Annual fuel consumption is determined by the following equation

$$FC_0 = \frac{M_0}{FE}$$

Let CT_t denote carbon tax per ton of carbon, CI denote carbon intensity. Carbon tax per gallon of fuel is determined by the following equation

$$CT_g = \frac{CT_t \left(\frac{\$}{tonne}\right)}{10^6 \left(\frac{g}{tonne}\right)} \times CI \left(\frac{g}{MJ}\right) \times 132\left(\frac{MJ}{gallon}\right)$$

Carbon tax values begin in 2021 at \$25/tonne carbon and increase to \$150/tonne carbon in 2050.

Model Availability Cost

Model availability cost is the perceived extra cost of purchasing a vehicle due to limited availability. Model availability cost of a novel technology *i* will be relatively high at the beginning. It levels off until it is, for example, introduced by an OEM, and drops dramatically but starts to flatten out towards 0 asymptotically. Figure 7 demonstrates the trend
Model availability cost is quantified by a step cost function which enters total generalized cost as a positive cost. Each technology is assigned a model availability cost value in base year and a year when the technology will be introduced by an OEM.

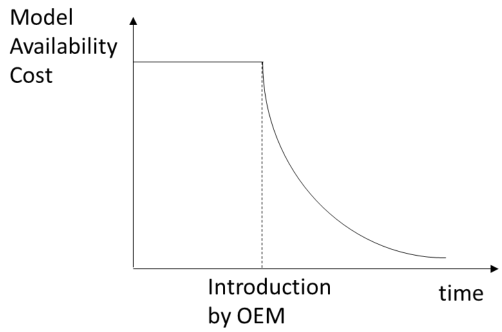


Figure 6. Functional form of the Model Availability factor.

Let t denote time (year), $\hat{t}_i$ denote the year when technology *i* will be introduced by an OEM, $c_i(t)$ denote the model availability cost of technology *i* in the year t, c_i^0 denote the initial model availability cost of technology *i*. α is a positive parameter which allows us to tune the rate of decay. Then mathematically,

$$c_i(t) = \begin{cases} c_i^0 & t \leq \hat{t}_i \\ c_i^0 \times e^{-\alpha(t-\hat{t}_i)} & t > \hat{t}_i \end{cases}$$

Factors such as capital cost, fuel cost, maintenance cost, incentives, and carbon tax are relatively easy to incorporate into the generalized cost framework because they are actual costs, but the other factors must be monetized in some way. We can estimate capital costs of new technologies by trying to understand the projected cost of vehicle components, but there is no straightforward method to determine an appropriate uncertainty value.

We interviewed a number of fleet managers and convened a fleet workshop to discuss how fleets make purchase decisions. These discussions were quite helpful in educating us on certain details of fleet purchases such as appreciating the wide diversity of fleets, understanding how few fleets are early adopters, and understanding the importance of model availability. Nevertheless, those discussions were less useful in monetizing uncertainty, green PR, model availability, and refueling inconvenience. We believe that follow up meetings with modest groups of fleets could help by exploring very specific situations where the fleet managers could give feedback on their response to such situations. Such responses could help us perhaps get upper and lower bounds to factors requiring monetization. In addition, those meetings could indicate what conditions would cause the factors to change significantly.

Figures 8 and 9 show the contribution of the various factors toward the generalized cost for short haul trucks in 2030 and 2050 for the sub-category of early adopters. As the capital cost, refueling inconvenience, and model availability decrease for battery electric and fuel cell vehicles, their generalized cost approaches the value for diesel vehicles.

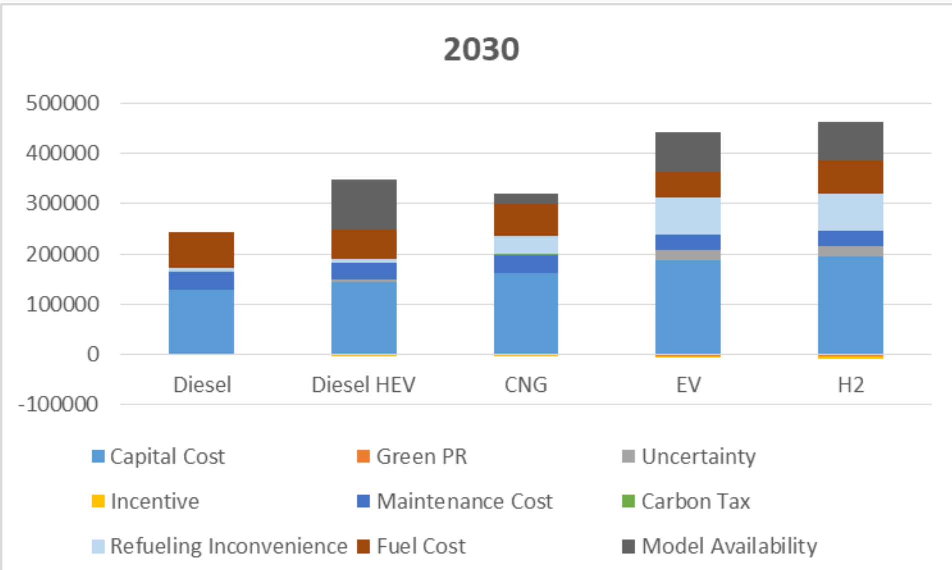


Figure 7. Generalized cost for short haul trucks in 2030 for the early adopter sub-category.

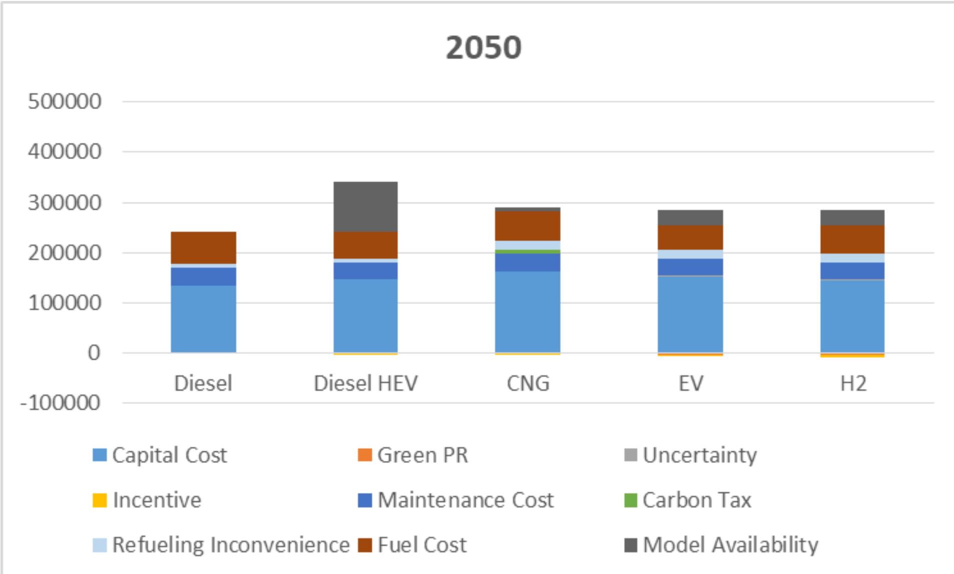


Figure 8. Generalized cost for short haul trucks in 2050 for the early adopter sub-category.

The Total Generalized Cost Effect on Purchase Probabilities

In the model, total generalized costs undergo a monotone transformation to yield purchase probabilities: the technology with the highest total generalized cost has the lowest purchase probability; the technology with the second highest total generalized cost has the second lowest purchase probability and so on. Below are two examples illustrating how changes in total generalized costs affect purchase probabilities.

Urban Buses

Consider the in-between risk group for urban buses as an example. For the business as usual scenario, only Diesel, Diesel HEV, and CNG have significant purchase probabilities over the period of 2010-2050. For a particular set of inputs the total generalized costs of Diesel and CNG stay around $505,000 and $550,000, respectively. The total generalized cost of Diesel HEV, however, gradually decreases from $737,783 in 2010 to $508,063 in 2050. Figure 10 illustrates the trends.

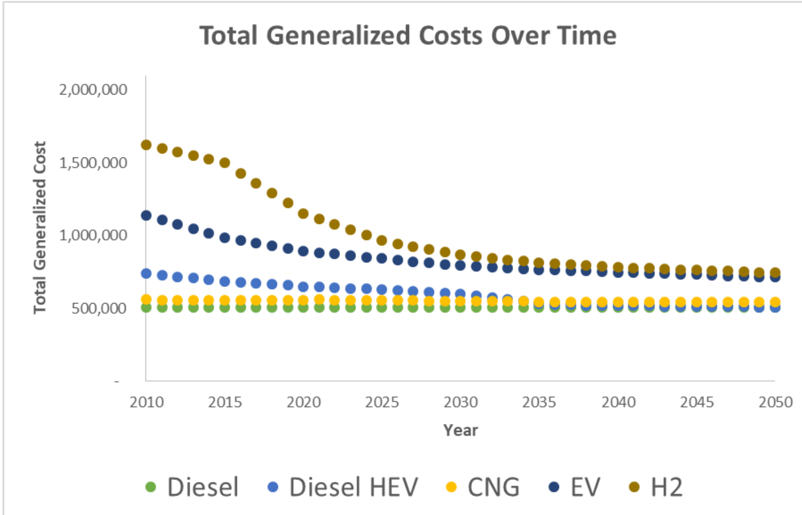


Figure 9. Total generalized costs for urban buses for the in-between category.

The total generalized cost of Diesel HEV decreases by approximately $230,000 from 2010 to 2050. For illustrative purposes, we divide the generalized cost into five equal parts with each part being roughly $46,000. Table 3 summarizes the changes in total generalized costs and purchase probabilities.

Table 3. Total generalized costs and purchase probabilities for urban buses for the in-between category.

	Diesel	Diesel HEV	CNG
2010	$505,704 / 93.4%	$737,783 / 0.00090%	$559,081 / 6.56%
2014	$505,030 / 92.7%	$695,911 / 0.00696%	$556,051 / 7.32%
2021	$506,115 / 93.4%	$645,847 / 0.089%	$559,714 / 6.49%
2030	$507,013 / 88.6%	$595,955 / 1.06%	$550,111 / 10.4%
2034	$506,984 / 78.3%	$546,782 / 10.8%	$546,546 / 10.9%
2050	$505,115 / 49.1%	$508,063 / 42.4%	$540,154 / 8.58%

Figure 11 illustrates purchase probabilities over time.

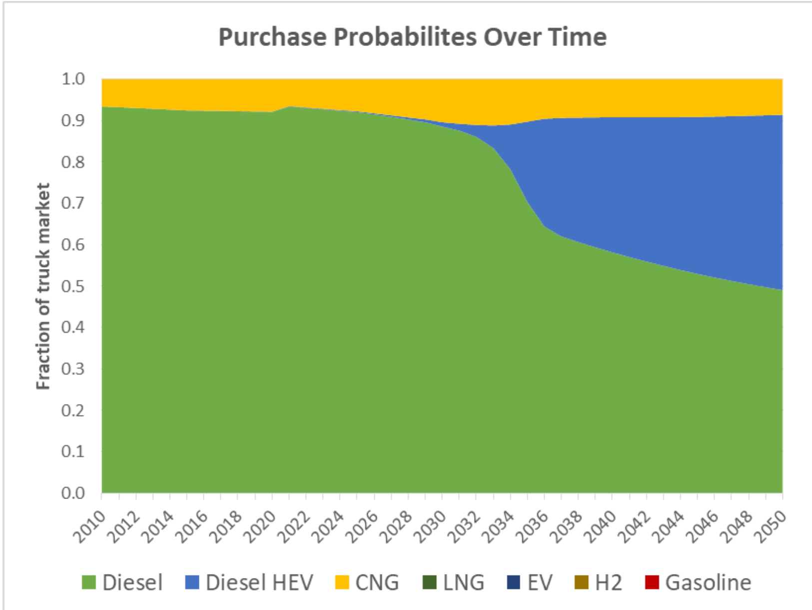


Figure 10. Purchase probabilities for urban buses for the in-between category.

From 2010 to 2014, the total generalized cost of Diesel HEV decreases by the first $46,000, but the purchase probability only increases by 0.00606%. From 2014 to 2021, the total generalized cost of Diesel HEV decreases by the second $46,000, and the purchase probability increases by 0.082%. From 2021 to 2030, the total generalized cost of Diesel HEV decreases by another $46,000, and the purchase probability increases by almost 1%. From 2030 to 2034, the total generalized cost of Diesel HEV decreases by the fourth $46,000, and the purchase probability increases by 9.7%. From 2034 to 2050, the total generalized cost of Diesel HEV decreases by the fifth $46,000, and the purchase probability increases by 31.6%.

Medium-duty Vocational

Consider the in-between risk group as an example. For the business as usual scenario, only Diesel and Diesel HEV have significant purchase probabilities over the period of 2010-2050. The total generalized costs of Diesel stays around $217,000. The total generalized cost of Diesel HEV, however, gradually decreases from $391,927 in 2010 to $227,062 in 2050. Figure 12 below illustrates the trends.

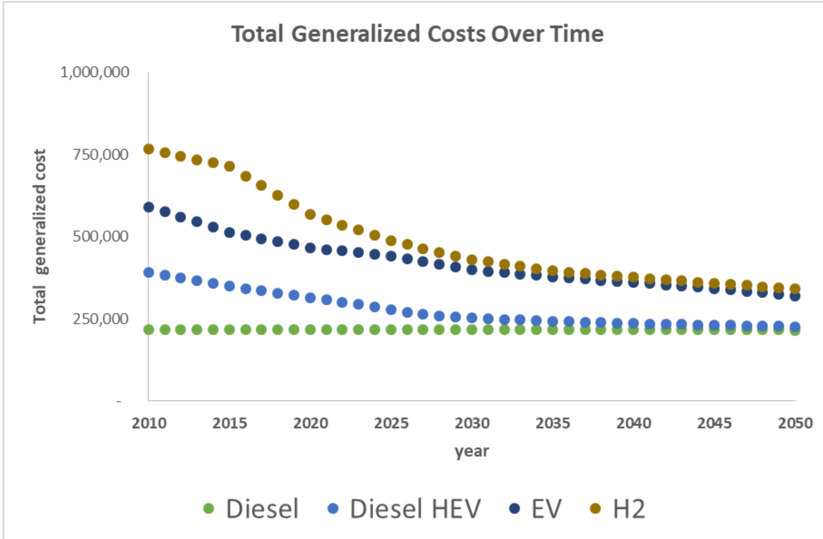


Figure 11. Total generalized costs for medium-duty vocational trucks for the in-between category.

The total generalized cost of Diesel HEV decreases by approximately $164,865 from 2010 to 2050. We divide it into five equal parts with each part being roughly $33,000. Table 4 summarizes the changes in total generalized costs and purchase probabilities.

Table 4. Total generalized costs and purchase probabilities for medium-duty vocational trucks for the in-between category.

	Diesel	Diesel HEV
2010	$217,719 / 99.98%	$391,927 / 0.02%
2014	$216,819 / 99.91%	$357,194 / 0.09%
2018	$217,179 / 99.61%	$328,856 / 0.38%
2023	$216,702 / 97.92%	$294,123 / 2.08%
2028	$216,985 / 89.07%	$259,163 / 10.92%
2050	$216,119 / 62.99%	$227,062 / 36.54%

Figure 13 illustrates purchase probabilities over time.

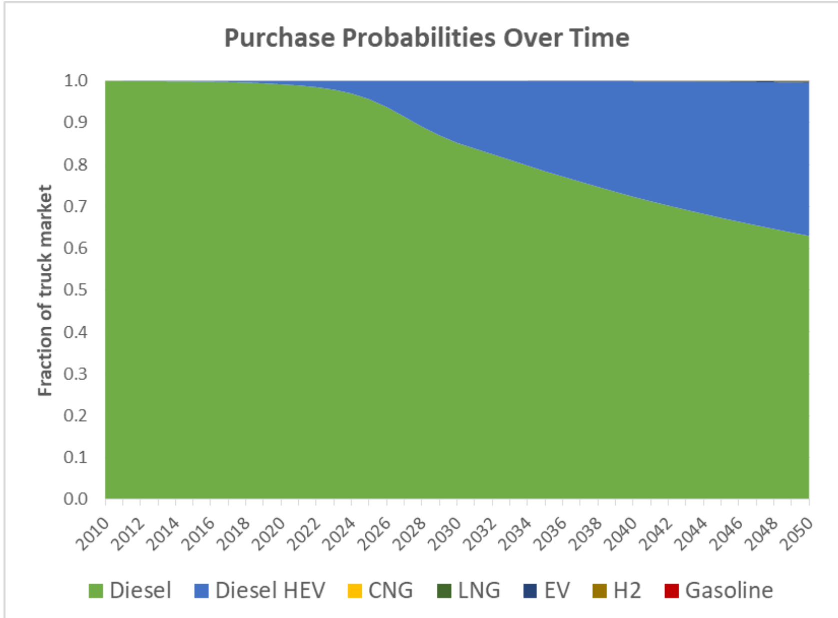


Figure 12. Purchase probabilities for medium-duty vocational trucks for the in-between category.

From 2010 to 2014, the total generalized cost of Diesel HEV decreases by the first $33,000, but the purchase probability only increases by 0.07%. From 2014 to 2018, the total generalized cost of Diesel HEV decreases by the second $33,000, and the purchase probability increases by 0.29%. From 2018 to 2023, the total generalized cost of Diesel HEV decreases by another $33,000, and the purchase probability increases by almost 1.7%. From 2023 to 2028, the total generalized cost of Diesel HEV decreases by the fourth $33,000, and the purchase probability increases by 8.84%. From 2028 to 2050, the total generalized cost of Diesel HEV decreases by the fifth $33,000, and the purchase probability increases by 25.62%.

Transition Scenarios Model

The Transition Scenarios Model assesses the potential for advanced vehicle technology and fuels to reduce GHGs in the California on-road transportation sector while also estimating the total cost for deployment of these technologies. The model incorporates detailed information on California vehicles including fleet stock, capital costs, fuel costs, vehicle miles traveled, and fuel economy from the present through 2050. The model also includes a fuel module which calculates fuel costs and carbon intensities. This fuel module provides a representation of economic costs and includes a detailed representation of fuel infrastructure deployment and scale required to adequately assess the full impacts of shifting to low-carbon fuels and vehicles.

Based on the Argonne VISION model, this model covers light-duty vehicles, medium-duty, and heavy-duty vehicles. The model further disaggregates these sectors based upon different vehicle requirements and application characteristics (e.g. trucks are disaggregated into long-haul, short-haul, medium-duty urban, etc.). This level of disaggregation enables the determination of which vehicle and fuel technologies may be appropriate for specific vehicle types (e.g. battery electric vehicles as unsuitable for long-haul trucks, but possible for short-haul trucks). The model also includes relevant economic costs associated with these vehicles based upon a detailed component level analysis for key technologies, such as fuel storage, batteries, fuel cells, and electric drivetrains. Figure 14 shows a simplified schematic of the spreadsheet model.

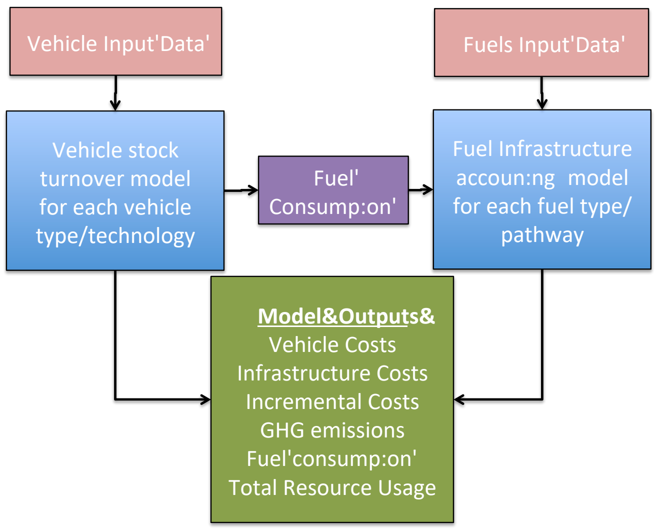


Figure 13. Simplified Schematic of the Transition Scenarios model.

The truck vehicle types included in the Transition Scenarios model are the same as those in the Decision Choice model. These types are:

- Long haul
- Short haul
- Heavy-duty vocational
- Medium-duty vocational
- Medium-duty urban
- Urban bus
- Other bus
- Heavy-duty pickups and vans

The model uses two approaches to estimate vehicle fuel economy based on the vehicle type. Diesel, gasoline, and natural gas vehicle fuel economies were estimated using present values from EMFAC 2014 and information from available literature to project future fuel economies. Fuel cell, battery electric, and hybrid vehicle fuel economies were estimated using dynamic vehicle simulations and tying the results to present EMFAC values for diesel vehicles.

Vehicle costs were calculated by considering the total cost as a sum of component costs. The components for vehicles include:

- Glider
- Engine
- Transmission
- Engine after treatment system (EATS)
- Fuel storage
- Fuel cell
- Battery
- Motor/controller

The cost of full vehicles for the different categories was identified from either published sources or from a survey of prices on commercial vehicle sales websites.

The model calculates GHG emissions each year based on vehicle stock, fuel economies, vehicle miles traveled, and the fuel carbon intensities. A detailed description of the model along with all the relevant values for vehicle fuel economies and costs used as inputs to the Decision Choice model can be found in the technical documentation (Miller 2017).

Market Scenarios and Results

We created scenarios to investigate aspects of the decision choice model. These scenarios included a business as usual (BAU) scenario and several zero-emission vehicle (ZEV) scenarios. The BAU scenario represents a situation where there is no attempt to influence truck choice using policies such as incentives or mandates. This scenario will differ from a scenario that includes the effects of present federal or state rules. The ZEV scenarios include a specified market share (i.e. sales per year) for ZEVs (either fuel cell vehicles or battery electric vehicles).

For the ZEV scenarios, we imagine a ZEV mandate requiring that a set percentage of new trucks sales in each truck type be ZEVs for each year through 2050. The mandate can be satisfied using either fuel cells or battery electric trucks. The model decides which technology type the fleets will choose. To meet the mandated percentage, we add incentive funding for each truck type for every year. The incentive is set to the value necessary per truck to meet the goals. There are two ZEV scenarios. One scenario requires that the ZEV market share for each truck type reach 25% by 2050. The second scenario requires the ZEV market share to reach 50% by 2050.

In real fleet purchases the incentive value per vehicle is not required to come from public funding. Truck manufacturers could discount the price of their vehicles, fleet owners could pay an increased price, or public entities could supply incentive funding. Alternatively, the incentive value could be split among manufacturers, fleets, and public entities. The sum of these incentives over a given period could be viewed as an investment.

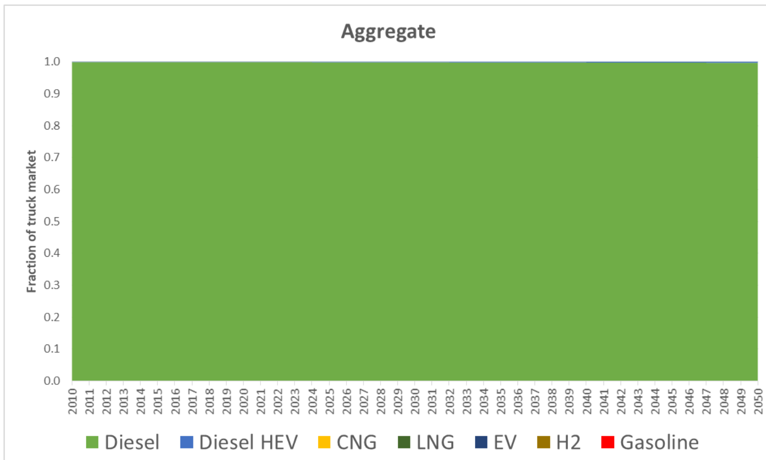
Business as usual (BAU)

BAU outputs are generated by setting scenarios to “Low Oil Price”, “High Carbon Intensity”, “Expected Carbon Tax”, “Expected Green PR”, “Expected Incentive”, and by setting discount rate to 7%, analysis period to 4 years, and trucker time cost to $40/hour. Annual mileage of different truck types are summarized in the Table 5.

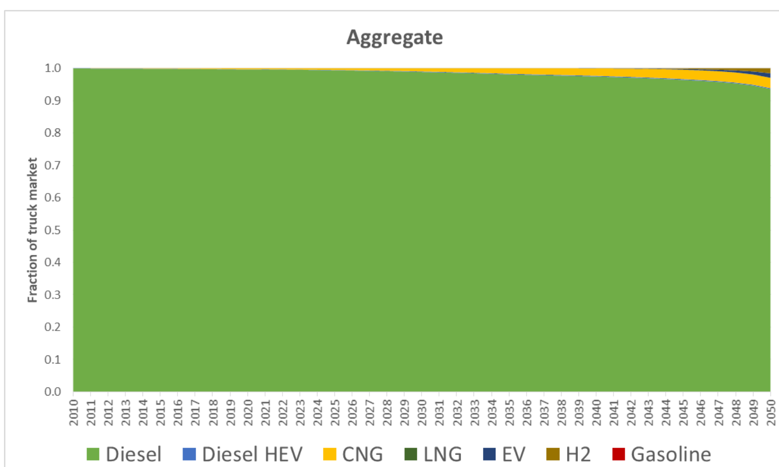
Table 5. Annual mileage for the 8 truck types.

Truck Type	Annual Mileage
Long Haul	125,000
Short Haul	50,000
Heavy-duty Vocational	25,000
Medium-duty Vocational	25,000
Medium-duty Urban	25,000
Urban Bus	30,000
Other Bus	30,000
Heavy-duty Pickup	25,000

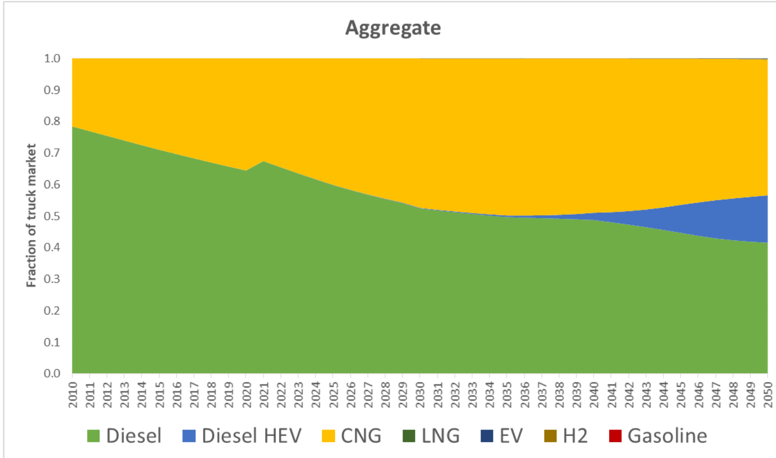
Not surprisingly, different truck types are very heterogeneous in penetration of new technologies. Diesel still dominates the markets of long haul and short haul trucks. Heavy-duty vocational, medium-duty vocational, and urban bus markets have significant penetration of Diesel HEV and/or CNG. The medium-duty urban market represents the most diverse penetration of different technologies. The other bus market is dominated by Diesel but starts to have considerable penetration of zero-emission technologies (i.e. EV and H_2) and Diesel HEV towards the end of the period. Heavy-duty pickup market is mostly shared by Diesel and Gasoline with gradually increasing zero-emission technologies and Diesel HEV after 2025. Figure 15 shows aggregate purchase probabilities over time for all eight truck types.



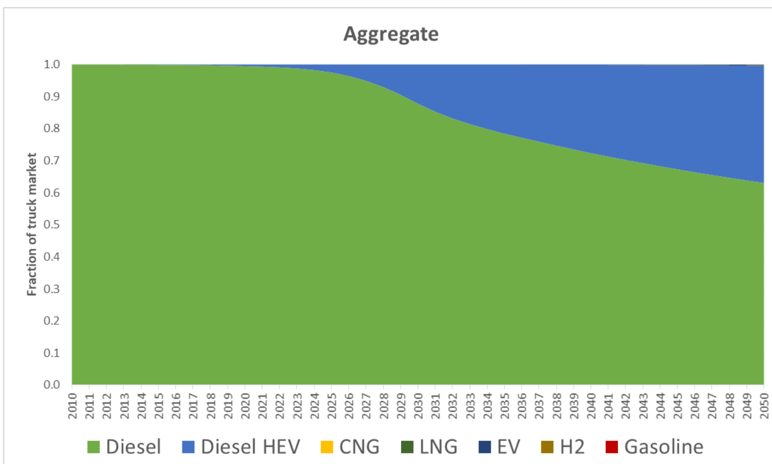
Long Haul



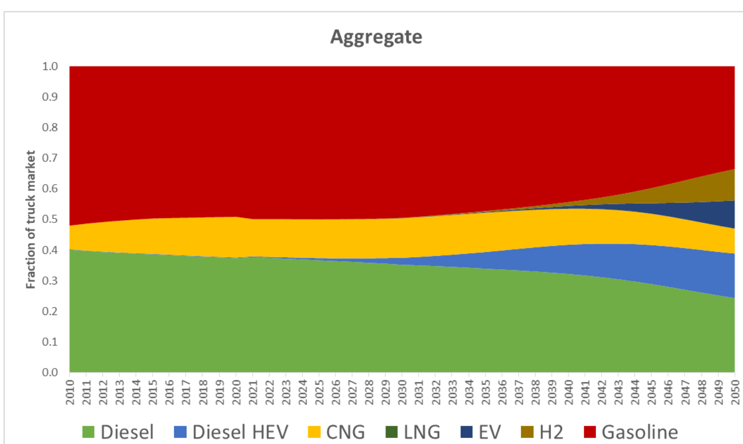
Short Haul



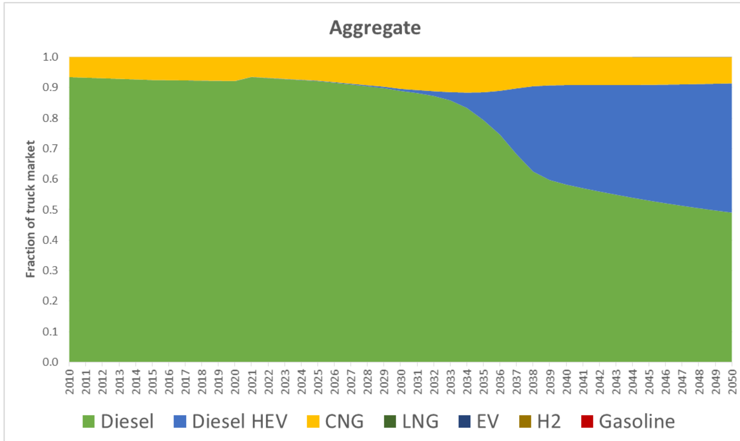
Heavy-duty Vocational



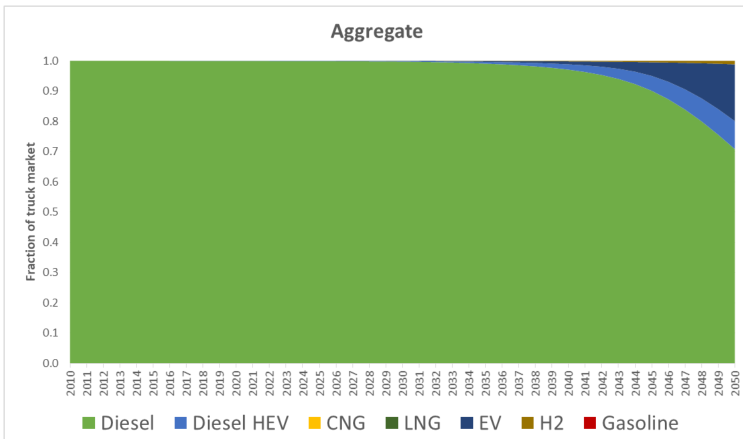
Medium-duty Vocational



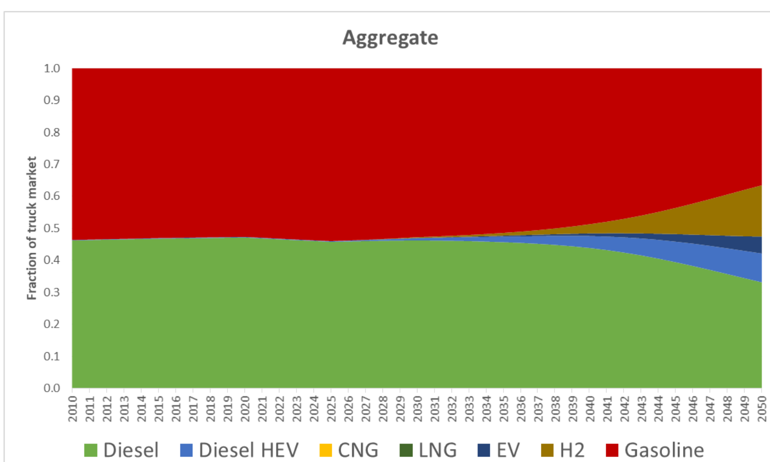
Medium-duty Urban



Urban Bus



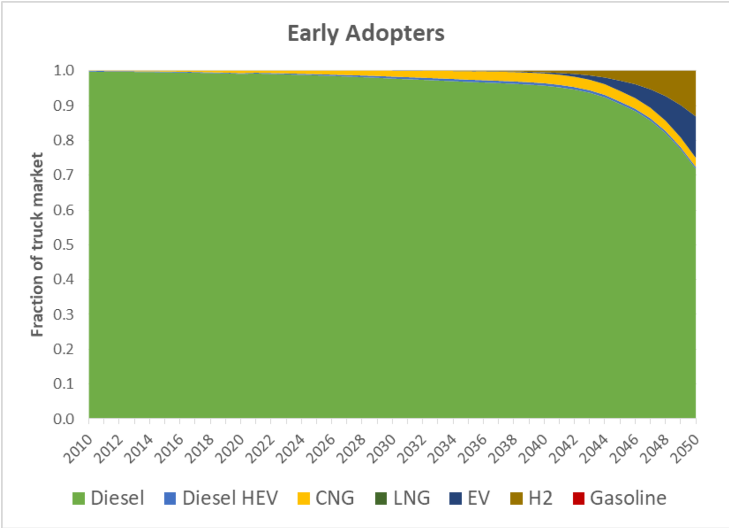
Other Bus



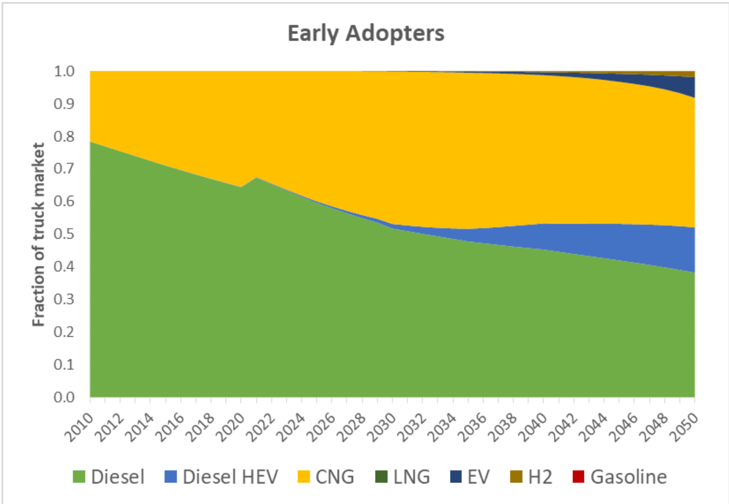
Heavy-duty Pickup

Figure 14. Aggregate market shares for the truck types and technologies.

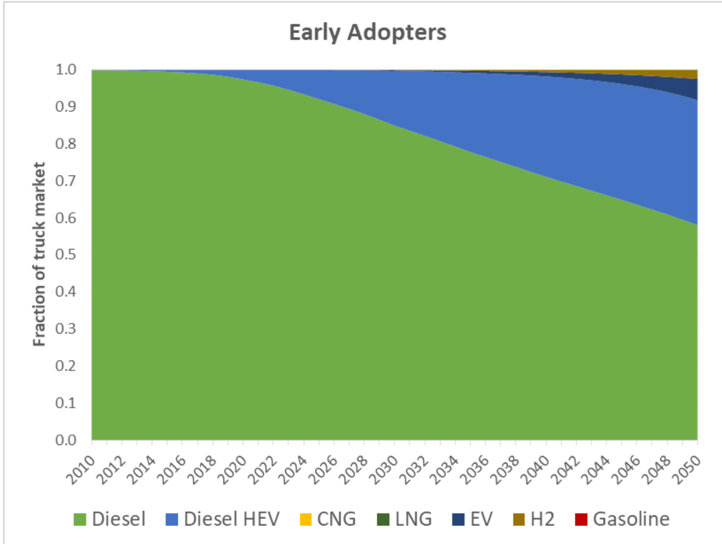
Although very unlikely to be purchased in several aggregate markets, namely, short haul, heavy-duty vocational, and medium-duty vocational, battery electric vehicles (BEV) and fuel cell vehicles start to play a more important role in the corresponding early adopter markets. Figure 16 shows early adopter purchase probabilities over time for the three above mentioned truck types.



Short Haul



Heavy-duty Vocational



Medium-duty Vocational

Figure 15. Market shares for early adopter categories for short haul, heavy-duty vocational, and medium-duty vocations trucks.

ZEV Scenarios

Two scenarios were generated to investigate the potential costs of ZEV mandates. In both scenarios, buyers of BEVs and fuel cell trucks receive the same amount of incentive per vehicle. The mandate requires a series of increasing market shares of ZEVs (BEVs and fuel cell trucks combined) throughout the period of 2025 to 2050. Table 6 summarizes the mandates in each year for the two scenarios and includes a proposed CARB ZEV mandate (CARB 2017), The CARB proposed mandate would cover truck classes 2b-7 and is slightly more aggressive than our scenario 2. Our ZEV scenarios include all truck classes (i.e. 2b-8).

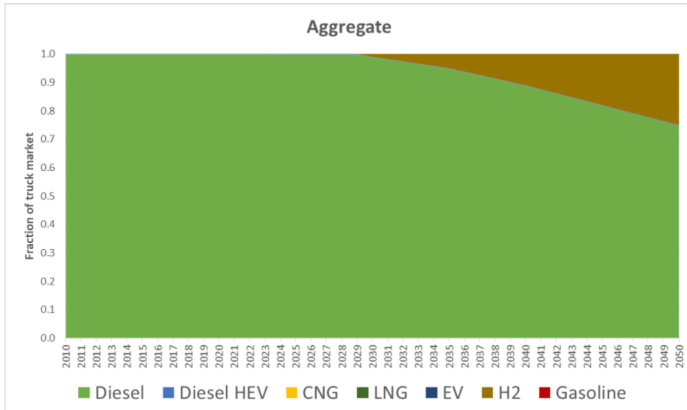
In the real world, various factors could result in a failure to meet the mandate. For example, some ZEVs might be too unreliable, too difficult to sell into secondary markets, or have high maintenance costs. In this study, we assume that truck manufacturers and fleets are able to produce and purchase enough ZEVs to meet any mandate.

Table 6. Market share of ZEV by year for the two ZEV scenarios.

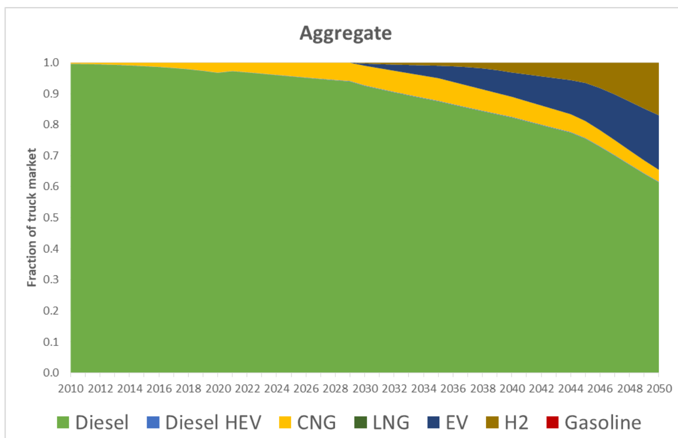
Year	Scenario 1 ZEV Market Share	Scenario 2 ZEV Market Share	CARB Proposed ZEV Mandate (Classes 2b-7)
2025	0.0%	3.0%	7.0%
2026	0.0%	4.4%	8.5%
2027	0.0%	5.8%	10.0%
2028	0.0%	7.2%	10.0%
2029	0.0%	8.6%	13.0%
2030	1.0%	10.0%	15.0%
2031	1.8%	12.0%	
2032	2.6%	14.0%	
2033	3.4%	16.0%	
2034	4.2%	18.0%	
2035	5.0%	20.0%	
2036	6.2%	22.6%	
2037	7.4%	25.2%	
2038	8.6%	27.8%	
2039	9.8%	30.4%	
2040	11.0%	33.0%	
2041	12.4%	35.0%	
2042	13.8%	37.0%	
2043	15.2%	39.0%	
2044	16.6%	41.0%	
2045	18.0%	43.0%	
2046	19.4%	44.4%	
2047	20.8%	45.8%	
2048	22.2%	47.2%	
2049	23.6%	48.6%	
2050	25.0%	50.0%	

We considered two variants of scenario 1. In Scenario 1a, the calculation of refueling inconvenience for all technologies follows the method in the model description. In Scenario 1b, the calculation of refueling inconvenience for Diesel vehicles follows the method in the model description while the refueling inconvenience for all other technologies are set equal to Diesel. Scenario 1b represents a situation where there is no disincentive due to inconvenient refueling. For example, public funding could be available to fleets to build enough fueling stations such that new technology vehicles can easily refuel.

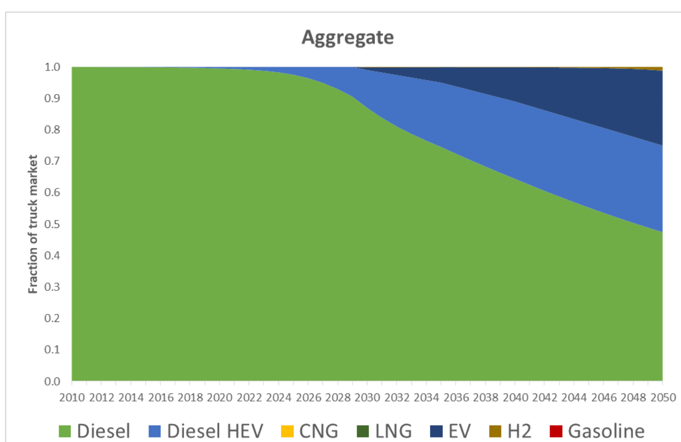
Market shares of the two scenarios show a sharp contrast to the BAU scenario as expected. Figure 17 shows the aggregate market shares for some truck types in Scenario 1b.



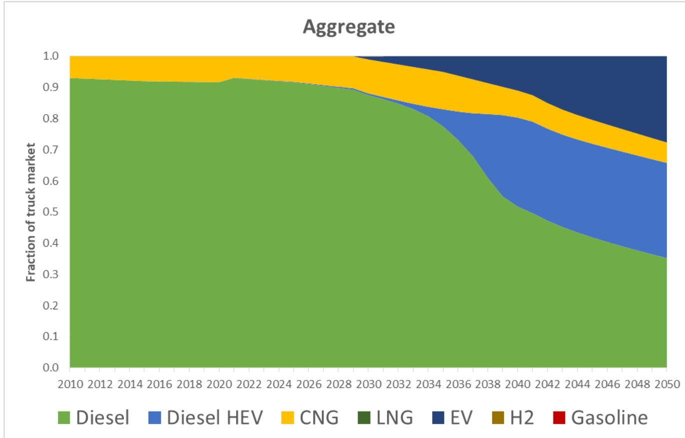
Long Haul



Short Haul



Medium-duty Vocational



Urban Bus

Figure 16. The aggregate market shares for certain truck types in Scenario 1b.

Figures 18 and 19 show the market share for the various technologies for short haul trucks in 2030 and 2050 respectively for each of the four scenarios (BAU, 25% ZEV scenario 1a, 25% ZEV scenario 1b, and 50% ZEV).

Appendix B includes plots for the market shares of all trucks types for all four scenarios. Costs of the mandate in scenarios 1a and 1b are very different. As an example, Table 7 compares the necessary rebate per vehicle of long haul trucks in each year. Table 8 shows the maximum and minimum yearly incentives as well as the sum of all yearly incentives from 2030-2050 for each truck type necessary to meet the ZEV mandate for scenario 1a. The sum of yearly investments can be viewed as an investment.

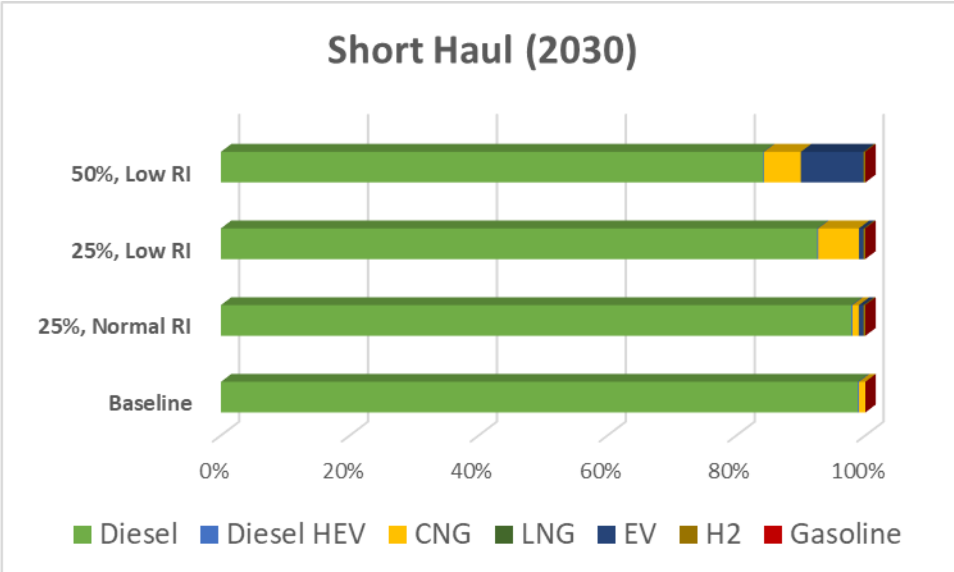


Figure 17. Market share for the various technologies for short haul trucks in 2030 for the four scenarios.

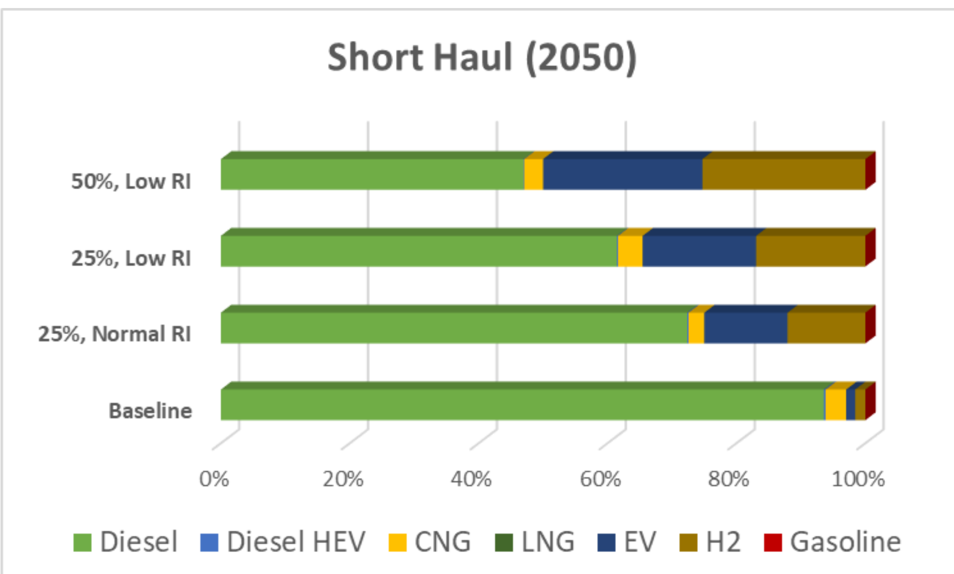


Figure 18. Market share for the various technologies for short haul trucks in 2050 for the four scenarios.

Table 7. Incentives per long haul vehicle necessary to meet the ZEV mandate for scenarios 1a and 1b.

Year	Scenario 1a	Scenario 1b
2030	$287,100	$227,500
2031	$275,000	$219,100
2032	$255,200	$202,750
2033	$233,750	$184,650
2034	$213,700	$167,900
2035	$196,400	$153,850
2036	$184,800	$145,380
2037	$173,720	$137,320
2038	$162,900	$129,450
2039	$152,580	$121,990
2040	$143,140	$115,300
2041	$136,420	$111,270
2042	$130,370	$107,800
2043	$124,780	$104,700
2044	$119,500	$101,810
2045	$114,420	$99,040
2046	$109,850	$96,700
2047	$105,420	$94,400
2048	$101,130	$92,150
2049	$96,980	$89,950
2050	$92,970	$87,800

Table 8. Value of incentives to meet ZEV mandate scenario 1a for each truck type.

Truck Type	Maximum yearly incentive ($)	Minimum yearly incentive ($)	Total investment from 2030-2050 (million$)
Long haul	287,100	92,970	3,689
Short haul	149,900	1,390	303
Heavy-duty vocational	125,500	12,850	364
Medium-duty vocational	99,100	24,780	177
Medium-duty urban	46,530	11,050	1,218
Urban buses	148,000	0	62
Other buses	56,800	3,580	63
Heavy-duty pickups and vans	35,350	7,260	3,046

Table 9 shows the maximum and minimum yearly incentives as well as the total value of all yearly incentives from 2030-2050 for each truck type necessary to meet the ZEV mandate for scenario 1b.

Table 9. Value of incentives to meet ZEV mandate scenario 1b for each truck type.

Truck Type	Maximum yearly incentive ($)	Minimum yearly incentive ($)	Total investment from 2030-2050 (million$)
Long haul	227,500	87,800	3,143
Short haul	86,800	0	116
Heavy-duty vocational	121,500	11,570	334
Medium-duty vocational	94,800	23,480	165
Medium-duty urban	41,500	7,020	834
Urban buses	142,500	0	53
Other buses	51,100	2,340	48
Heavy-duty pickups and vans	23,750	6,200	2,202

Scenario 2 incentive values are significantly higher due to the increase in mandated market share. Table 10 shows the maximum and minimum yearly incentives as well as the total value of all yearly incentives from 2025-2050 for each truck type necessary to meet the ZEV mandate for scenario 2.

Table 10. Value of incentives to meet ZEV mandate scenario 2 for each truck type.

Truck Type	Maximum yearly incentive ($)	Minimum yearly incentive ($)	Total investment from 2025-2050 (million$)
Long haul	312,950	110,980	11,163
Short haul	169,570	12,520	880
Heavy-duty vocational	202,800	34,790	2,115
Medium-duty vocational	157,550	41,030	813
Medium-duty urban	100,100	29,805	7,278
Urban buses	257,500	20,220	577
Other buses	105,600	23,130	500
Heavy-duty pickups and vans	65,800	27,355	19,577

To calculate GHG reductions for each scenario the market shares for each truck type and technology are used as inputs for the Transition Scenarios model. The model calculates GHG emissions for each year from 2010 through 2050. Table 11 shows the GHG emissions reductions from 2010 by 2050 for the BAU, ZEV scenario 1, and ZEV scenario 2 for the total truck fleet. The default settings for the analysis were 5% renewable diesel fuel as a percentage of diesel fuel and low electricity and hydrogen carbon intensities. For the ZEV scenario 1 we added another run with biofuels reaching 50% renewable diesel fuel as a percentage of diesel fuel by 2050.

Table 11. Greenhouse gas emissions reductions from 2010 by 2050 for various scenarios for the entire truck fleet.

Scenario	GHG reductions (%) from 2010 by 2050
BAU	10
ZEV scenario 1	22
ZEV scenario 1 with high biofuels	45
ZEV scenario 2	46

Given the total investment and the reductions in GHGs, we can calculate the $/tonne CO_2e reduced for each scenario. Table 12 shows the total investment, the reduction in GHGs, and the $/tonne CO_2e reduced for each scenario. Results for scenarios 1a and 1b are given both with and without biofuels reaching 50% of diesel fuel by 2050 (high biofuels). The cost does not include additional fuel cost for biofuels. GHG reductions are taken from the year that incentives were initiated (2030 for scenarios 1a and 1b, 2025 for scenario 2).

Table 12. Greenhouse gas reductions and cost efficiency for the ZEV scenarios.

ZEV scenario	Investment (billions $)	GHG reductions (ktonne CO_2e)	Cost efficiency ($/tonne)
1a	8.9	13.8	648
1b	6.9	13.8	297
1a with high biofuels	8.9	30.0	501
1b with high biofuels	6.9	30.0	230
2	42.9	32.0	1,339

Summary and Future Work

Summary

A decision choice model was developed that includes:

- Disaggregation into 8 truck types
- Advanced technologies with a bottom up cost model and fuel economies that are functions of time through 2050
- Critical choice factors with monetized functional forms and dependences
- Production of market shares year by year for new technologies through 2050
- Ability to investigate policies such as sales mandates, carbon taxes, and incentives

The market share outputs can be used as inputs to a Transition Scenarios model to calculate GHG emissions, vehicle and fuel costs, and vehicle stock associated with those market shares. The model was used to investigate several scenarios including a BAU with no policy levers and several ZEV mandates.

In general, the BAU scenario market shares change relatively little through 2040 and include only very modest penetration of new technologies such as battery electric vehicles or fuel cell vehicles and only toward the end of the timeframe mostly in the early adopter fleet category. The overall GHG reductions from this scenario are small (10%) mostly due to increased fleet vehicle miles traveled balancing out increases in fuel economy.

Two ZEV scenarios were explored to understand the need for incentive funding that might be needed to overcome various disincentives for ZEV technologies such as the higher capital cost, perceived uncertainty toward new technologies, refueling inconvenience, and initial low model availability. The hypothetical mandates in these scenarios reached 25% and 50% ZEV market shares by 2050.

Different ZEV technologies were used to meet the mandate for differing truck types. For example, fuel cells met the entire mandate for long haul trucks because our model does not include battery electric trucks in that truck type due to weight considerations. Battery electric and fuel cell trucks reached similar market shares in short haul trucks, but battery electric trucks dominated the ZEV market share in medium-duty vocational and transit buses because the capital costs of battery electric vehicles are lower than the cost of fuel cells in those truck types.

The necessary incentive per vehicle starts as a significant percentage of the capital cost but drops to a small fraction of that cost in most cases as market shares of ZEV technologies rise. Short haul trucks required no incentives toward 2050 to meet the mandate for scenario 1b (with refueling inconvenience equal to diesel refueling inconvenience).

The total incentives required to meet even the 25% mandate for all truck types are quite high ($6.9 and $8.9 billion for the low refueling inconvenience and normal refueling inconvenience cases respectively). For certain truck types the total incentives necessary are much more modest. In scenario 1b transit buses require $53 million, medium-duty vocational trucks require $165 million, and short haul trucks require $116 million from 2030 – 2050.

The ZEV scenarios reach modest GHG reductions compared to the 80% reduction goal in California across all sectors in 2050. Scenario 1 (25% ZEV market share by 2050) with biofuels and scenario 2 (50% ZEV market share) almost reach 50% reductions in 2050 from 2010 levels.

Model Limitations and Future Work

The present model has limitations which could be reduced through additional work. Future work that could reduce these limitations and provide more accurate results is discussed below.

Add plug-in hybrid vehicle technology

For some truck types plug-in hybrid vehicles could play an important role in the transition from conventional vehicles to full electrification. We plan to add this vehicle technology as an option for most truck types.

Create better capital cost models

Presently capital costs are calculated by developing models to estimate component costs and then summing these component costs. This method may work reasonably well once sales reaches sufficiently large volumes; however, vehicle costs during early market penetration may require additional inputs such as technology development and engineering design. We plan to work with truck manufacturers to better understand capital costs during this early market penetration period.

Better understand decision choice factors

Four decision choice factors must be monetized before including them in the total generalized cost. Those factors are uncertainty, green PR, model availability, and refueling inconvenience. Understanding the proper values for each as a function of time for each truck type and technology is rather challenging. While we believe that the equations should model the behavior of the factors reasonably well, we feel that more work is needed to better quantify those values.

Given our present experience with the model and effect of the factors, we are in a much better situation to meet with fleet managers and owners and ask more detailed, specific questions that could allow us to better quantify those factors. Important considerations include both how quickly the factors should reach diesel vehicle values and what specific events cause significant changes in the values.

Include additional factors

One particular factor that is not included in the model is payload reduction due to weight of the new technology. Both batteries and fuel cells with hydrogen storage are heavy and would reduce the payload for trucks that weigh out. A study by the US Department of Transportation found that tanker trucks weigh-out over 80% of the time while enclosed van trailers weigh-out less than 20% of the time (US DOT 2000). While these components may become lighter with advances in technology, the potential penalty in reduced payload could adversely impact fleets. Adding payload reductions as an additional factor could account for a perceived disincentive to adopting those technologies based on reduced payload.

Include lifecycle cost in benefits

Our model presently includes only those factors that are relevant to fleets in making purchase decisions. We do not include societal benefits such as lowered emissions in our calculations. While these benefits would have little or no impact on the actual fleet purchase decisions, their value could be significant. We plan to include calculations of some societal benefits to use in comparisons of various scenarios.

Include option for lower battery electric vehicle costs

Recent results have indicated that battery costs are significantly less expensive than previously thought and future costs could reach values lower than expected. Our battery cost model takes some of these results into account; however, discussions with battery electric manufacturers (especially transit bus manufacturers) seem to indicate that our vehicle costs may still be higher than those manufacturers project. We plan to revisit cost details including battery, vehicle, and maintenance costs with manufacturers to include a lower battery electric vehicle option which may be closer to their projected future costs.

References

(AFDC 2017) Alternative Fuels Data Center, US Department of Energy. https://www.afdc.energy.gov/laws

(CARB 2009) Attachment B: 2050 Greenhouse Gas Emissions Analysis: Staff Modeling in Support of the Zero Emission Vehicle Regulation. California Air Resourcs Board, 2009. http://www.arb.ca.gov/msprog/zevprog/2009zevreview/2009zevreview.htm. 1/10/2010

(CARB 2012) Vision for Clean Air: A Framework for Air Quality and Climate Planning. California Air Resources Board, Sacramento, 2012. https://www.arb.ca.gov/planning/vision/docs/vision_for_clean_air_public_review_draft.pdf

(CARB 2017) Advanced Clean Local Trucks Workshop, California Environmental Protection Agency, Air Resources Board, April 25, 2017. https://www.arb.ca.gov/msprog/actruck/mtg/170425workshoppresentation.pdf

(CCST 2011) California's Energy Future - The View to 2050. California Council on Science and Technology. 2011. http://ccst.us/publications/2011/2011energy.pdf

(E3 2015) Pathways Model. Energy and Environmental Economics. https://ethree.com/public_projects/energy_principals_study.php.

(EIA 2014) US Energy Information Administration Annual Energy Outlook 2014, accessed at: http://www.eia.gov/forecasts/aeo/er/tables_ref.cfm

(Greenblatt 2013) Greenblatt, J.B., Estimating Policy-Driven Greenhouse Gas Emissions Trajectories in California: The California Greenhouse Gas Inventory Spreadsheet (GHGIS) Model Lawrence Berkeley National Laboratory, Berkeley, 2013.

(IPCC 2014) IPCC International Panel on Climate Change, Climate Change 2014: Impacts, Adaptation, and Vulnerability, Summary for Policy Makers, 2014.

(Jacobson 2014) Jacobson, M.Z., Delucchi, M.A., Ingraffea, A.R., Howarth, R.W., Bazouin, G., Bridgeland, B., Burkart, K., Chang, M., Chowdhury, N., Cook, R., Escher, G., Galka, M., Han, L., Heavey, C., Hernandez, A., Jacobson, D.F., Jacobson, D.S., Miranda, B., Novotny, G., Pellat, M., Quach, P., Romano, A., Stewart, D., Vogel, L., Wang, S., Wang, H., Willman, L., Yeskoo, T., A roadmap for repowering California for all purposes with wind, water, and sunlight. Energy 73, 875-889, 2014.

(McCollum 2012) McCollum, D., Yang, C., Yeh, S., Ogden, J., Deep greenhouse gas reduction scenarios for California: Strategic implications from the CA-TIMES energy-economic systems model. Energy Strategy Rev 1, 19-32, 2012.

(Miller 2017) Miller, M., Burke, A., Fulton, L., Ogden, J., Ouellette, P., Yang, C., and Zhao, H., Transition Scenarios Technical Documentation, Institute of Transportation Studies, University of California, Davis, 2017.

(Morrison 2015) Morrison, G.M., Yeh, S., Eggert, A.R., Yang, C., Nelson, J.H., Greenblatt, J.B., Isaac, R., Jacobson, M.Z., Johnston, J., Kammen, D.M., Comparison of low-carbon pathways for California. Climatic Change 131, 545-557, 2015.

(NRC 2013) National Research Council. *Transitions to Alternative Vehicles and Fuels*. Washington, DC: The National Academies Press. https://doi.org/10.17226/18264, 2013.

(Roland-Holst, D. 2015) Roland-Holst, D., California Climate Policy to 2050: Pathways for Sustained Prosperity. Next10. http://next10.org/emissionpathways, 2015.

(Sharpe 2013) Sharpe, B. Examining the Costs and Benefits of Technology Pathways for Reducing Fuel Use and Emissions from On-road Heavy-duty Vehicles in California, dissertation thesis, University of California, Davis, 2013.

(US EPA 2016) Inventory of U.S. greenhouse Gas Emissions and Sinks: 1990 – 2014, US EPA 430-R-16-002, April 2016.

(US DOT 2000) The US Department of Transportation's Comprehensive Truck Size and Weight Study, FHWA-PL-00-029, HPTS/August 2000.

(Yang 2009) Yang, C., McCollum, D.L., McCarthy, R.W., Leighty, W., Meeting an 80% Reduction in Greenhouse Gas Emissions from Transportation by 2050: A Case Study in California. *Transportation Research Part D* 14D (3), 147 – 156, 2009.

(Yang 2011) Yang, C., Ogden, J., Sperling, D., and Hwang, R., *California's Energy Future: Transportation Energy Use in California*. California Council on Science and Technology. December 2011.

Glossary of Terms

BAU	business as usual
BEV	battery electric vehicle
CARB	California Air Resources Board
CNG	compressed natural gas
CT	carbon tax
EATS	Engine after treatment system
FC	fuel cost
FE	fuel economy
FP	fuel price
GHG	greenhouse gas
HEV	hybrid electric vehicle
IPCC	International Panel on Climate Change
LNG	liquid natural gas
M	annual mileage
MC	maintenance cost
NMNL	nested multinomial logit
PR	public relations
PV	present value
R	range
RI	refueling inconvenience
RT	refueling time multiplier
ZEV	zero emission vehicle

Appendix A. Factor constants for the decision choice model

Market Composition

Early Adopter	2%
In-between	40%
Late Adopter	58%

Green PR (in dollars) of novel technology j in base year (g_j^0)

Scenario	Diesel	Diesel HEV	CNG	LNG	EV	H_2	Gasoline
Low	0	100	200	200	400	500	0
Expected	0	200	400	400	800	1000	0
High	0	400	800	800	1600	2000	0

Cumulative Sales Point at Which the Green Value Of The New Technology Is Reduced By Half ($\hat{q}$)

Long Haul	Short Haul	HD Vocational	MD Vocational	MD Urban	Urban Bus	Other Bus	HD Pickup
62,800	54,000	36,350	12,550	135,900	17,425	12,900	445,300

Risk Premium Multiplier of Technology j (δ_j)

Truck Type	Diesel	Diesel HEV	CNG	LNG	EV	H_2	Gasoline
Long Haul	0	0.2	0.3	0.4	0.5	0.5	0
Short Haul	0	0.2	0.1	0.4	0.5	0.5	0
HD Vocational	0	0.2	0	0.4	0.5	0.5	0
MD Vocational	0	0.2	0.3	0.4	0.5	0.5	0
MD Urban	0	0.2	0.1	0.4	0.5	0.5	0
Urban Bus	0	0.2	0	0.4	0.5	0.5	0
Other Bus	0	0.2	0.3	0.4	0.5	0.5	0
HD Pickups	0	0.2	0.3	0.4	0.5	0.5	0

The Dollar Quantity for Group i to Avoid or Gain the Opportunity to Purchase a Truck with Novel Technology per period (P_i)

Truck Type	**Early Adopter**	**In-between**	**Late Adopter**
Long Haul	12,500	37,500	62,500
Short Haul	11,500	34,500	57,500
HD Vocational	23,000	69,000	115,000
MD Vocational	17,000	51,000	85,000
MD Urban	5,500	16,500	27,500
Urban Bus	40,000	120,000	200,000
Other Bus	10,000	30,000	50,000
HD Pickups	4,000	12,000	20,000

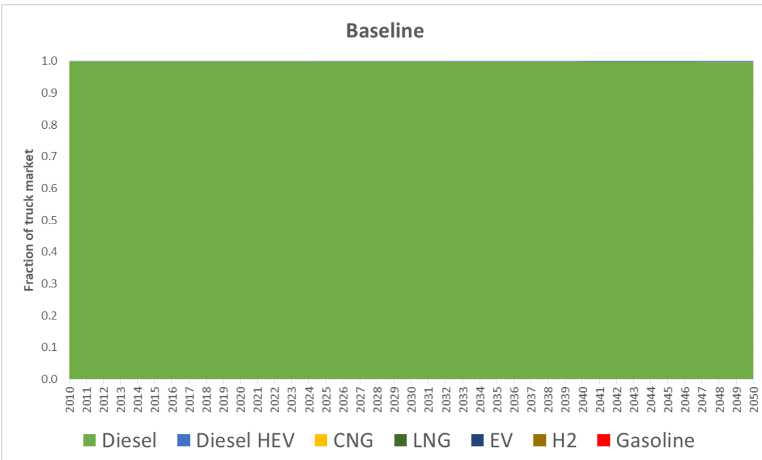
The Cumulative Sales Point at Which the Risk or Novelty Value of the New Technology is Reduced by Half for Group i ($\widehat{Q_i}$)

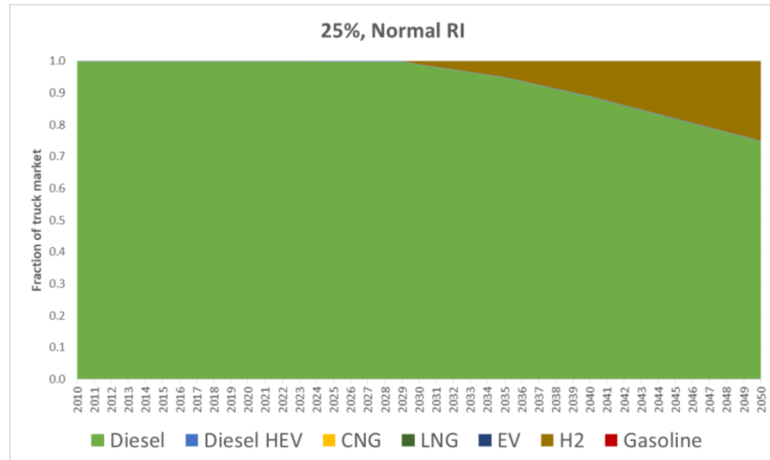
Truck Type	**Early Adopter**	**In-between**	**Late Adopter**
Long Haul	126	419	1,256
Short Haul	54	180	540
HD Vocational	73	242	727
MD Vocational	25	84	251
MD Urban	272	906	2718
Urban Bus	35	116	349
Other Bus	52	172	516
HD Pickups	2,227	7,422	22,265

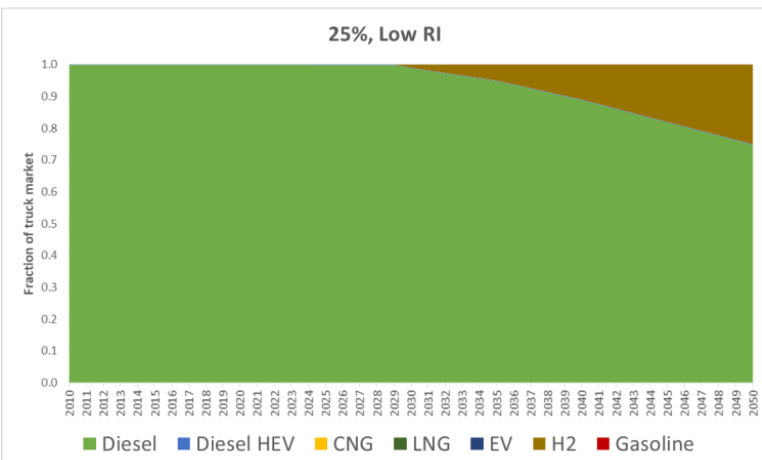
Appendix B. Additional plots

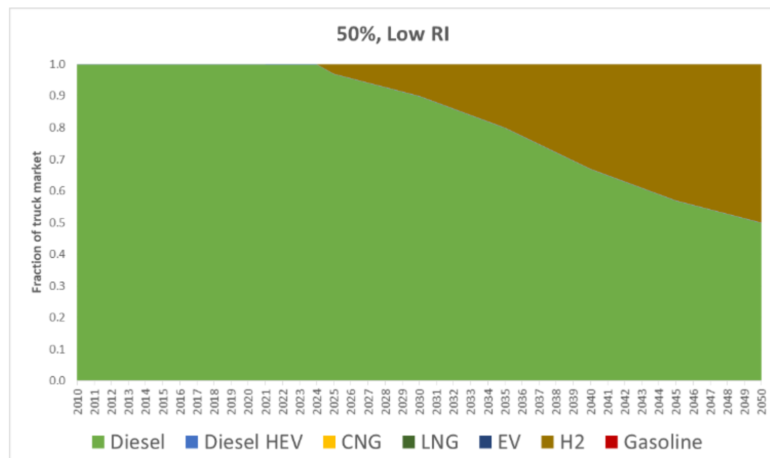
Markets shares for each truck type for all four scenarios are shown below.

Long Haul

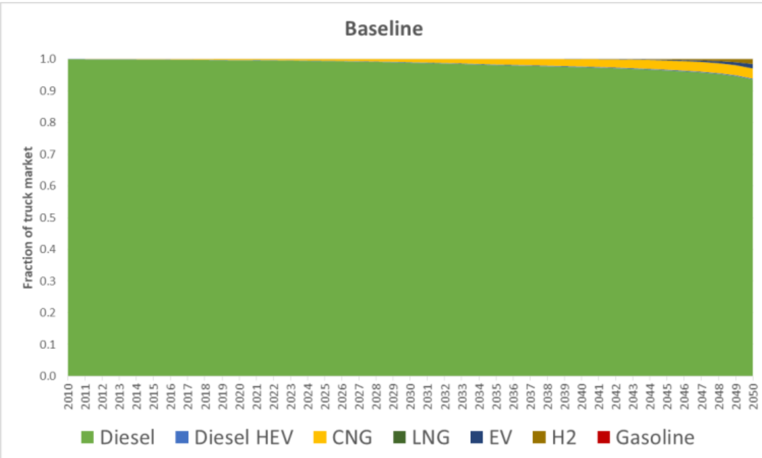


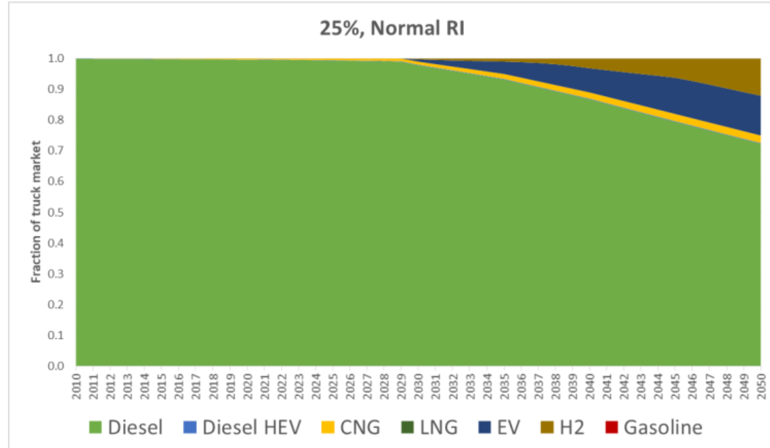


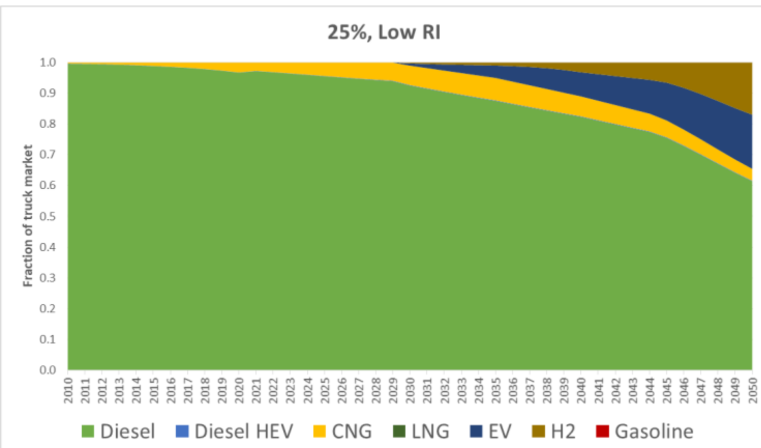


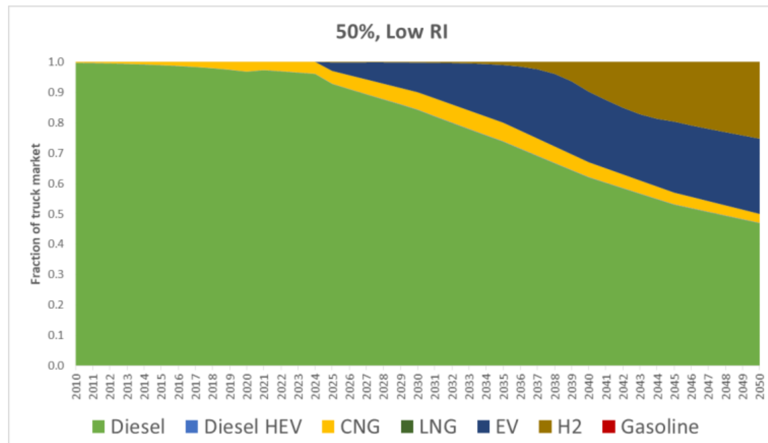


Short Haul



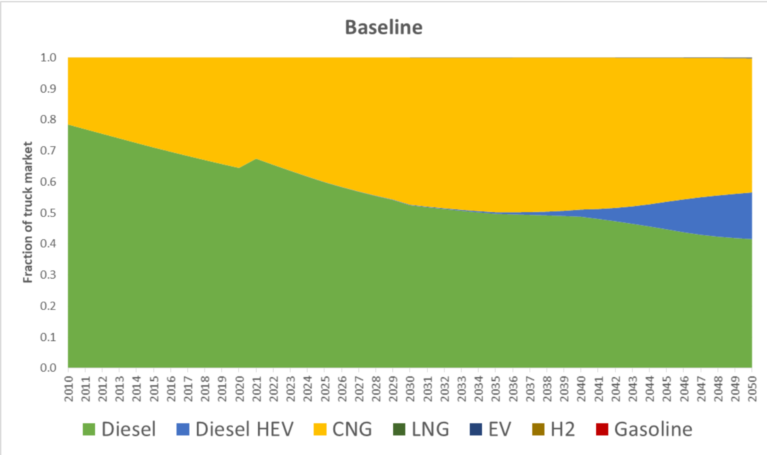


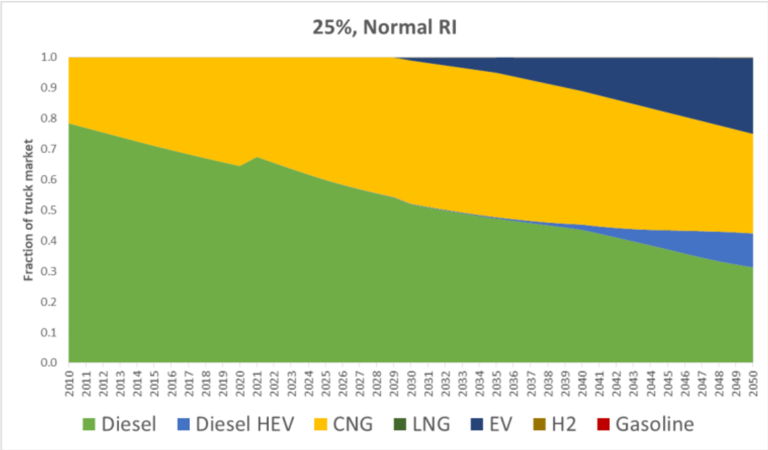


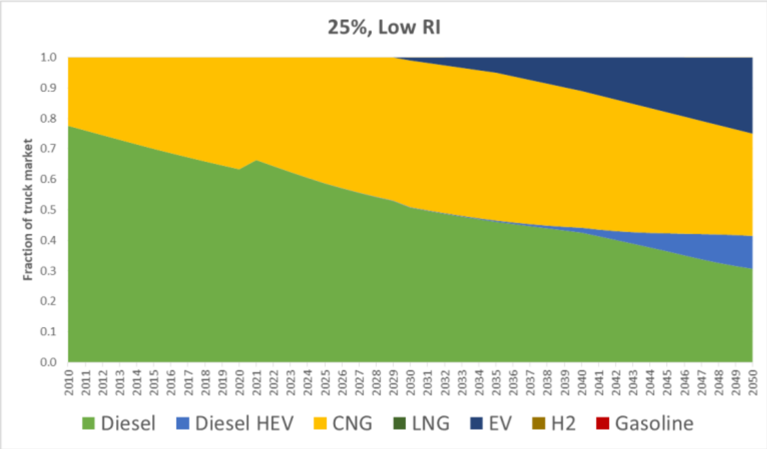


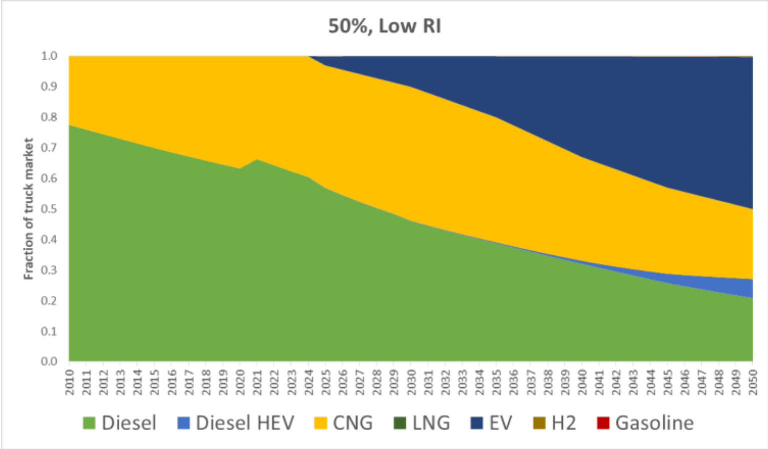
NCST

Heavy-Duty Vocational

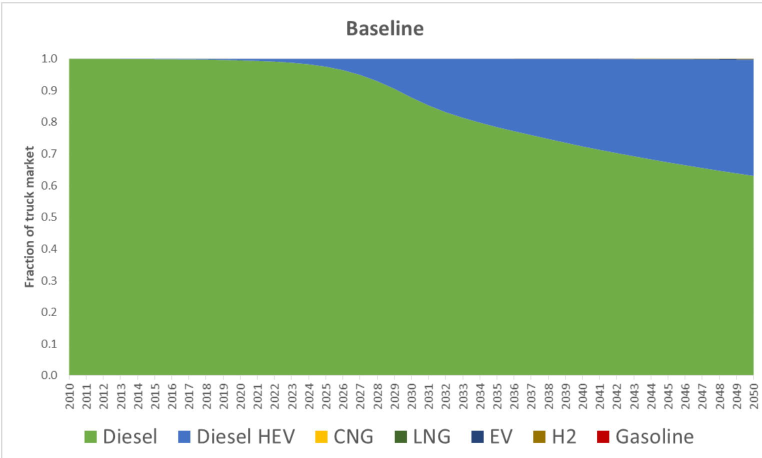


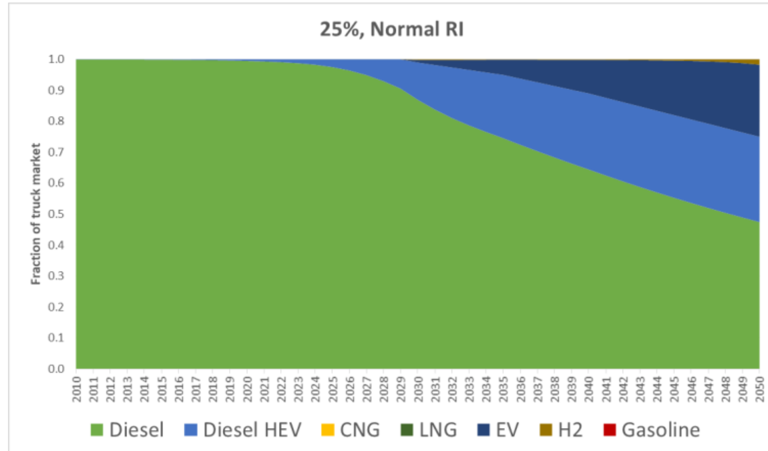


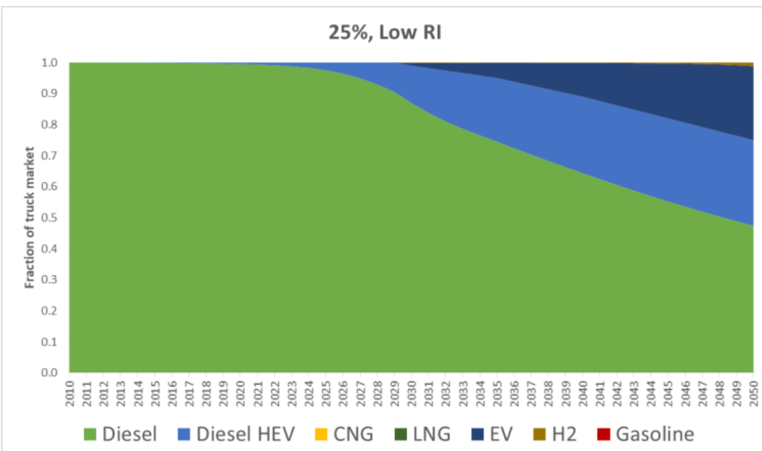


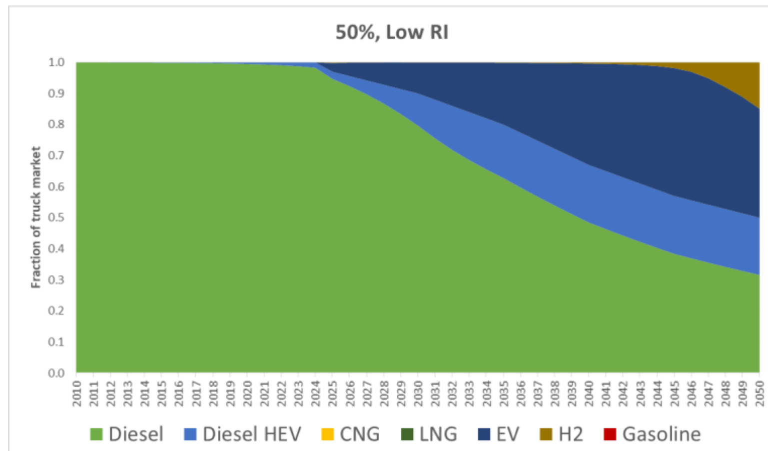


Medium-Duty Vocational

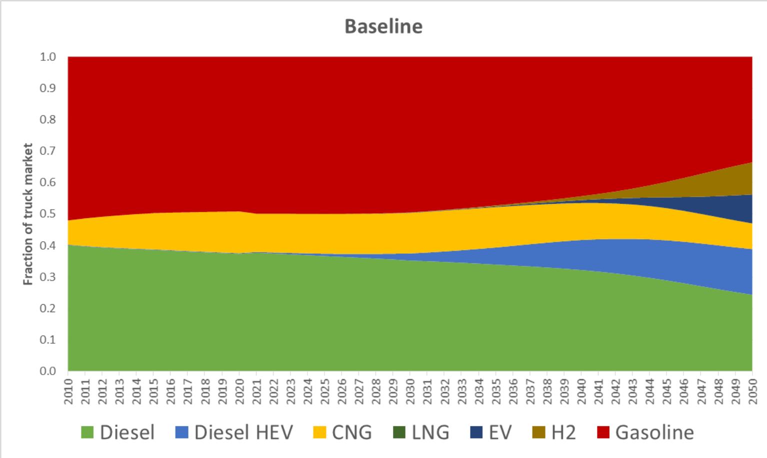




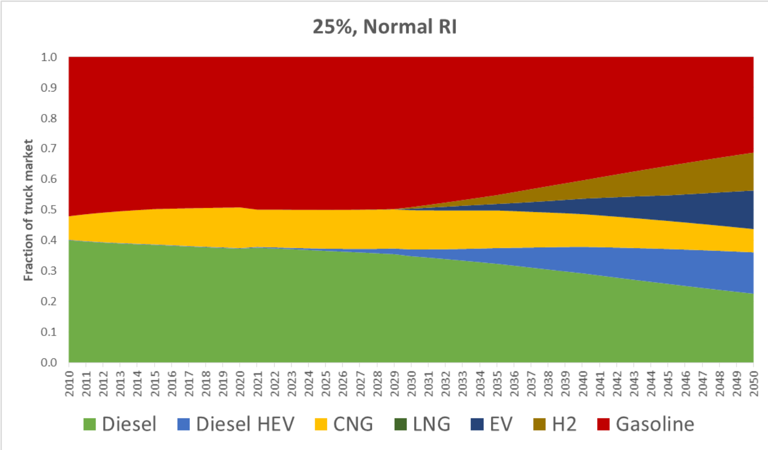




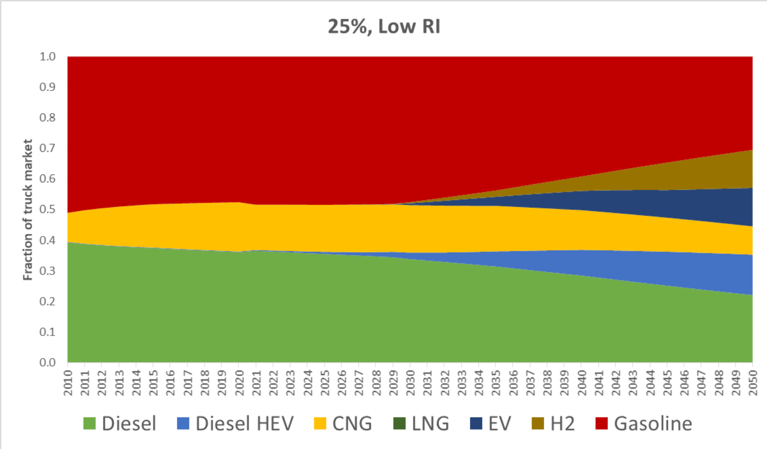
MD Urban



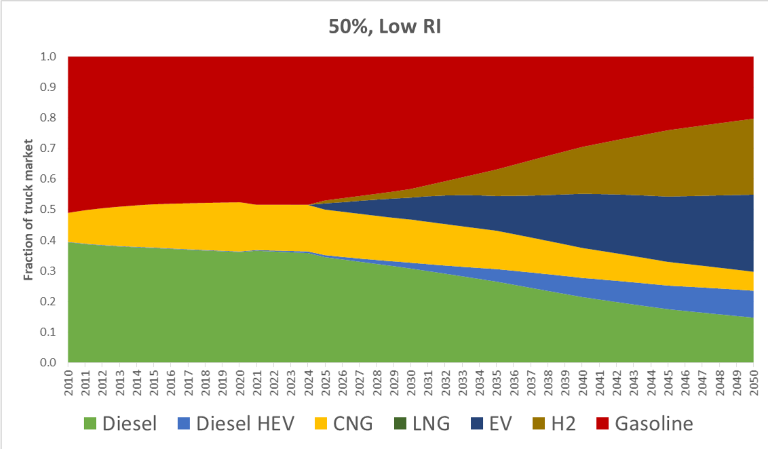
Baseline
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline



25%, Normal RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

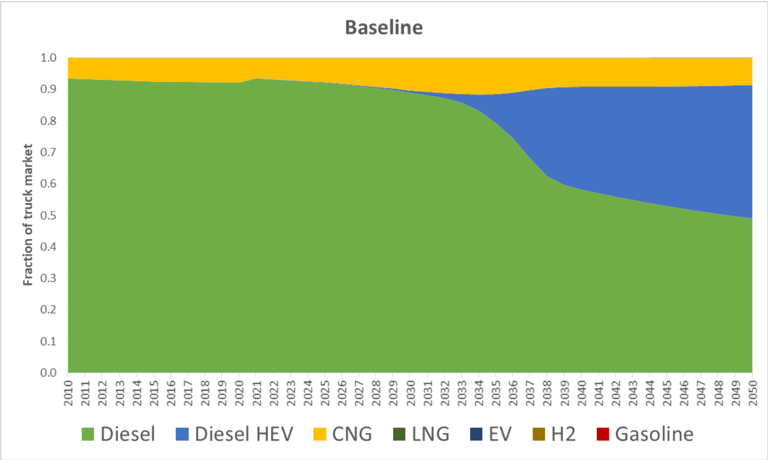


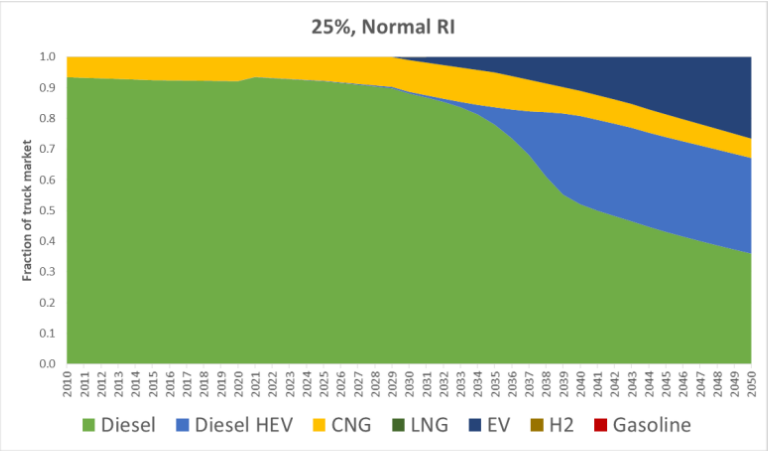
25%, Low RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

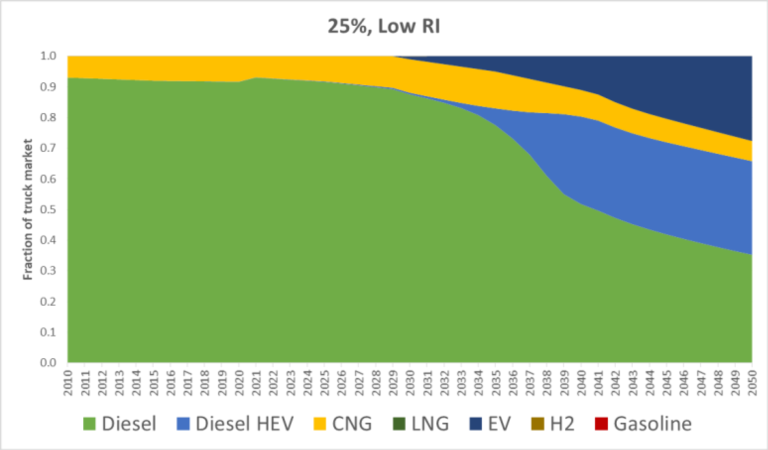


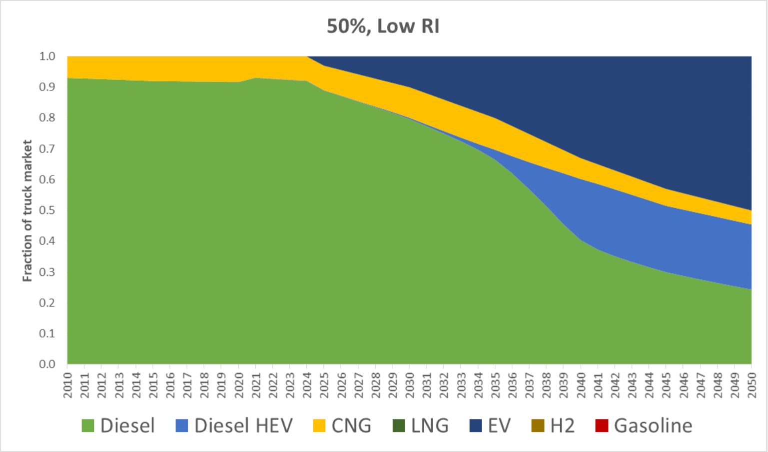
50%, Low RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

Urban Buses



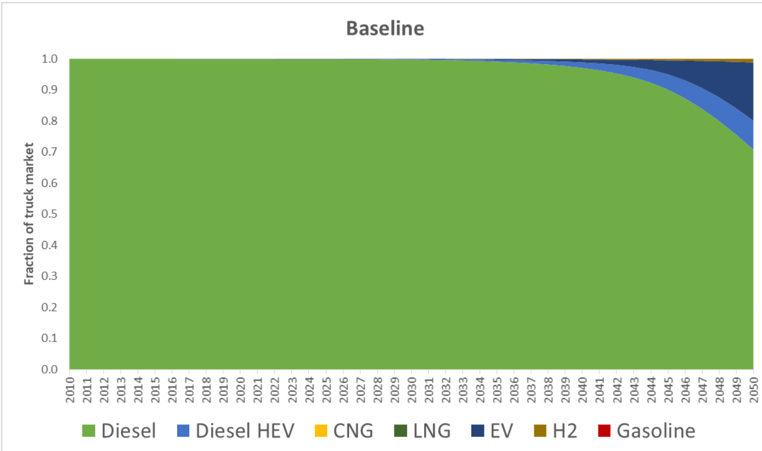


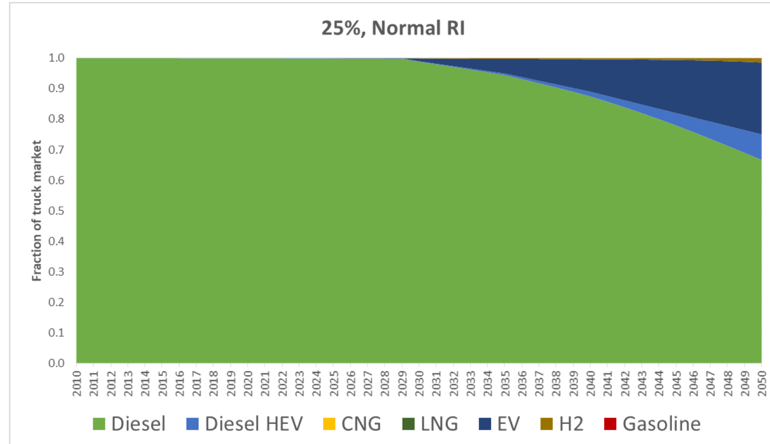


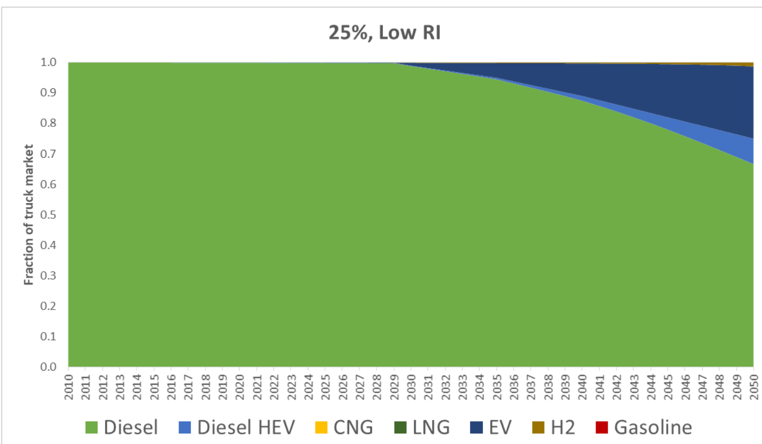


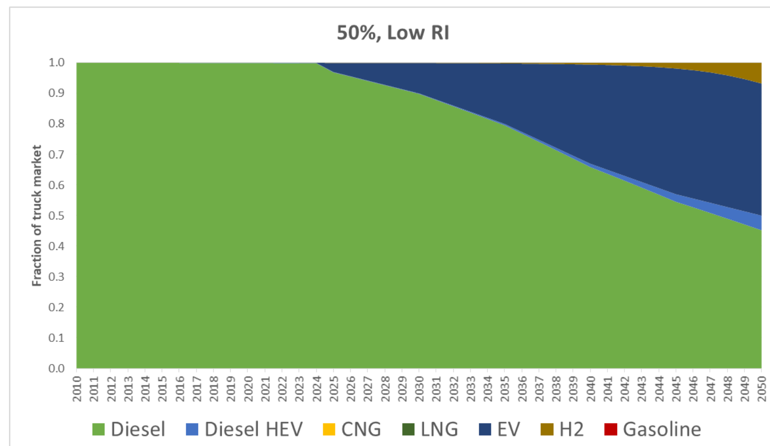
NCST

Other Bus

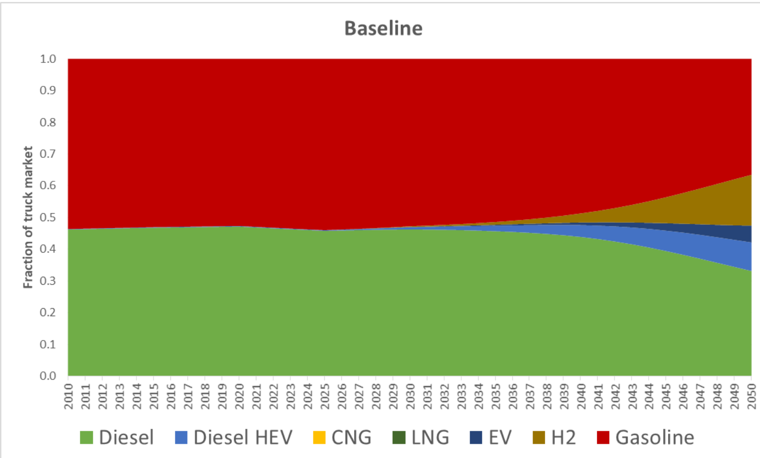

Baseline
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

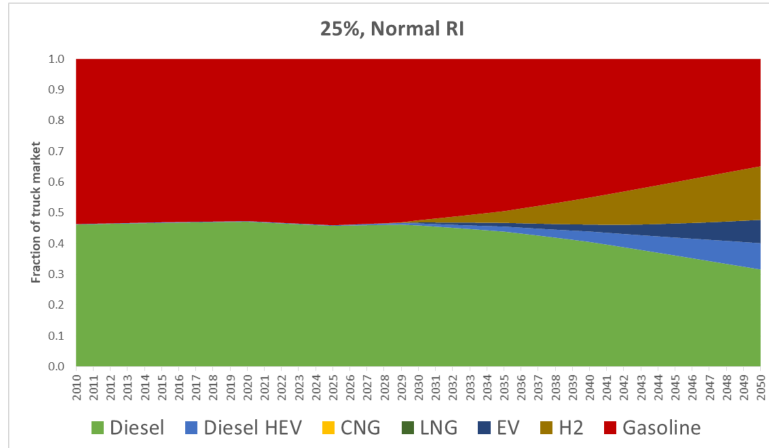

25%, Normal RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

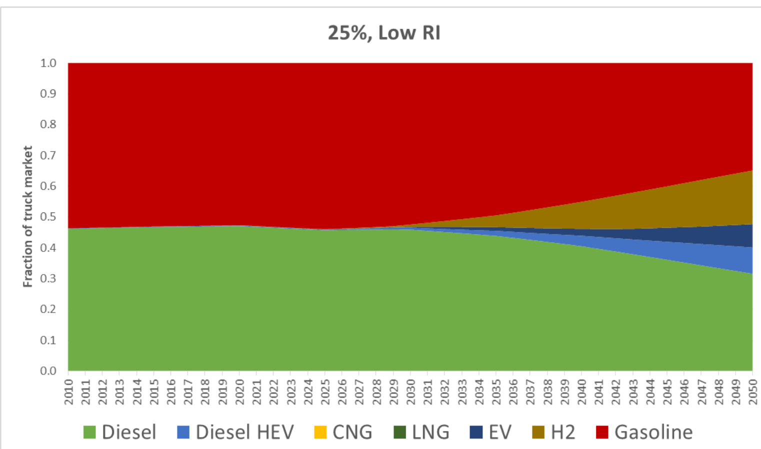

25%, Low RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

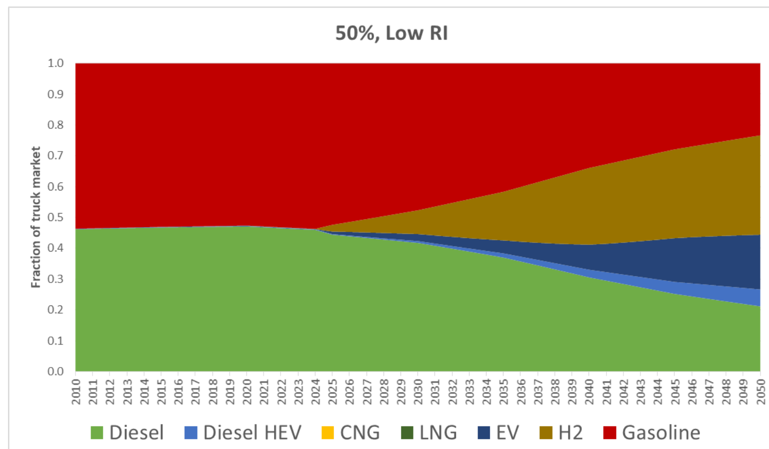

50%, Low RI
Fraction of truck market
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

Heavy-Duty Pickup

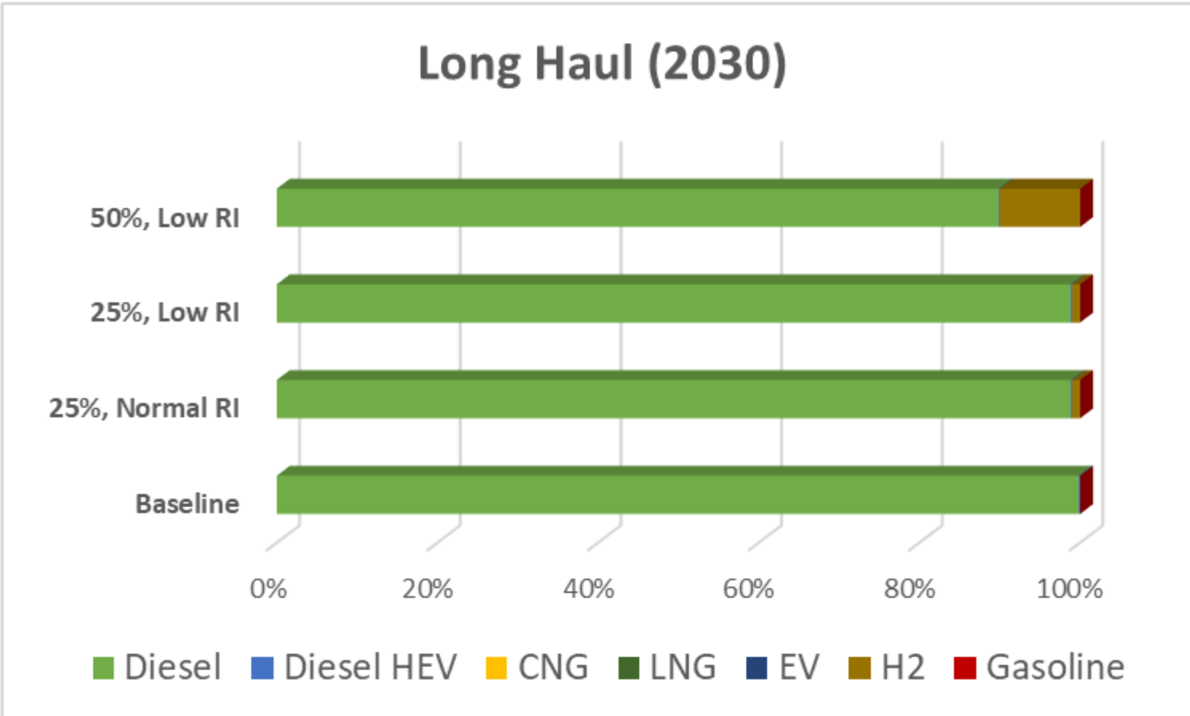


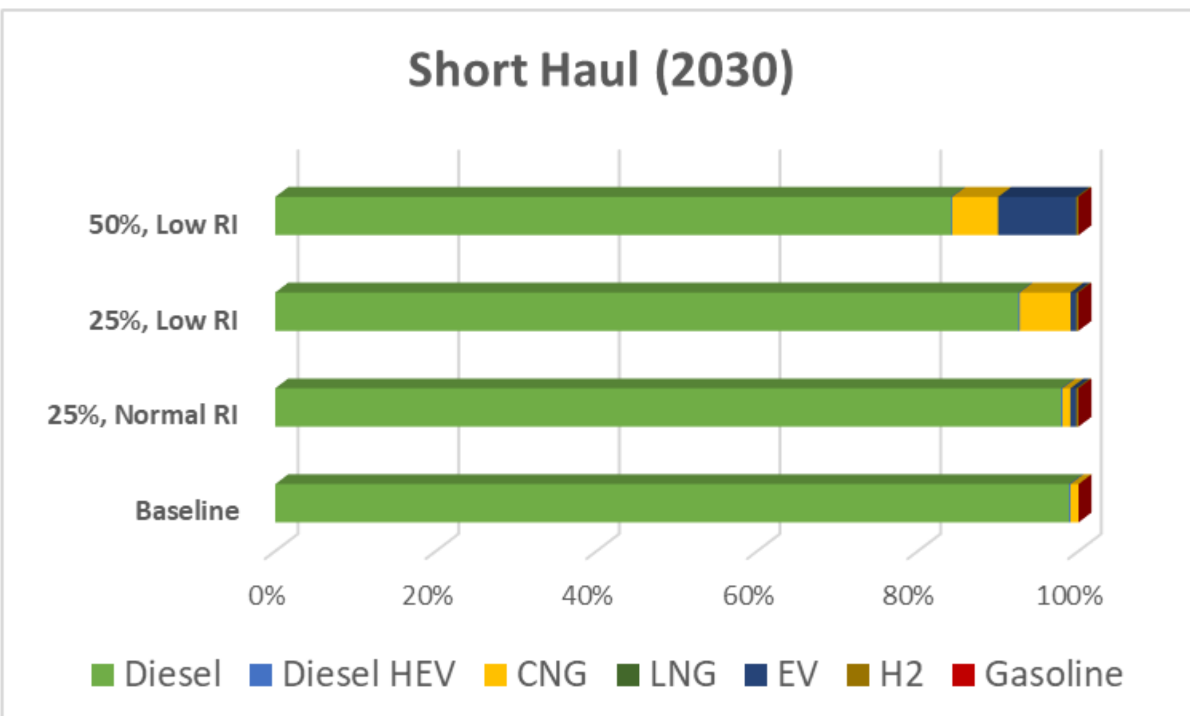


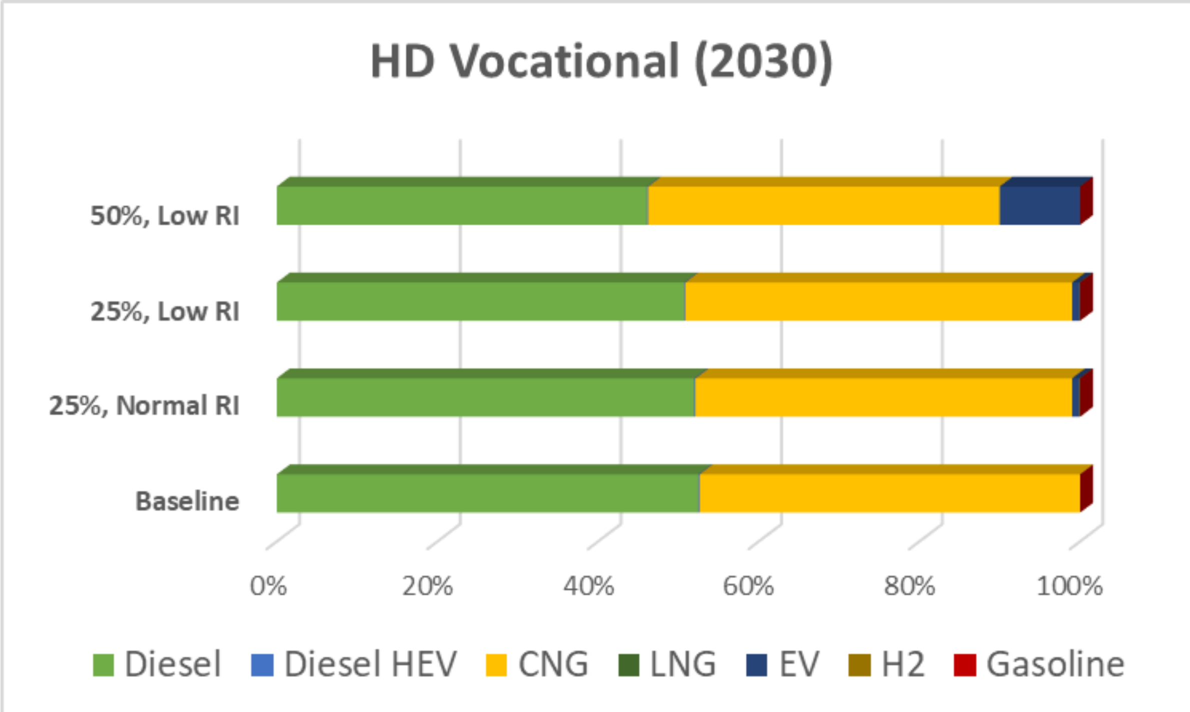




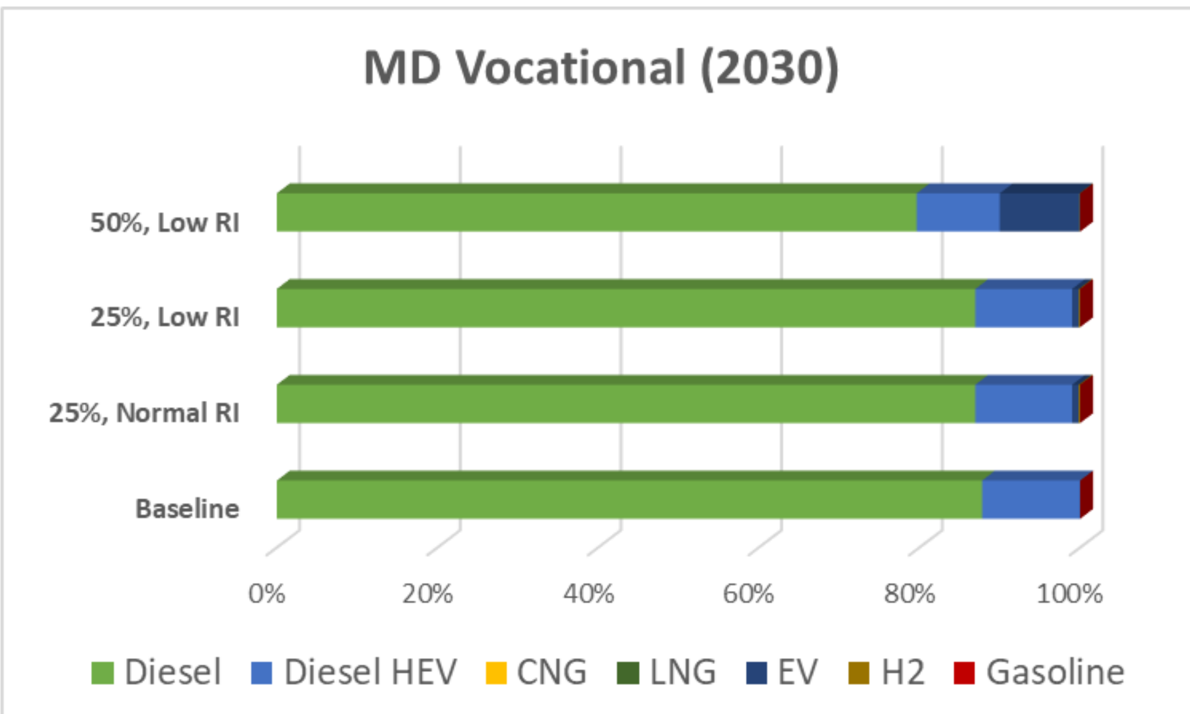
The following bar graphs show the market shares for each truck type for all four scenarios in years 2030 and 2050.



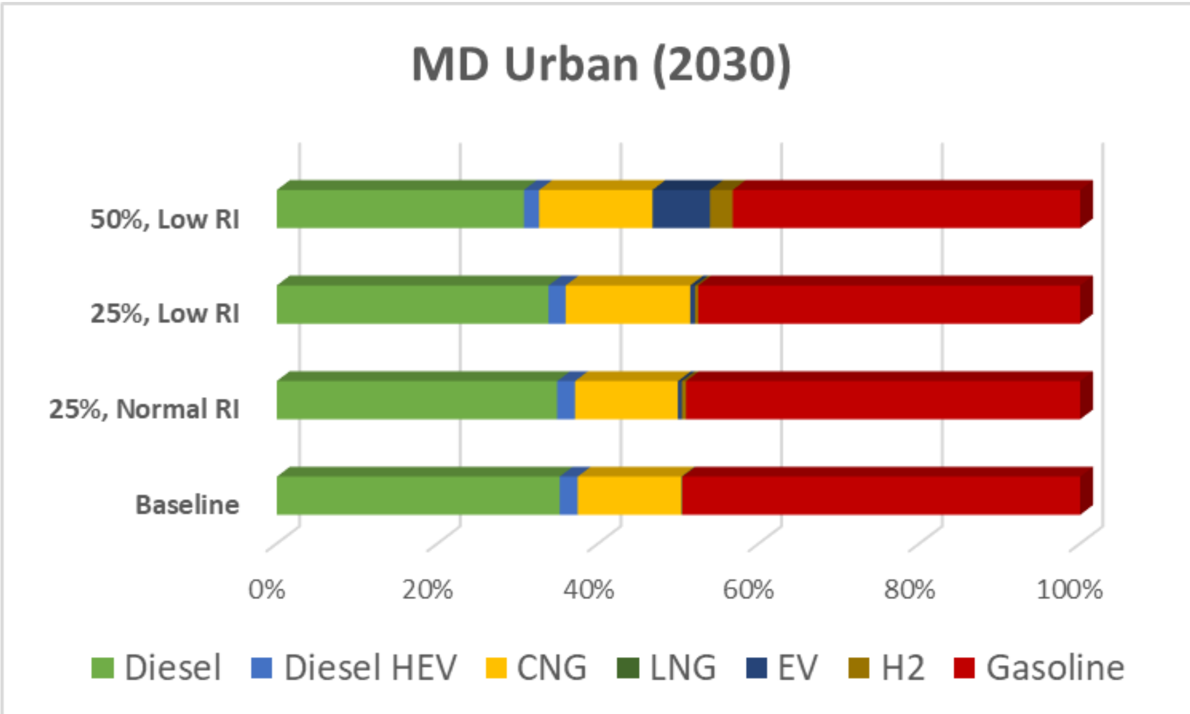


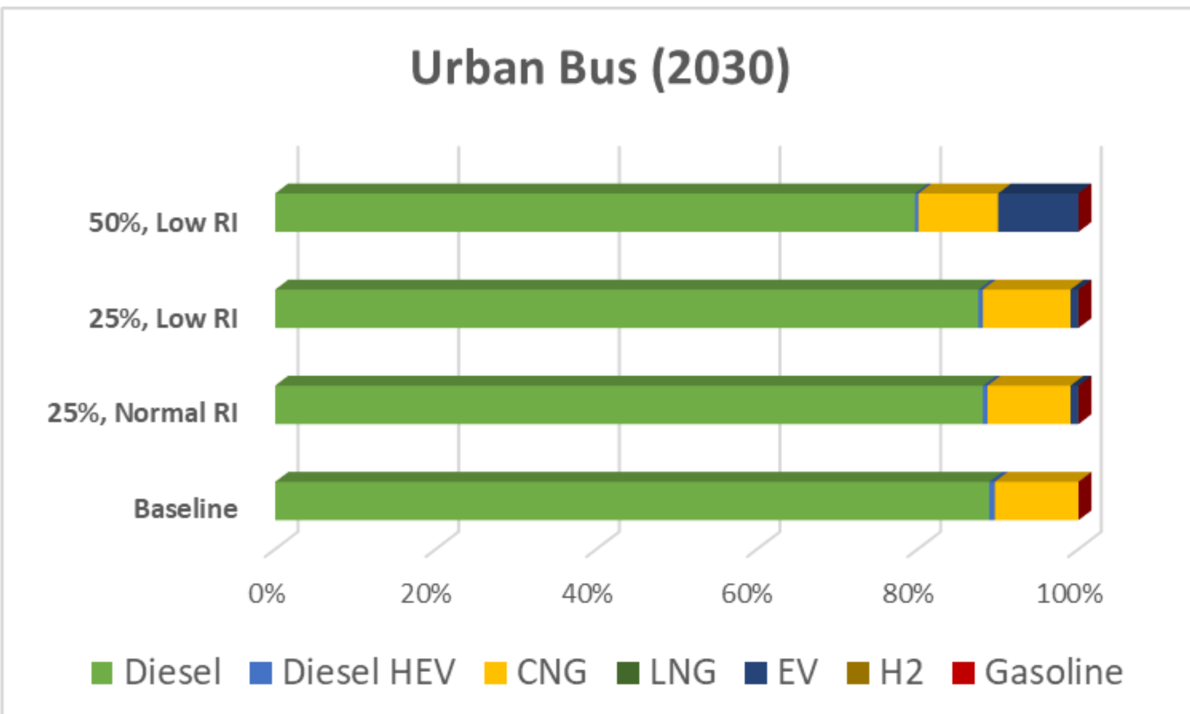


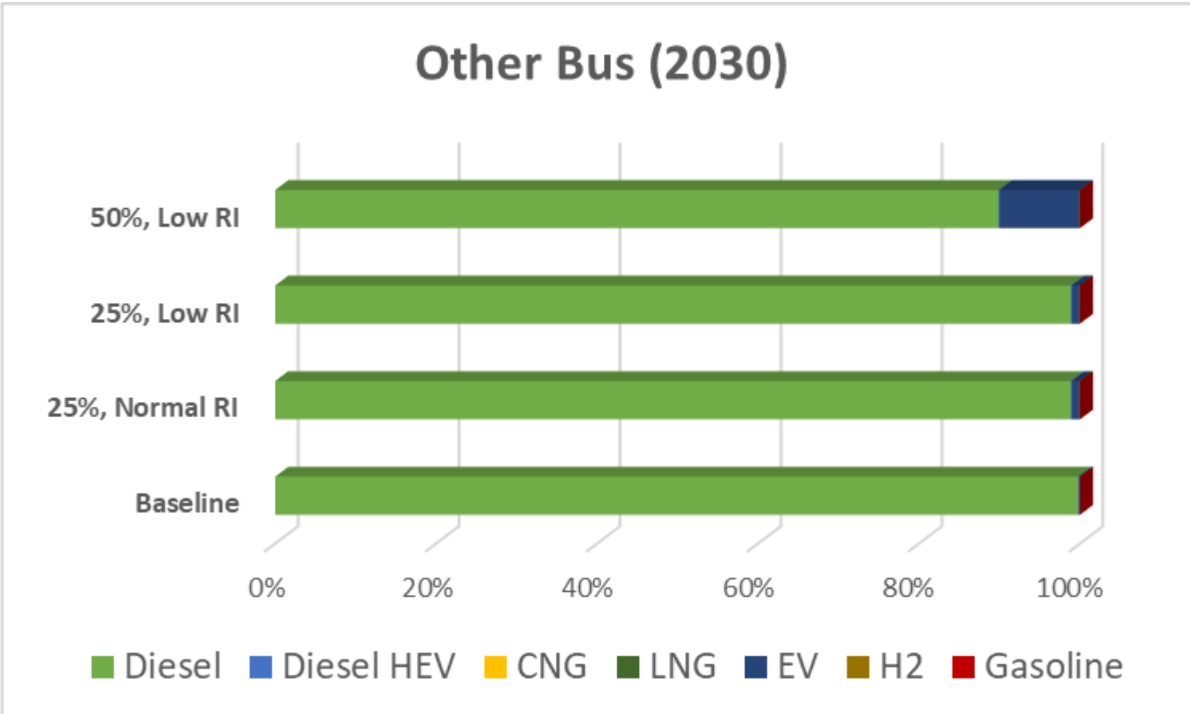
HD Vocational (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

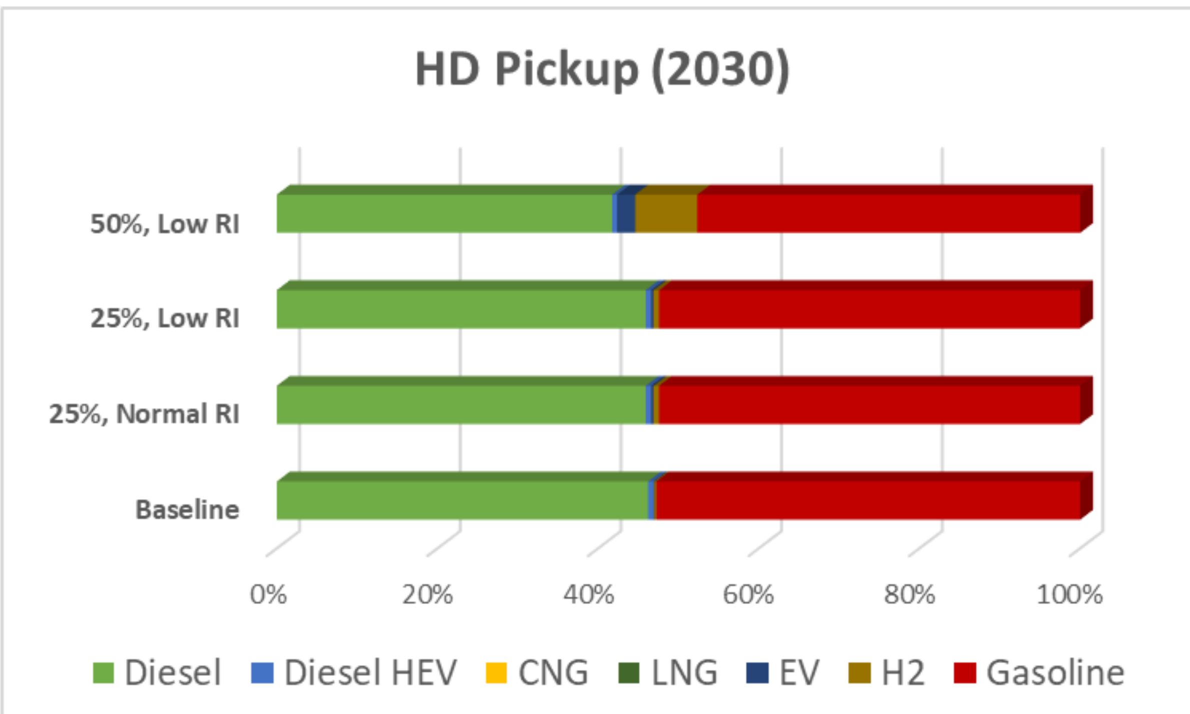


MD Vocational (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

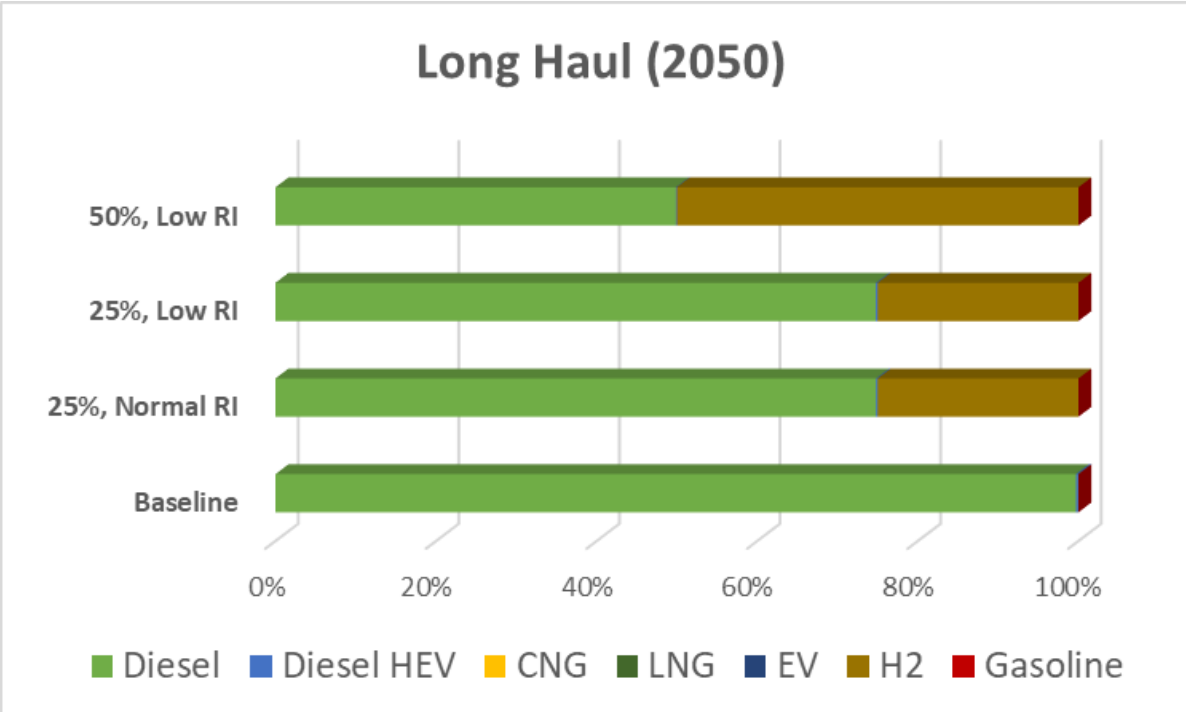

MD Urban (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

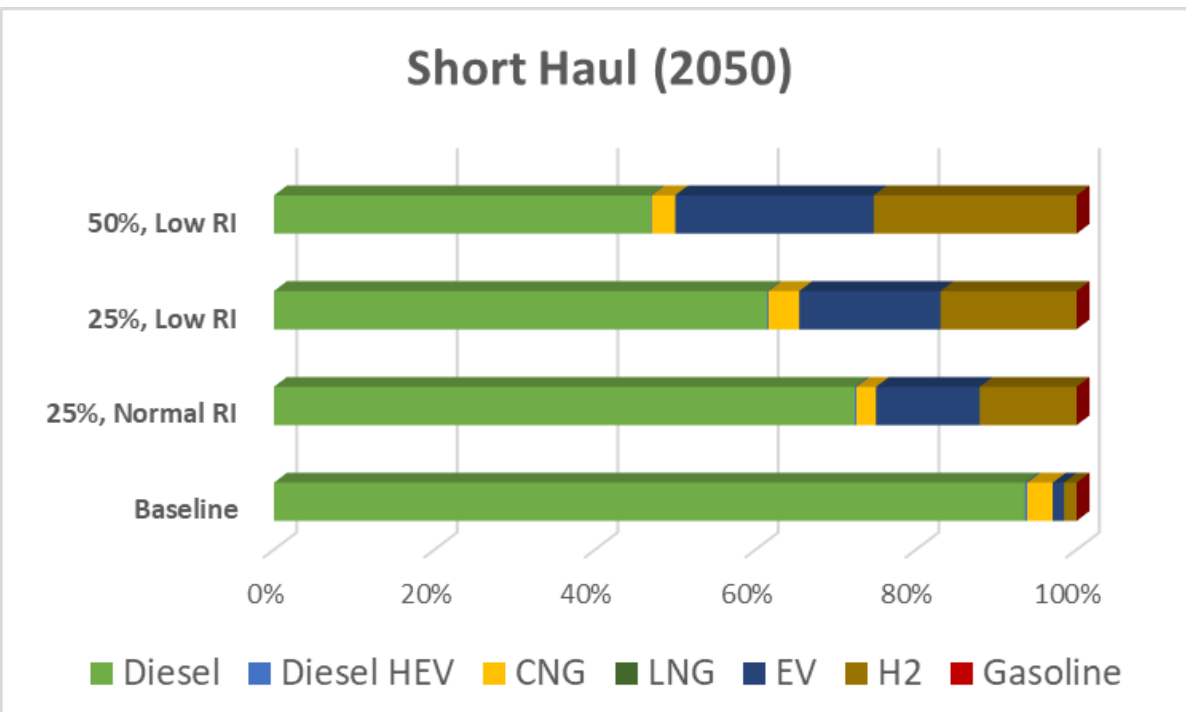

Urban Bus (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

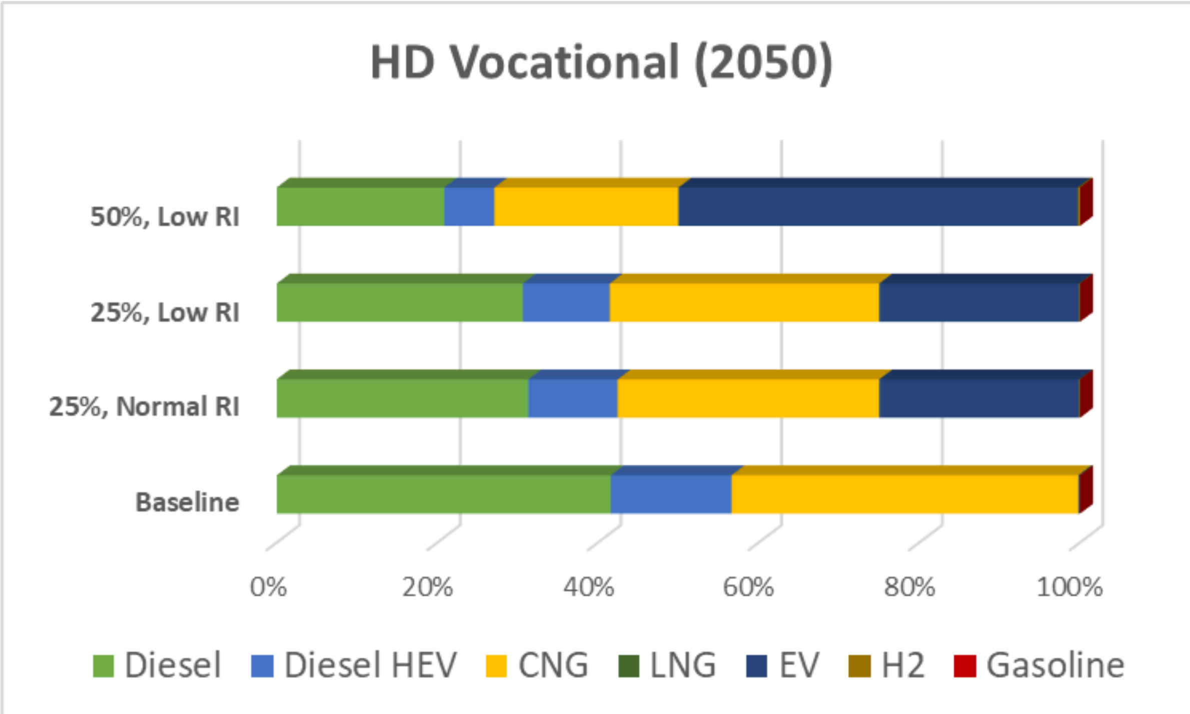

Other Bus (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

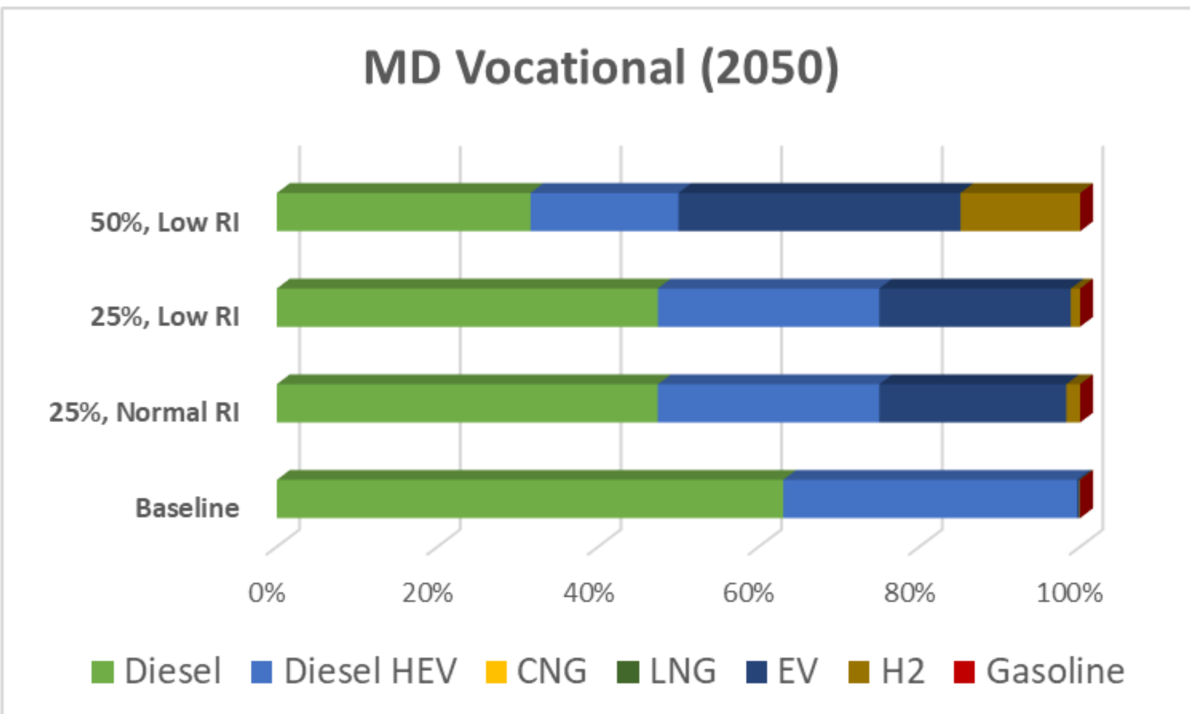

HD Pickup (2030)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

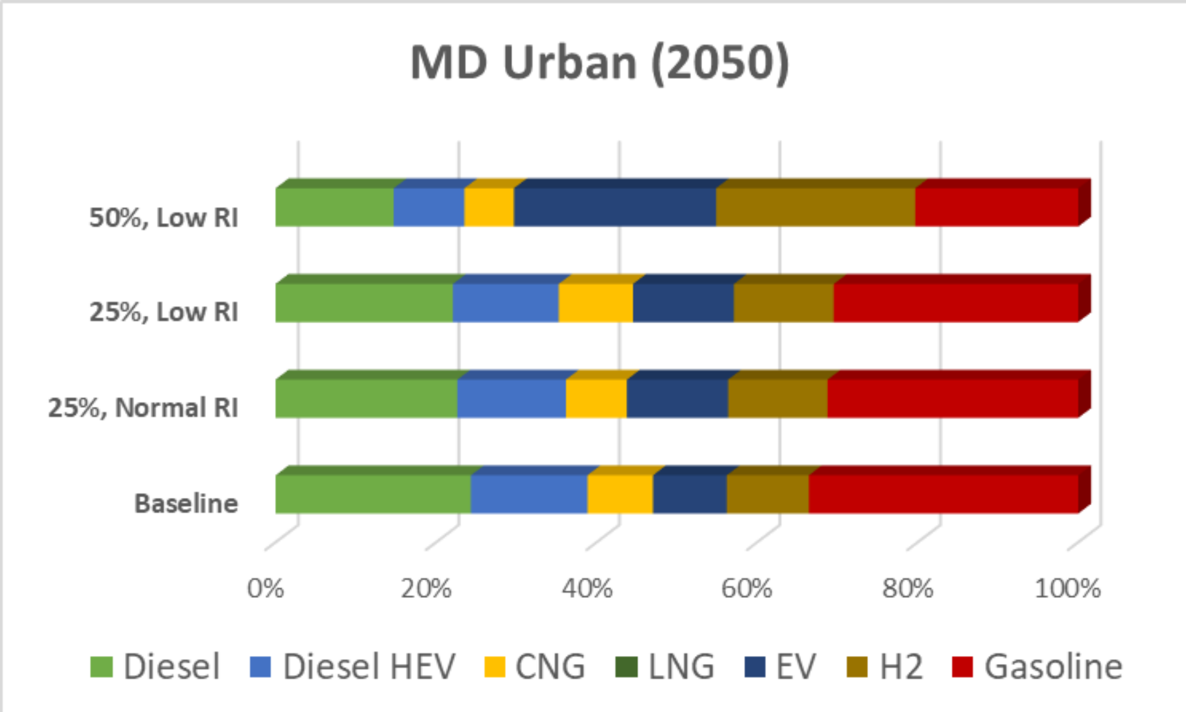
Bar graphs (aggregate market share in 2050)

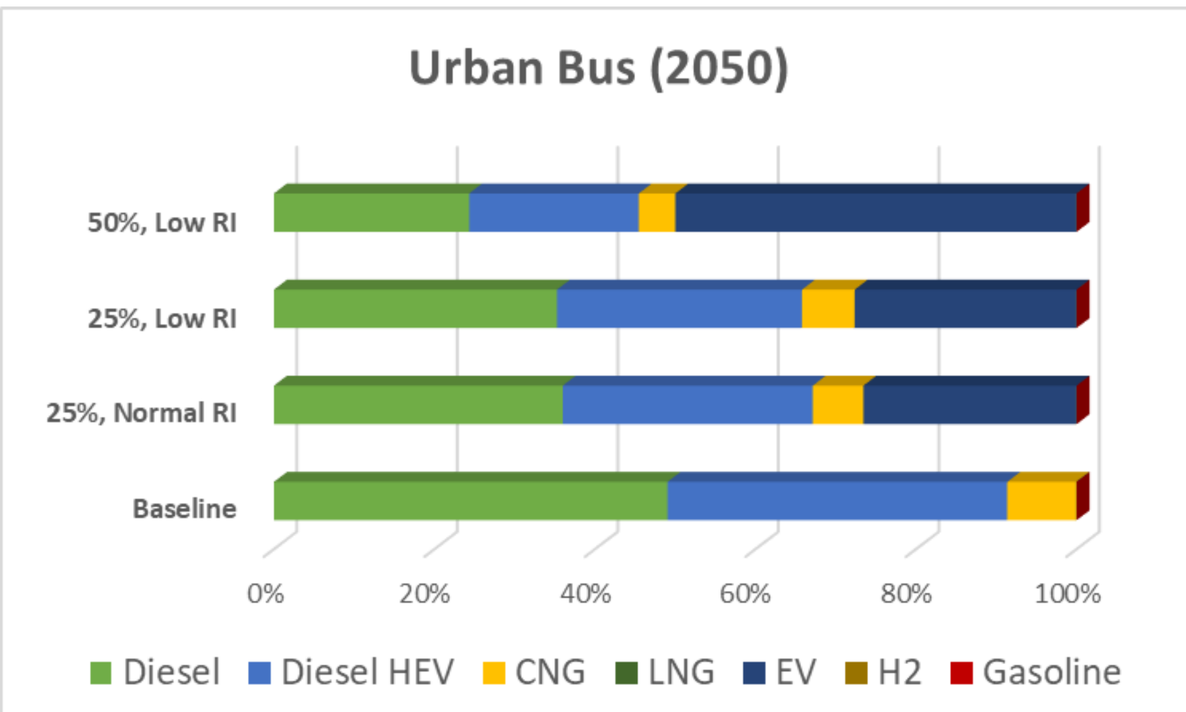


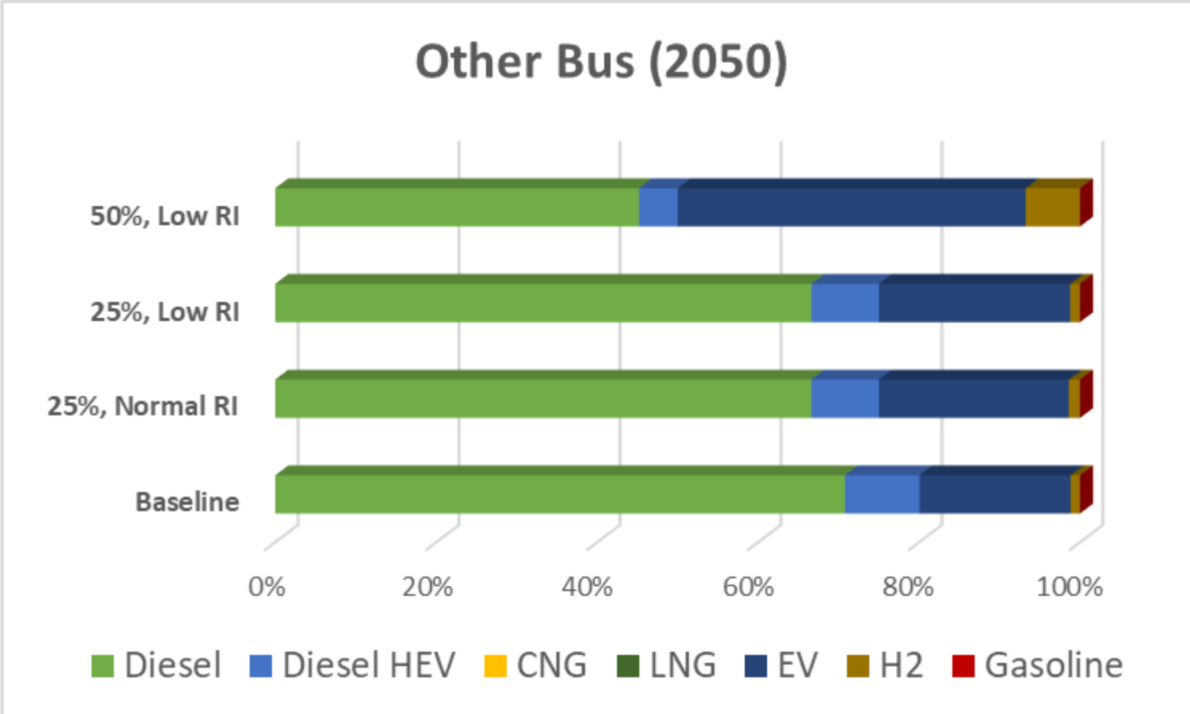



HD Vocational (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline

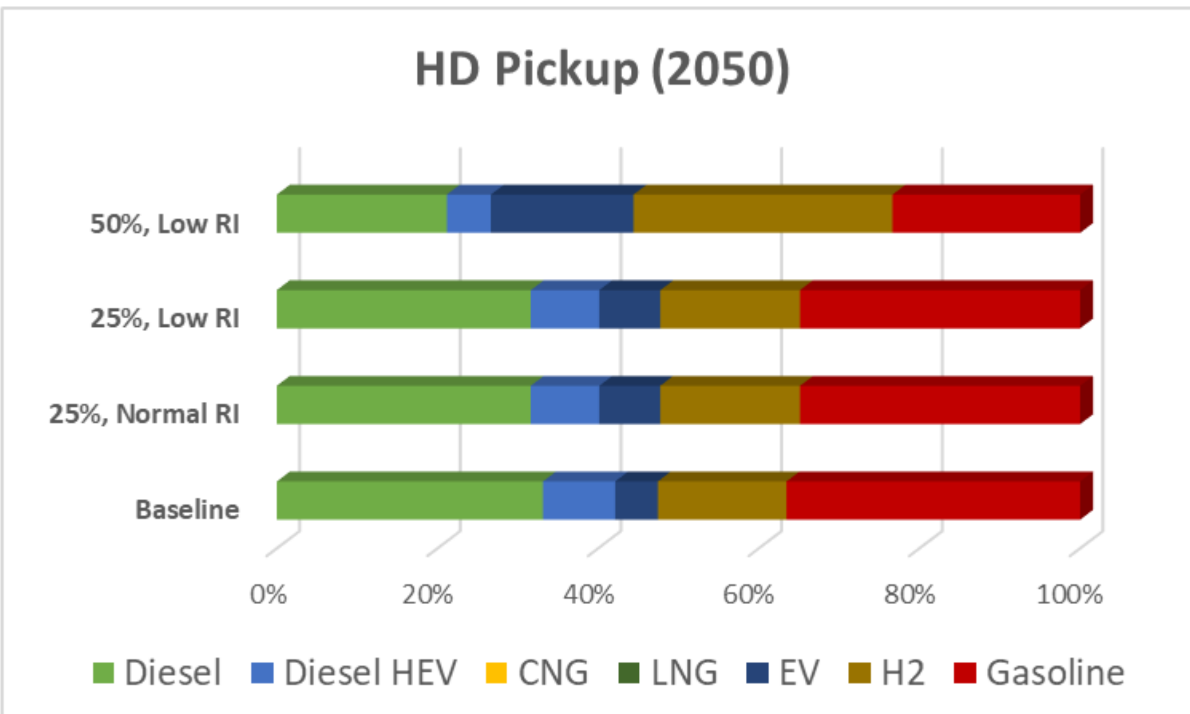

MD Vocational (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline


MD Urban (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline


Urban Bus (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline



Other Bus (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline



HD Pickup (2050)
50%, Low RI
25%, Low RI
25%, Normal RI
Baseline
0%
20%
40%
60%
80%
100%
Diesel
Diesel HEV
CNG
LNG
EV
H2
Gasoline