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Heavy-Duty Vehicle Incentive Project Analysis: Measuring Emissions & Socioeconomic Benefits of CARB Incentive and Regulatory Policy

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Introduction

The Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) promulgated by the California Air Resources Board (CARB) is designed to enable the market penetration of clean technology trucks, buses, vans, and other types of vehicles in California. HVIP provides "point of sale" vouchers that private and municipal fleets have used to help lower the costs of purchasing clean technology commercial vehicles in California. HVIP was created by CARB in 2009. Administration of the program has been managed by CALSTART, including verifying incentive program payments and reporting out-of-program metrics. The primary program website is https://californiahvip.org.

The HVIP is now being oriented to promote the adoption of zero-tailpipe emission vehicles (ZEVs) in accordance with the latest state policies move to zero-net carbon emissions in California's transportation sector by 2045. In the past, natural gas and hybrid vehicles were also included in HVIP, however the latest eligible vehicle catalog (https://californiahvip.org/vehiclecatalog/) includes only electric vehicle models with zero tailpipe emissions. Since its inception in 2009, the HVIP has provided over 11,000 vouchers for clean fuel vehicles as of October of 2022. Of these, 52% of the vouchers have been provided for zero-tailpipe emission vehicles, and in recent years only these types of vehicles (battery and fuel cell electric) can qualify for voucher awards.

This report seeks to address the California State Auditor (CSA)'s report "Improved Program Measurement Would Help California Work More Strategically to Meet Its Climate Change Goals," published in February 2021. The research team attempted to evaluate data on behavioral changes that result from CARB's incentive programs and provide suggestions that CARB expand its efforts to measure the greenhouse gas (GHG) emissions reductions from its regulatory and incentive programs.

While CARB can make progress collecting additional data going forward, making a quantitative determination of the effect of an individual or multiple incentive programs on purchases of ZEVs requires knowledge of consumer and supplier decision-making and behavior, which can be impossible to measure. Furthermore, because the various ZEV programs work in concert, the role of any one policy is impossible to disentangle in the context of various consumer and business decisions to purchase or lease ZEVs.

Despite these structural limitations, this report examines the implementation of HVIP over the past several years and presents suggestions that have the potential of further assessing program effectiveness in the future. This includes both the direct effects of the program in terms of stimulating vehicle sales, as well as potential broader market development effects for clean fuel vehicles. We note, however, in making these recommendations, that vehicle market dynamics are complex and include both supply-side (vehicle market offering) and demand-side (fleet adoption decision) factors. Additionally, there are spatial and temporal aspects to fleet adoption, as well as structural ones related to the type and size of the fleet and the management structure involved in purchasing new vehicles. In the spatial sense, visibility of vehicle operation by other fleets can have a potential impact, along with vehicle road shows and vehicle demonstration events organized by local air districts and other organizations. In the temporal dimension, there are time lags between receiving information and making vehicle purchase decisions, sometimes slowed by decisions by (for example) transit fleet management boards. All of this adds complexity to the program analysis, and the state-wide rollout of the program makes it impossible to capture these market dynamics. Therefore, we were not able to estimate the impact of the program, but we did characterize the distribution of the vouchers with respect to year and county.

We also note that CARB uses actual and credible ZEV population data from the Department of Motor Vehicles (DMV) and fuel sales data from the California Department of Tax and Fee Administration (CDTFA) to create emissions inventories of greenhouse gases and criteria air pollutants from on-road vehicles, including the EMission FACtor (EMFAC) inventory model and greenhouse gas emissions inventory. These emissions inventories, rather than the emission reduction estimates for individual regulations and incentive programs, are used to determine whether the State is on track to meet air quality or climate goals. The emission reduction estimates for individual incentive programs are instead intended to be used to roughly evaluate and compare the relative potential impact of each program to inform program design and investment decisions.

Current HVIP Program Guidelines

In the most recent set of program rules, in the relatively light “2b” Utility Vehicle category, there are four included models based on battery technology with a voucher payment amount of $7,500. In the vocational category known as “ePTO” for electric power take-off for utility uses, there are seven vehicle models listed with incentive voucher amounts of $20,000 to $50,000.

For Heavy-Duty Buses, there are 31 models listed in the catalog, with incentive amounts of $85,000 to $120,000 for battery-based solutions, $240,000 per vehicle for a few hydrogen/fuel cell models, and also including one electric retrofit solution with a voucher value of $60,000. The Medium-Duty Bus category includes 21 models, all for battery-based buses with incentive amounts from $45,000 to $80,000, except for one school bus model (set aside program) with an incentive from $99,000-350,000 for select applications.

The latest HVIP program for various sizes of Refuse Trucks includes 11 models, with incentive values ranging from $120,000 to $150,000 for the largest (Class 8) vehicles, and $85,000 to $113,750 for smaller Class 6-7 vehicles. There are 25 School Bus models in the HVIP catalog, with voucher values ranging from $70,125 (for an EV conversion) up to $375,000 per vehicle in the most advantageous settings and for the largest vehicles – with all of these based on battery ZEV operation. In the Step and Panel Van category, incentives range widely from $7,500 for a Class 2b offering, to $45,000 for a Class 3 vehicle, to $60,000 for Class 4-5 vehicles, to $85,000 for Class 6-7 vehicles – all being battery powered ZEV models.

In the Class 4-8 Straight Truck category, there are a total of 32 models currently listed (all battery ZEVs), with vouchers ranging in value from $60,000 (Class 4) to $85,000 per vehicle (Class 6) to $120,000 per vehicle (Class 8). Finally, in the Heavy-Duty Tractor category, there are 12 Class-8 models listed with $120,000 incentive levels for 8 battery models and $240,000 for 4 hydrogen fuel cell-based models.

The latest reports by CARB indicate the following funding levels for the program, as shown in Table 1.

Table 1: Mid-2023 California Air Resources Board HVIP Funding Status

Funding Category	FY21-22 Funding Remaining	Total FY22-23 Funding – Available unless otherwise indicated
Standard HVIP	$62M* Remaining	$250M**
Transit	$46M Remaining	$65M
Public School Bus Set-Aside	FY21/22 Public School Bus Set-Aside is fully subscribed. School bus funding is also available in Standard HVIP.	Limited funding remains available on a first-come, first-served basis. See Purchasers page for updates.
Drayage Truck	FY 21/22 drayage truck set-aside is fully subscribed. Drayage truck funding is also available in Standard HVIP.	$147M**
Innovative Small e-Fleet	FY21/22 ISEF is closed for voucher requests. Small fleets can be funded through Standard HVIP.	Opened August 30, 2023. Now available: $26M for Innovative Provider Requests, and $6M for Standard Purchases. See the Purchasers page for more details.
Local Education Agency School Bus Replacement Grants		Funds to be available in FY23-24

Notes:
*The funding amount for Standard HVIP fluctuates due to the determination of valid voucher requests, voucher enhancements, and cancellations.
**Out of these funds, 70% of Standard HVIP and the Drayage set-aside will be reserved for private fleets with 100 vehicles or fewer and all public fleets, starting January 1, 2023. Since more than $100 million remained in the reserve on July 1, 2023, HVIP released 30% of the remaining funding to private fleets with more than 100 vehicles. If funding remains in the reserve on November 1, 2023, HVIP will open all remaining HVIP standard funding and drayage set-aside funding to private fleets with more than 100 vehicles. The reserve only applies to the FY22-23 allocation – any remaining FY21-22 funds will be available for fleets of all sizes.
Source: https://californiahvip.org/funding/

HVIP program assessment methods

There are no suitable methods that can be employed to assess the full behavioral impact of the HVIP program for the medium/heavy duty market for clean fuel vehicles in California. If it were possible, there would be several overall questions including:

- How have HVIP vouchers *succeeded in introducing* clean fuel vehicles to California fleets of MDV/HDVs?
- What has been the *importance* of the HVIP program to commercial vehicle fleet purchases of clean fuel vehicles?
- What are the *broader market impacts* of the HVIP to stimulate adoption of clean fuel commercial vehicles including spillover effects, with broader awareness, stimulation of market offerings on the supply side?
- What can be understood with current and *potential additional data* in the future?

While we cannot estimate the isolated effect of HVIP, we can summarize where HVIP vouchers have been used. This relatively straightforward assessment of the location of HVIP voucher usage shows the number of vehicles of different types and weight classes in different areas of the state that have been supported by the HVIP program. Additional questions include those around how the program might assist in adoption moving into the future.

Vouchers may have benefits extending beyond their direct impact, such as through demonstrating the efficacy of vehicles in real-world conditions and making their use more apparent in the marketplace. Techniques such as technology adoption curves could be used to forecast the markets for clean fuel vehicles in the future, with a focus on the impact of the HVIP vouchers to reduce the transaction prices of vehicles for fleets, with some market segmentation around buses versus trucks and battery electric versus fuel cell technologies that are the future focus of the program. However, such curves are highly sensitive to user choices.

In general, a program like HVIP could have a number of broader market impacts, beyond the direct impacts of simply placing vehicles on the streets. These could include:

- What economists call "imitator" effects where fleets might see some other fleets adopt clean fuel vehicles with HVIP support and choose to follow, with or without support from the HVIP;
- Critical distribution of information and lessons learned from early adoptions, that if successful can reduce adoption risk for future adopters and embolden them to adopt clean fuel vehicles with or without HVIP support; and
- On the supply side, where manufacturers might use vehicle adoption through the HVIP program to embolden them to expand manufacturing in the future, based on economies of scale in production and ability to leverage initial "non-recurring" engineering costs.

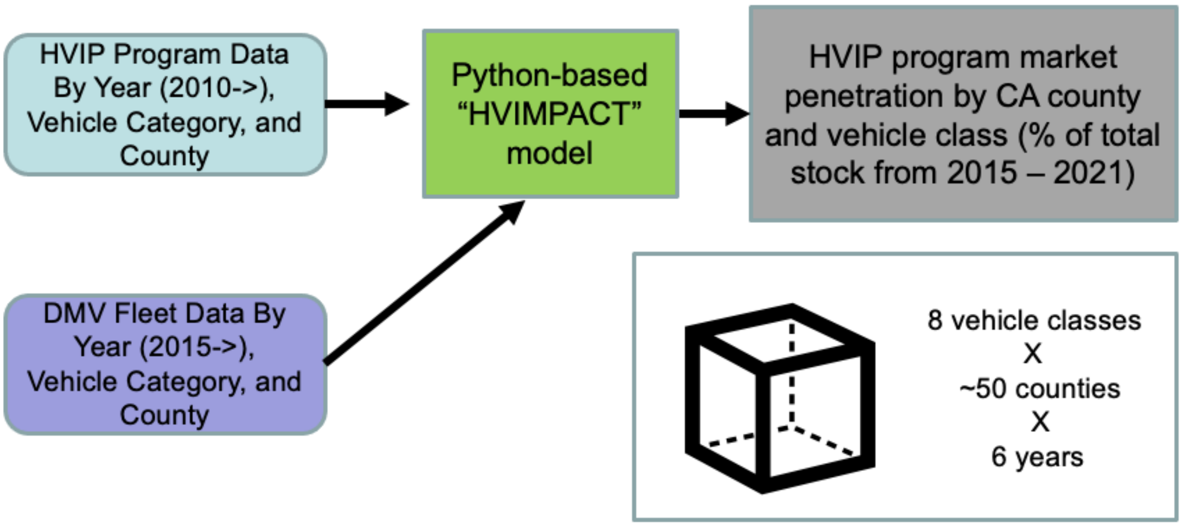
Like first order effects, we are not able to estimate these secondary types of effects. In this project, we summarize where and when HVIP vouchers have been used. These efforts are summarized below. We are not able to assess whether use of the voucher resulted in a purchase that would not otherwise have been made.

HVIMPACT model description

The analysis of voucher usage for this project uses a model called HVIMPACT that examines the market penetration of vehicles that received HVIP vouchers over time, and geographically on a county level basis. The goal of the analysis effort is to compare the populations of clean fuel vehicles that have received HVIP vouchers with the overall population of vehicles in each relevant vehicle category. This analysis provides a sense of how HVIP is being used over time and around the state, across various vehicle categories and fuel types. The key findings from this analysis are discussed below.

CARB reports overall fleet data starting with 2015, whereas there are HVIP voucher data going back to 2010 but when the program had a significantly different character (supporting CNG and hybrid vehicles as well as zero-tailpipe emission vehicles). As shown in Figure 1, the initial focus for HVIMPACT is thus the period from 2015-2020 where the two databases overlap.

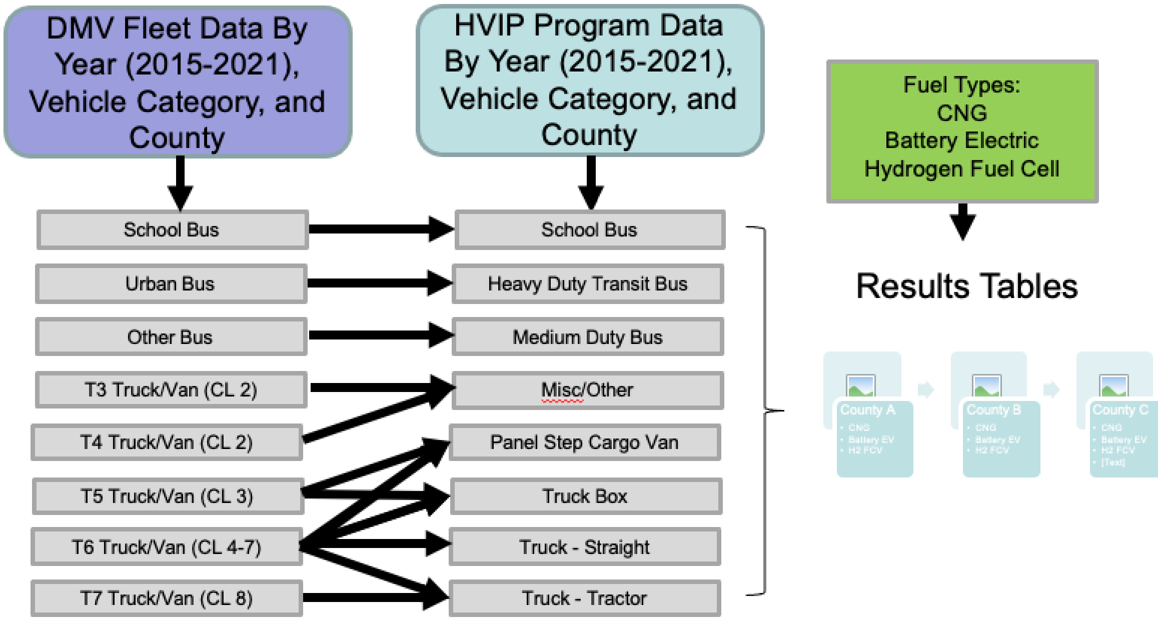
Figure 1: General Structure of HVIMPACT Analysis



The first challenge associated with this analysis is that the HVIP voucher database and the overall DMV fleet database maintained by CARB (https://arb.ca.gov/emfac/fleet-db/) use different vehicle category definitions. The fleet database includes three bus categories and five truck/van categories designated T3-T7 based on vehicle weight. The HVIP voucher data also include three bus categories, that map well to the fleet database categories, but then there are five other categories that refer to vehicle types. Examining the vehicle type and weight information in the databases allows for the DMV data to be mapped onto the HVIP vehicle categories, but the data are not complete enough to exactly align the categories, leading to one of our recommendations for future improvements.

For purposes of building the HVIMPACT model structure and providing an initial, first-order assessment of the market impact of the HVIP, we split the T5 category in the fleet database evenly into two HVIP categories: panel step cargo van and box truck. We split the large T6 category into four relevant HVIP categories: panel step cargo van, box truck, straight truck, and tractor trailer truck. The T7 category consists entirely of Class 8 trucks and therefore maps directly to the tractor trailer truck category in the HVIP data. A schematic of this mapping is shown in Figure 2. Recommendations described below include a suggestion to better map these categories across databases in the future so that more nuanced estimates of the relative use of the vouchers across vehicle categories can be obtained.

Figure 2: Vehicle Category Mapping for HVIMPACT Analysis



The HVIMPACT model employs the Python language to sort the databases and then uses R language to further analyze data and compile tables of results. One set of tables shows the HVIP voucher vehicles in each year, for the three currently/recently supported fuel types (CNG, battery electric, and hydrogen fuel cell), and for each vehicle type. The voucher vehicles in each year are summed to arrive at cumulative totals, so that they can be compared with the overall DMV fleet database totals. An assumption is made that HVIP voucher vehicles introduced from 2015 onward are still in the fleet, with no attrition.

A second set of tables reports the total fleet data from the fleet registration database, as sorted into the HVIP vehicle categories. The fleet data includes a wider range of fuel types than the HVIP data because it represents all the vehicles in the California fleet including gasoline, diesel, and gasoline/electric hybrid vehicles.

Then, a final set of tables calculates the percentages of the HVIP vehicles relative to the total fleet, for each year, vehicle type, fuel type, and county where the vehicles are domiciled. The steps in the analysis are:

1. HVIP data are sorted by vehicle category into different spreadsheet tabs
2. HVIP data by vehicle category are sorted by year of voucher receipt with “unredeemed” data not included (Python script)
3. HVIP data are compiled by year of voucher receipt and fuel type, for each vehicle category and county (R script)
4. HVIP data are converted to cumulative annual totals by fuel type, for each vehicle type and county (R script)
5. DMV data are apportioned into HVIP vehicle types using initially assumed vehicle category splits and for each analysis year and county (R script)

6. Final results tables are compiled comparing HVIP voucher vehicles and overall DMV fleet vehicles, by vehicle category, fuel type, year, and county, as well as statewide totals

Overall, for each vehicle category, fuel type, and county, the ratio of HVIP funded vehicles to the total vehicle stock in each year (2015 to 2020) is:

$$\frac{\sum_{t=1}^{x} HVIP\ vehicles}{EMFAC\ fleet\ vehicles}$$

HVIMPACT Limitations

The application of the HVIMPACT model allows for characterizing when and where HVIP vouchers were used. There are some limitations to the application of the model, based on currently available data. These include:

- The assumption that all voucher-award vehicles are still on the road and have not been removed from service for whatever reason – additional survey data could help to nuance this assumption and identify the extent to which some vehicles have been removed from service or migrated out of state;
- The assumed splits to apportion the DMV fleet database vehicles into the HVIP categories is assumed to be even based on the relevant vehicles categories in this initial assessment but this is an approximation – this could be done more accurately with additional vehicle data; and
- The current analysis only examines where vehicles are domiciled; if air quality impacts are a metric of interest, then vehicle activity would need to be examined including to what extent vehicles may be operated in disadvantaged community areas for equity assessments.

HVIMPACT Model Results

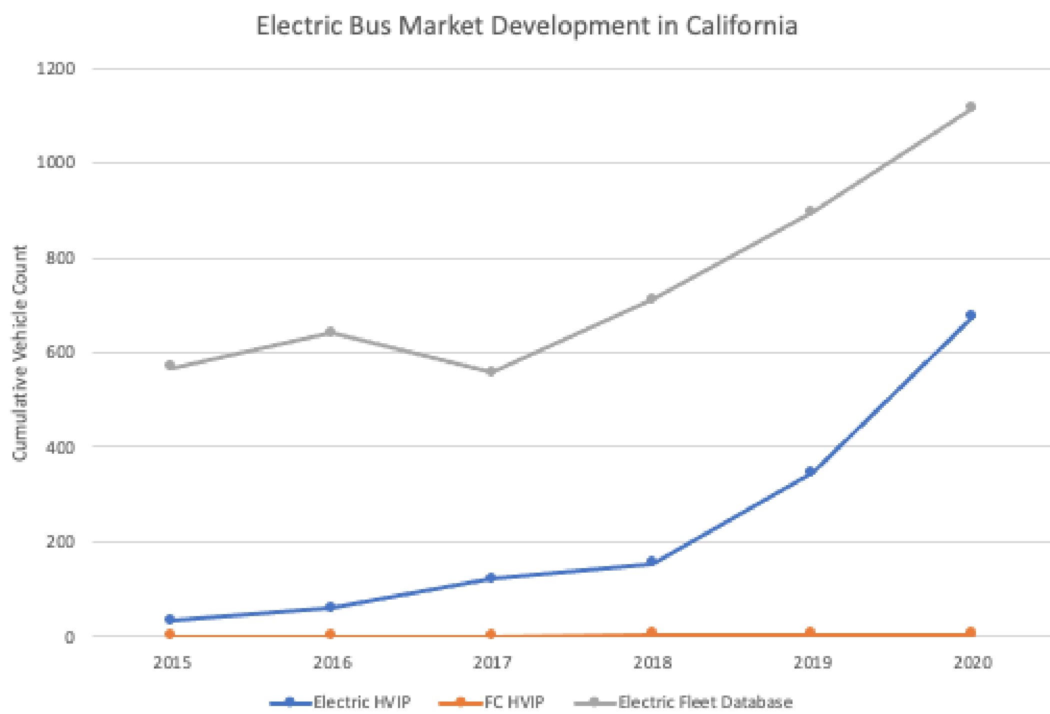
The source code for the HVIMPACT model is linked in Appendix A. The full set of HVIMPACT results is presented in Appendix B. This includes both individual county-level totals as well as a summation of statewide voucher usage results that are also presented in Table 2 below. As shown, HVIP vouchers have been used in all of the vehicle and fuel types that have been eligible for HVIP funding. The usage has been particularly high in the battery electric bus market, where approximately 60% of the vehicles in the California fleet were supported by HVIP vouchers in 2020. One caveat is that the vehicle population in the fleet database include the impact of any attrition of vehicles from year to year from 2015-2020 (vehicles taken out of service from year to year for whatever reason) whereas there is no estimated attrition in the HVIP data because there are no current data to support that estimation.

Table 2: HVIMPACT Output Statewide Results – Cumulative Market Totals

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020	2021	2022	2023
California	Bus	Natural Gas	0	0	0	0	285	704	704	704	704
California	Truck/Van	Natural Gas	0	0	25	81	216	375	375	375	375
California	Misc./Other	Natural Gas	0	0	244	527	740	975	975	975	975
California	Bus	ZEV-BEV	33	60	121	155	347	677	897	920	920
California	Truck/Van	ZEV-BEV	5	10	17	73	143	219	366	489	505
California	Misc./Other	ZEV-BEV	1	1	1	1	3	16	25	25	25
California	Bus	ZEV-FCV	0	0	0	5	5	5	48	48	48
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
California	Bus	Natural Gas	8,672	9,101	9,602	10,829	10,139	10,106	NA	NA	NA
California	Truck/Van	Natural Gas	7,987	8,543	9,739	10,954	11,697	13,682	NA	NA	NA
California	Misc./Other	Natural Gas	2,723	2,365	2,843	2,570	2,767	2,487	NA	NA	NA
California	Bus	ZEV-BEV	569	640	558	712	896	1,115	NA	NA	NA
California	Truck/Van	ZEV-BEV	214	254	229	323	773	622	NA	NA	NA
California	Misc./Other	ZEV-BEV	627	619	609	578	349	3,636	NA	NA	NA
HVIP Vehicle Share (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
California	Bus	Natural Gas	0	0	0	0	2.81	6.97	NA	NA	NA
California	Truck/Van	Natural Gas	0	0	0.88	3.15	7.81	15.08	NA	NA	NA
California	Misc./Other	Natural Gas	0	0	8.58	20.51	26.74	39.20	NA	NA	NA
California	Bus	ZEV-BEV	5.80	9.38	21.68	21.77	38.73	60.72	NA	NA	NA
California	Truck/Van	ZEV-BEV	2.34	3.94	7.42	22.60	18.50	35.21	NA	NA	NA
California	Misc./Other	ZEV-BEV	0.16	0.16	0.16	0.17	0.86	0.44	NA	NA	NA

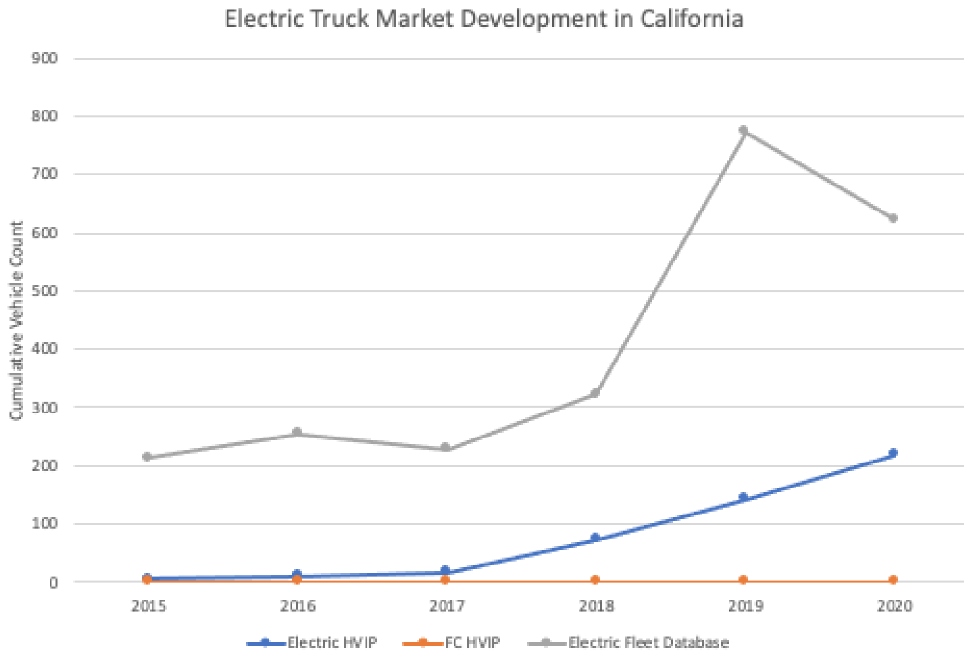
Figure 3 shows the usage of the HVIP for the electric bus market, where again the program has clearly been used substantially for electric buses. Almost all of the electric buses that received HVIP vouchers were battery-powered during this period, but some sales of fuel cell buses are starting to appear.

Figure 3: HVIMPACT Output Results – Electric Bus Market



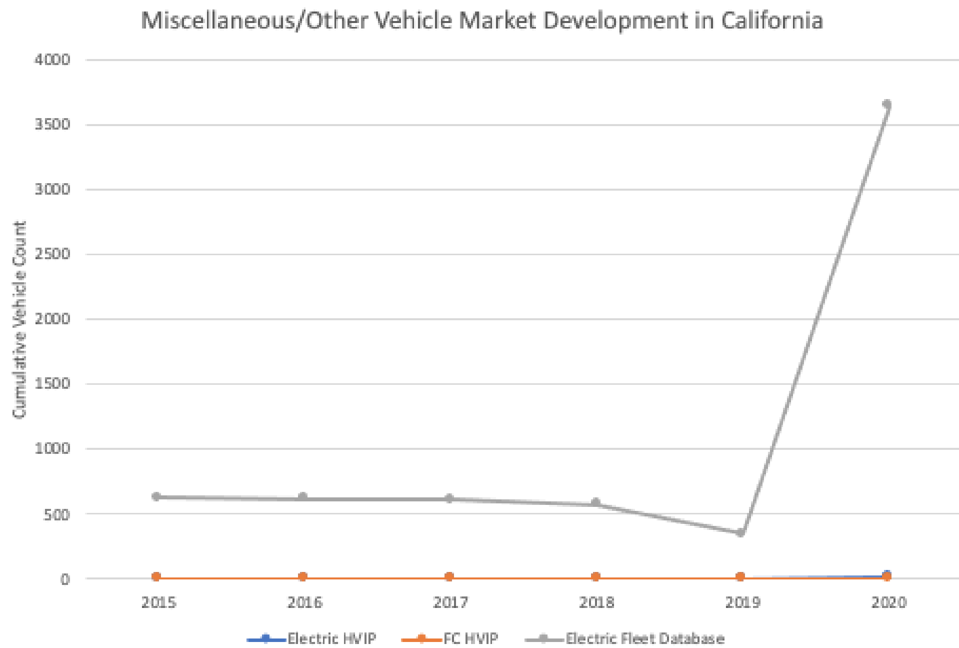
As shown in Figure 4, a significant portion of the overall fleet of electric trucks as reflected in the DMV database also received HVIP vouchers. There was a drop-off in the fleet totals in 2020, presumably because some vehicles were removed from California fleets due to either lack of charging infrastructure or vehicle performance issues, but the numbers of vehicles receiving HVIP vouchers continued to increase throughout the study period.

Figure 4: HVIMPACT Output Results – Electric Truck Market



With regard to the final category of "miscellaneous and other" electric vehicles receiving HVIP vouchers, there are very few of these vehicles relative to the total population in the DMV data. In 2019, about 1% of the DMV total fleet of electric vehicles in this category were HVIP supported, but this percentage dropped sharply in 2020 with a large overall uptick in the fleet population, even while the number of HVIP vehicles also increased significantly but from a very small base. The large increase in 2020 is mostly due to T3 and T4 class vehicles, where is seems that new market offerings have allowed for more adoption of electric vehicles in these classes than have been seen historically. Most of the electric vehicles in this class are in the T3 category, where these vehicles are too small to qualify for HVIP funding. We focus on the electric vehicle segments of these markets in these figures because the HVIP program is no longer supporting the purchase of CNG vehicles.

Figure 5: HVIMPACT Output Results – Electric Miscellaneous/Other Vehicle Market



The detailed results tables in Appendix B reveal some anomalies for some counties in the county-level data, where in some cases there are more reported HVIP vouchers for some vehicle categories than are reflected in the DMV data. This is likely due to two primary factors. These are first that there appears to be a lag in time between the year in which vouchers are awarded and when they appear in the DMV data. This could be because vehicles are provided with HVIP vouchers and purchased in a given year but that are not actually registered with DMV until the following year due to (for example) delays in setting up vehicle recharging or refueling with hydrogen. A second factor is the simplified assumption for vehicle category splits in the truck categories, as the DMV data are mapped to the HVIP vehicle categories, in the absence of better data – a factor discussed in the recommendations section below.

Based on the available data, many counties in California appear to have relied entirely or almost entirely on HVIP for their electric vehicle purchases. For electric buses, counties that appear in the data to have used vouchers for all or nearly all of their electric bus purchases include: Alameda, Contra Costa, El Dorado, Fresno, Humboldt, Kern, Los Angeles, Marin, Monterey, Orange, Placer, Riverside, San Bernardino, San Diego, Santa Clara, Solano, Sonoma, Tulare, and Yolo. For electric truck adoption, the counties making heavy use of HVIP vouchers for all or nearly all of their purchases are: Alameda, Kern, Riverside, Sacramento, San Bernardino, San Diego, San Francisco, San Joaquin, San Mateo, Shasta, Solano, Stanislaus, and Sutter.

Figure 6, below, presents a map of HVIP utilization by county reflecting these findings. The map depicts the counties that have made heavy use of HVIP for vehicle adoption based on analysis of the voucher data and overall DMV vehicle populations of trucks and buses by vehicle type. We define heavy usage as that 90%+ of ZEV adoption over the 2015-2020 analysis period has been supported by the HVIP vouchers. The full county level results are shown in Appendix B.

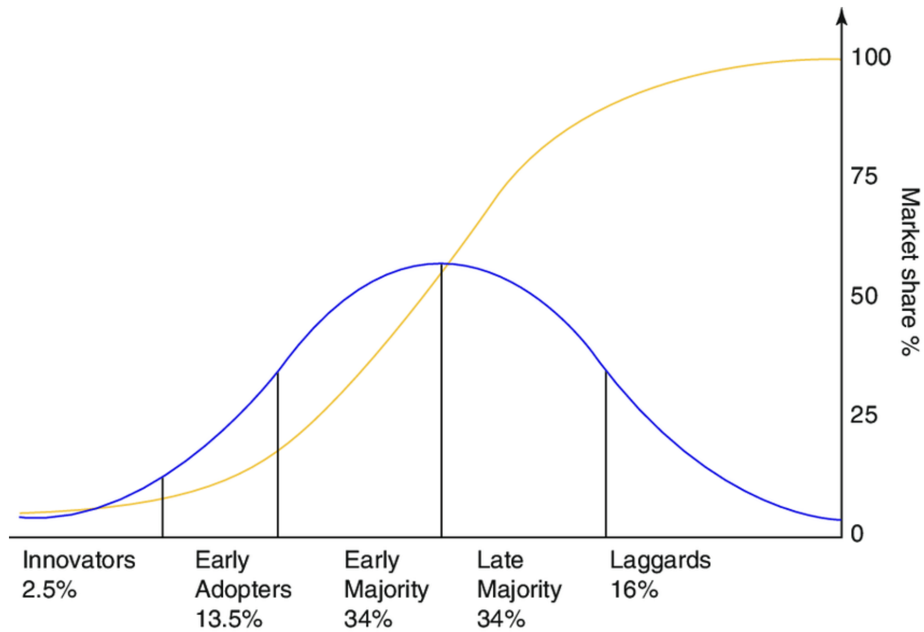
Figure 6: Map of Heavy Levels of HVIP Utilization by Vehicle Type and County

Diffusion Curve Analysis of Market Development

Another type of analysis of market development is based on diffusion curve theory, which uses historical data to estimate parameters to then forecast market development into the future. This type of theory dates back to the early 1960s when it was popularized by Everett M. Rogers in his seminal book titled "Diffusion of Innovations."[1] In this theory, there are market stages led by innovators and early adopters, leading to what Rogers called the early majority, followed by the late majority and finally the laggards. As this is plotted in a cumulative market development sense, the curve resembles the letter "S" so these diffusion curves have been generally come to be called "S-curves." Figure 6 depicts a generalized version of this based on Rogers' early work.

[1] Rogers, E.M. (1962), *Diffusion of Innovations*, Free Press of Glencoe.

Figure 7: Diffusion of Innovation Curve General Example



Source: E.M. Rogers (1962)

There are several well-established model formulations for diffusion curves, and a growing body of literature where these are considered and applied. These include the Bass, Generalized Bass, Logistic, Gompertz, Willingness to Consider, and Centrone models. Figure 7 below presents an application of these models and the key parameters in the context of a previous study of plug-in hybrid electric vehicle adoption. As discussed below, the models vary in their functional parameters, assumed "end states", ability to consider "interventions" such as the HVIP voucher or other buy-down incentive and ability to include second-order "imitator" effects that can help to develop the market along with initial lead-adopter or "innovator" behavior.

Figure 8: Various Innovation Curves as Applied to an Early Plug-in Hybrid Electric Vehicle Analysis

PHEV Bass Model

Bass Parameter	Estimate
Market Potential (m)	1,922,806
Innovation (p)	0.00262
Imitation (q)	0.70935

PHEV Generalized Bass Model

Bass Parameter	Estimate
Market Potential (m)	1,925,920
Innovation (p)	0.000185
Imitation (q)	0.63746
PHEV Premium (b1)	(0.68986)
Real Fuel Price (b2)	0.73502

The set of cells to the right of this box are for testing the impact on the Generalized Bass results of (1) launching with a lower price and (2) rising or falling fuel prices.

Intro Disc (10% - 50%)	0%
Begin (2010 to 2015)	2010
How Long (1 to 5) yrs	1
Real infl. Fuel Price '10 +	0%

PHEV Logistic Model

Parameter	Estimate
b1	1,884,564
b2	0.73111
b3	7.81574

y = b1 / (1 + exp(-b2(x - b3)))

PHEV Gompertz Model

Parameter	Estimate
b1	4,385,855
b2	0.22993
b3	9.74814

y = b1 exp(-(exp(-b2(x - b3))))

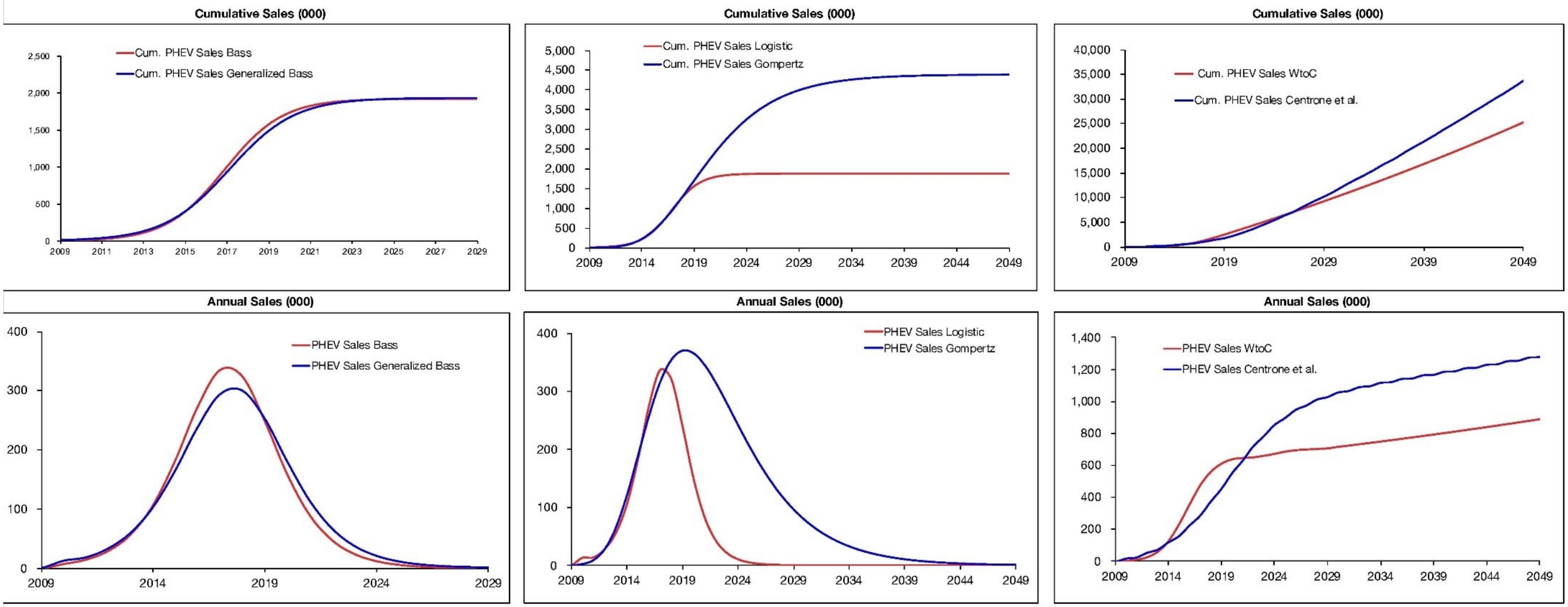
PHEV Willingness to Consider Model

Parameter	Estimate
exp(u1)	0.05000
WtoC Innovation (a)	0.00375
WtoC Imitation (b)	0.80000

Purch Prob 11	4.8%
Utility of PHEV	(3.00)
Utility of conventional	0.00

PHEV Centrone et al. Model

Parameter	Estimate
Initial M	1,850,000
M death rate	0.001
M birth rate	0.010
Innovation (p)	0.0088
Imitation (q)	0.33



For this project, we examined several models of technology adoption that have been used in marketing, economic, and policy analysis contexts.

1) the Bass Model[2]
2) the Generalized Bass Model[3]
3) the Centrone et al. Model[4]

We focus on the Bass models that have been used in many applications and that have the advantage of simplicity, but also offer the opportunity for important extensions to improve on the basic Bass model formulation.

In a broad sense, the producers (sellers) of a new product hope they can influence the rate at which potential users become users through the four Ps of marketing—product, price, place, and promotion. The rate at which potential users become users is also influenced by social and economic interaction between users and potential users—word-of-mouth and plainly visible (even conspicuous) consumption choices of neighbors, co-workers, and co-commuters. The four Ps are external interventions that aim to directly influence some potential users to become users. Word-of-mouth and conspicuous consumption are channels of influence that are internal parts of the social/market system.

The behavior of each of the Bass and Generalized Bass models is determined by differential equations. A differential equation is a mathematical equation for an unknown function (of time) in which the derivatives of the function appear as variables.

The Bass Model

The Bass Model was developed by Frank Bass. The seminal paper introducing the model was published in 1969.[5] The model has been applied to hundreds if not thousands of new technologies over the past fifty years. The Bass Model consists of a differential equation that describes the adoption of new products and technologies by consumers in a market. The model is based on intuitive assumptions about how adopters of a new product or technology interact in the market. The model assumes that potential adopters of the new product or technology can be either innovators or imitators. Innovators in the market spontaneously adopt the new technology at some given rate. Imitators adopt the new product or technology in response to the growing penetration of the new product or technology.

The overall speed of adoption depends on the degree of innovation and the degree of imitation among adopters. The Bass model has been widely used in forecasting, especially in forecasting the adoption of new products and technology. The notion of a Generalized Bass Model (GBM) was developed by Frank Bass and other researchers as they explored how a range of new products and technologies were adopted in markets. The paper first to use the GBM was published in 1994.[6]

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[2] Bass, F.M. (1969). A new product growth for model consumer durables, *Management Science* 15(5) 215–227.
[3] Krishnan, T.V., Bass, F.M., and Jain, D.C. (1999). Optimal Pricing Strategy for New Products, *Management Science*, v.45 n.12, 1650-1663).
[4] Centrone, F., A Gold, and E. Salinelli (2007). Demographic processes in a model of innovation diffusion with dynamic market. *Tech. Forecasting and Social Change*, March, 247-266.

[5] Bass, F., "A new product growth model for consumer durables," *Management Science* 15(5):214-227, January, 1969.
[6] Dipak, J., Bass, F., and Krishnan, T., "Why the bass model fits without decision variables," *Marketing Science* 13(3), 1994.

One feature common to both the simple Bass Model and the GBM is that the ultimate penetration of the new product is fixed. This means that changes in the parameters or starting values of these models can change the speed of adoption, but not the ultimate penetration. The new product or technology being examined can reach the ultimate penetration faster, but the level of the ultimate penetration is unchanged. In a dynamic and growing vehicle market it is likely that the penetration of new products and technologies will grow along with the market.

Researchers have more recently focused on models that allow researchers to examine to impacts of external factors on the adoption and usage of new products and technologies. External factors can include differences between conventional and ZEV vehicles in initial acquisition cost, ongoing operating costs, and other relevant external factors. By appending external factors into a GBM, the ultimate market penetration is still fixed, but external factors can be included in GBM. This allows research into how external factors can influence the pace of adoption. Other researchers have included model features that treat the ultimate market potential as endogenous. One such model has been implemented to model hybrid electric vehicle market development; similar ones can be applied to commercial truck and bus markets without assuming a fixed penetration level.[7]

In the following sections we define and discuss the significant features of each of the three Bass-type models that we are recommending to CARB. This is designed to introduce the models at a high level and to list some of the strengths and weaknesses of the models. The is further designed to show CARB the broad features of the models, not to describe in detail how to implement the models. The goal is to provide enough information to support CARB in choosing which of the models should be explored further, and ultimately to decide which should be implemented. Each model has at its core a differential equation that describes the behavior of potential adopters over time. A differential equation is a mathematical equation for an unknown function (of time) in which the derivative of the function appears as a variable. To implement any of these models, the relevant differential equation needs to have a mathematical solution, noting that not all differential equations have a solution.

The "Simple" Bass Model

In the differential equation below, F(t) is the fraction all potential adopters that have adopted up to time t and 1-F(t) is the fraction of potential adopters that have not adopted by time t. The fraction of adoption, F(t), ranges from zero to 1 at times zero and infinity, respectively. The fraction of adoption, F(t), can be defined as the number of adopters at time t divided by the total number of potential adopters. F'(t) is the derivative of F(t) with respect to time (t). Thus, F'(t) is the fraction of adopters that adopt at time t.

$$\frac{F'(t)}{1 - F(t)} = p + qF(t)$$

The Simple Bass Model assumes that new products and technologies are potentially adopted by two types of adopters: innovators and imitators. Innovators spontaneously (and without reference to what other potential adopters are doing) adopt the new product or technology. The parameter p refers to adoptions by innovators and q refers to adoptions by imitators.

[7] Liu, Y., Klampfl, E., Tamor, M., "Modified Bass Model with External Factors for Electric Vehicle Adoption," *SAE International*, 2013-01-0505, April 2013.

In the sales equation below, m is the ultimate market potential, m is the total number of customers who will ultimately adopt. This equation links the fraction of adoption to new sales (new adoptions).

$$sales(t_n) = m[F(t_n) - F(t_{n-1})]$$

The Simple Bass Model has three parameters: p, q, and m that can be estimated with nonlinear least squares. All three parameters are constants. There are no policy variables in the Simple Bass Model, so it is not appropriate for directly examining the impacts of policies on the adoption of new products or technologies. However, the Simple Bass Model is useful as a benchmark.

The Generalized Bass Model with External Factors

The GBM is an extension of the Simple Bass Model. The Simple Bass Model has no decision variables in its differential equation. The GBM, in contrast, potentially includes decision and other external factors. The GBM's differential equation is identical to the differential equation of the Simple Bass Model, but the differential equation of the GBM includes a vector of external factors that is multiplied by the differential equation of the Simple Bass Model. The vector of external factors is the scaling function, x(t) shown below.

Differential Equation:

$$\frac{F'(t)}{1 - F(t)} = [p + qF(t)]x(t)$$

Scaling Function:

$$x(t) = 1 + \frac{\propto_1 x'(t_1)}{x_1(t_0)} + \frac{\propto_2 x'(t_2)}{x_2(t_0)} + \frac{\propto_3 x'(t_3)}{x_3(t_0)}$$

Some variables that could be included in the scaling vector are differences between conventional and zero emission vehicles in several external factors. In this example we recommend including in the analysis difference between conventional trucks and buses and zero emission vehicles in three important external factors: differences in acquisition cost, differences in operating costs per mile, and new truck and bus registrations (conventional and ZEV). The vouchers that support sales of ZEV trucks and buses operate through differences in acquisition costs. This formulation directly measures the impact of the vouchers on ZEV truck and bus sales. Differences in cost per mile are based on costs of fuels and operation (diesel for conventional vehicles and electricity or for ZEVs). Including new registrations of all trucks and buses, both conventional and ZEV, captures the impact of the aggregate size of the fleet on ZEV versus conventional sales.

While the GBM is an improvement over the Simple Bass Model by its inclusion of relevant external factors, both models have a fixed ultimate penetration of ZEVs in the market.

Strengths and Weaknesses of the Generalized Bass Model

The GBM is an extension of the Bass model that incorporates marketing mix variables. The GBM is a more flexible model than the Bass model, and it can be used to forecast the sales of a new product over time under a wider range of conditions.

The GBM has several strengths. It is a more flexible model than the Bass model. This means that it can be used to forecast the sales of a new product over time under a wider range of conditions. Also, the GBM can be used to identify the factors that influence the rate of adoption of a new product. This information can be used to improve marketing and innovation strategies.

However, the GBM also has some weaknesses. First, the GBM is a more complex model than the Bass model. This means that it is more difficult to understand and use. Second, the GBM requires more data than the Bass model. This data may not be available for all products.

Overall, the GBM can be a valuable tool for marketers and innovation managers. It is a more flexible model than the Bass model, and it can be used to identify the factors that influence the rate of adoption of a new product. However, it is important to be aware of the limitations of the model when using it.

Summary of strengths and weaknesses of the Generalized Bass Model:

<u>Strengths</u>

- More flexible than the Bass model.
- Can be used to identify factors that influence the rate of adoption of a new product.

<u>Weaknesses</u>

- More complex than the Bass model.
- Requires more data than the Bass model.

Despite its weaknesses, the GBM is a valuable tool for marketers and innovation managers. It can be used to forecast the sales of new products, identify the factors that influence the rate of adoption, and make better decisions about marketing and innovation strategies.

A Modified Bass Model with External Factors and Unconstrained Ultimate Penetration

A new branch of research in Bass-type Models has recently been established using models that incorporate external factors as the GBM does, and at the same time treat the ultimate market penetration as endogenous to the model. Liu et al., 2013, presents an example of such a Bass-type model that incorporates both a set of external factors (as in the GBM) and an unconstrained ultimate penetration of ZEVs in the market. The "Modified Bass Model" of Liu et al. accomplishes the inclusion of external factors along with an unconstrained ultimate penetration of ZEVs. The GBM is the starting point in Lu et al. The GBM's scaling function (the x vector) is also part of the Modified Bass Model. In addition to including the external factors in the x scaling function, the Modified Bass Model makes the ultimate market adoption of EVs, m(t), a function of external factors. This is shown in the market potential function below. The resulting differential function has an unconstrained ultimate market penetration.

Differential Equation:

$$\frac{F'(t)}{1-F(t)} = [p + qF(t)]x(t)m(t)$$

Scaling Function:

$$x(t) = 1 + \frac{\propto_1 x'(t_1)}{x_1(t_0)} + \frac{\propto_2 x'(t_2)}{x_2(t_0)} + \frac{\propto_3 x'(t_3)}{x_3(t_0)}$$

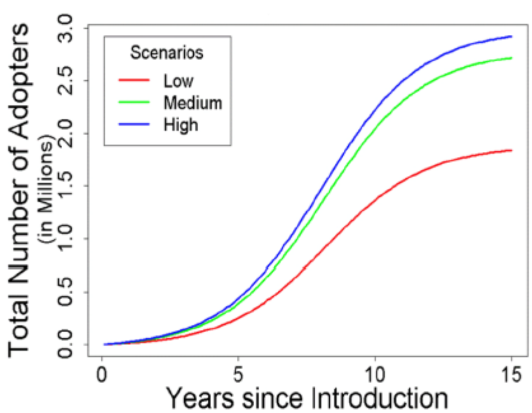
Market Potential Function:

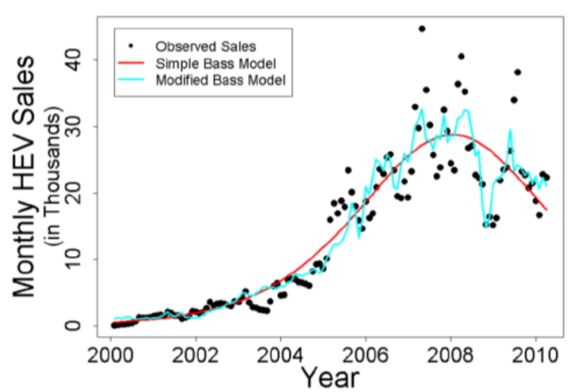
$$m(t) = m_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

As shown in the Liu et al. analysis and with the result in Figure 7 below, this type of adoption curve framework can be used to forecast market adoption in vehicle sectors based on classic Bass curve variables along with additional external factors. The Modified Bass formulation allows for better matching of the solution to initial sales data and a more nuanced forecast of market development in the future.

We note that this analysis incorporated three different levels of government incentives for the purchase of hybrid-electric vehicles in the light-duty sector, resulting in the scenario analysis under "low," "medium," and "high" assumptions for future market conditions. External factors examined here included the vehicle "pay off distance" (incorporating relative vehicle and fuel prices), gross domestic product, and the level of all new vehicle sales, along with a range of additional scenario analysis assumptions.

Figure 9: Plug-in Hybrid Electric Vehicle Market Adoption Analysis with Modified Bass Model with External Factors (Examples for Illustrative Purposes)

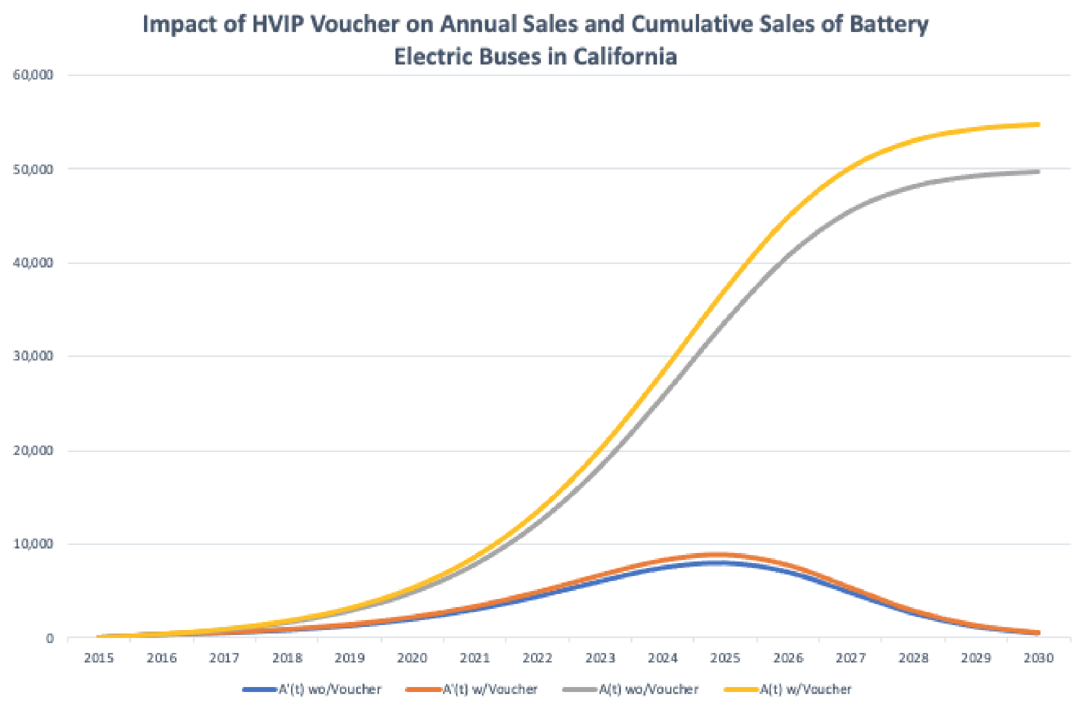




As an example of the application of a Bass model to estimation of the HVIP for the California MDV/HDV fleet market, we offer an illustrative example based on the battery electric bus segment. There are currently about 100,000 transit buses in California, and additional school buses, paratransit buses, and commuter buses. The current Innovative Clean Transit regulation requires all new transit buses to be electric-drive after 2029, but these can be either battery electric or fuel cell-battery hybrid types. The example shown below in Figure 9 shows vehicle adoption curves with and without the benefit of the

HVIP voucher program up until 2030, where various bus types and fuel options can still be purchased but where the market is expected to be increasingly dominated by zero-tailpipe emission types.

Figure 10: Hypothetical Bass Curve Analysis of Electric Bus Sales in California Through 2030



In this hypothetical example, we use 0.006 as a value for the innovation parameter "p," 0.63 as a value for the imitation parameter "q" and 100,000 and 110,000 as values for the year 2030 market potential. The market potential increases as a function of the lower effective vehicle price for the bus fleet adopter, resulting from the voucher program, relative to other vehicle and fuel types in the market.

To implement this approach with a somewhat larger historical data set (as shown in Figure 8), the following steps could be taken to establish market forecasts for each overall vehicle category and zero-emission fuel type (battery electric and hydrogen fuel cell):

1) Estimate initial parameters from the literature for a basic Bass model for the values of p and q;
2) Add additional variables for vehicle price premiums and fuel prices (electricity and hydrogen) and for vehicle prices with variable voucher amounts (current and potentially prospective, relative to a "no voucher" case) in a Generalized Bass model;
3) As in Liu et al. (2013) use Akaike's Information Criterion (AIC) to measure goodness of fit with zero to 3 or more external factors (e.g., California GDP, all new vehicle sales, etc.) to select the best model;
4) Adjust p and q values iteratively and repeat Step 3 as needed to establish best curve fit with the selected model; and
5) Further estimate the alpha (α) and beta (β) factors for the selected model using a non-linear least squares approach and an appropriate statistical package.

Overall Recommendations

Variables representing aspects of interventions such as incentive / cost buy-down policies to grow the market can be included in GBM type models with various potential modifications. This adds complexity; however, adding variables can help to understand impacts of interventions.

As suggested above, we recommend that a modified Bass model be considered to explore the potential future impact of the HVIP with three external factors (betas). The three external factors that we would include (similar to Liu et al., 2013) are:

1) California GDP (affects overall market conditions for commercial vehicle sales);
2) The "pay-off distance" for clean fuel commercial vehicles relative to incumbent technologies, that incorporates overall vehicle transaction costs (with and without incentives) as well as fuel cost variables; and
3) All new vehicle sales in each market segment.

This model could be formulated and solved in a very similar way to the Liu et al. model, using non-linear least squares estimation techniques, once the requisite data are available and with a somewhat longer data series as the basis for the estimation. We further recommend segmenting the commercial clean fuel market, now focusing on zero-emission technologies, into four segments: 1) battery-electric buses, 2) fuel cell-electric buses, 3) battery-electric trucks, and 4) fuel cell-electric trucks. This is because these segments are likely to follow somewhat different adoption patterns, especially for the different fuel types where fuel cell technologies are several years behind battery systems in their market uptake. Further segmentation across vehicle weight classes (especially for trucks) would also be possible, of course, but would add complexity to the analysis.

Finally, as discussed below, estimating the isolated effect of the HVIP program would require a more complete understanding *of all incentives* paid for the vehicles from federal and local sources as well as the statewide HVIP. Models could then be estimated with and without the impact of the HVIP (specifically) on vehicle pay-off distance, to isolate that impact on the future market. And this type of model importantly includes the adoption and innovator parameters that can (in theory) capture the magnification of the impact of the HVIP through additional market mechanisms via the estimation of the imitation parameter.

Enhanced Survey Methods to Better Understand HVIP Program Importance in Market Development

As described above, direct market observations reveal historical market development, and diffusion curve types of analyses can help to project future market development. However, a better understanding of fleet decision making requires additional survey insights, to further understand fleet decision-making processes and the full importance and impact of the HVIP. Also needed is better understanding of the supply side, where there may be synergies with OEM product offerings and subsequent uptake by fleets, emboldened by the presence of the HVIP and other incentive programs.

CARB currently requires HVIP voucher recipients to complete *ex post* surveys regarding their use of the incentive program. However, the reported response rates to the survey are not as high as the agency would need for a complete and proper analysis. The agency may wish to consider withholding a modest amount of voucher funds upon completion of the survey, or another means to increase compliance with the survey request such as an additional incentive for completion. However, particularly for assessing the impact of the program, withholding funds until the respondent completes the survey could reduce the integrity by creating the appearance that CARB would like for the respondent to state that they would not have purchased the vehicle without the program.

The results of the 2022 survey of HVIP recipients indicate a high degree of impact of the program on the decision to purchase clean fuel vehicles. On a 1 to 5 scale, the average response was a 4.5 in terms of the program importance to the purchase decision. A total of 73% of respondents indicated a response of 5, the highest rating for the importance of the program. However, the overall response rate to the survey was only 40%, raising some concerns about response bias and more generally about incomplete information. Also, the appendix of the report with the actual survey questions indicates that a question was asked: "would you have purchased/leased your [type of vehicle] if HVIP funding was not available?" but the results of this question are not provided in the summary report.[8] Results from this survey question would be helpful to further understanding how critical the HVIP support is to the individual vehicle purchase decisions, and along with other suggested survey data would help to better understand the importance of HVIP to the complex process of fleet purchase decisions.

Appendix C of this report includes suggestions for modifying one of the survey questions to be clearer to participants, as well as adding an additional question with regards to the importance of the HVIP to the vehicle purchase decision. Additionally, questions are suggested to better understand *all of the incentives received for the vehicle purchase,* as some degree of incentive "stacking" is often possible and achieved by fleet customer. These total incentives could then be compared to the full retail price of the vehicle (and comparison conventional vehicles) to examine and better isolate the specific role of the HVIP in contributing to the "vehicle pay-off" parameter discussed above, for inclusion in a prospective Modified Bass Model diffusion curve analysis with incentive level as a variable.

In addition to enhancing the survey of HVIP voucher recipients, we recommend a more comprehensive survey effort to better understand the larger impacts of the program. This would entail:

1. Surveying HVIP voucher recipients to probe in greater depth the program importance to fleet purchase decisions;
2. Surveying adopters of commercial HDZEVs who also *did not* receive HVIP support;
3. Surveying fleets that had no HDZEV adoption; and
4. Surveying manufacturers of commercial HDZEVs to understand their perceptions of the market impacts of HVIP and to what extent the program has positively impacted their product development and production plans.

This more comprehensive type of survey effort could further address important questions that are not currently assessed, including the combined (and then potentially disentangled) effect of incentives discussed above. These include:

- If the vehicle that was purchased (with or without the HVIP voucher) had not been available, then what vehicle would your fleet have purchased?

[8] Industrial Economics Inc. (2023), "2022 Annual Survey of Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) Voucher Recipients," Draft Final Report, February 17.

- For purchasers of HDZEV without the voucher: Why did your fleet not use voucher? Unaware of the program? Ineligible? Funding ran out? Some other reason?
- For purchasers of HDZEV with and without the voucher: What information sources have you used to make the HDZEV purchase decision? Did you learn from other fleet experiences with similar vehicles? What (in brief) was the decision process?
- How did the voucher use affect your calculation (if made) of vehicle TCO as well as first cost?
- For fleets without HDVZEV adoption: What information sources have you used to consider the HDZEV purchase decision, if this was done? Did you employ information from other fleet experiences with similar vehicles? Are you aware of the HVIP support program? What (in brief) was the decision process to delay or forego an HDZEV purchase?
- More generally, how are smaller versus larger fleets being impacted by HVIP?
- Supply side for manufacturers: Have there more vehicle offerings over time in recent years? If so are these apparently stimulated by the HVIP program in any way, e.g., through reduced product development risks, scale effects, and/or manufacturing cost reductions?

Clearly, achieving these survey results and findings at ideally a statistically meaningful (versus anecdotal) level would be a significant undertaking. This would require carefully developed and pre-tested survey instruments, recruitment procedures and participation incentives, and data collection and analysis efforts.

Additional Recommendations

In addition to these concepts for better understanding the HDZEV market, fleet adoption, and supply side effects relative to the HVIP, we also recommend a few additional measures to improve future analysis of the impact of the HVIP.

As noted above, there is a basic misalignment between the data fields collected in the HVIP voucher database and in the fleet registration database. This is a significant barrier to understanding the historical impact of the HVIP program across vehicle and fuel types, especially at the county level, but also at the statewide level. For purposes of this analysis, a simplifying set of assumptions was made to map the fleet data to the HVIP vehicle categories, but these are not entirely accurate based on ambiguities in the relative individual vehicle class definitions. In the future, CARB could either continue to map the fleet data to the HVIP vehicle categories, as done here, using an additional data field that would code the fleet data with the appropriate HVIP vehicle category. Alternatively, CARB could map the HVIP voucher data to the more detailed set of vehicle categories, also using an additional data field to allow a direct comparison of the two data sets using the more extensive set of vehicle categories.

As for the fundamental issue of assessing the importance of the HVIP program to fleet purchases of HDZEVs, the enhanced survey information and subsequent diffusion curve analysis could address this, if always somewhat imperfectly. It is clearly not the case that fleets would not purchase *any* HDZEVs in the absence of HVIP, as many have done so. But for those fleets that do employ HVIP vouchers in their purchases, better survey techniques could both shed more light on the importance of the program for those purchases, nuancing the current assumption that the vouchers were critical to the purchases, as well as providing useful information for forward-looking market projections. Different types of commercial fleets (small and large, private and transit agency, truck and bus, etc.) have different processes for making vehicle purchase decisions. It is not really possible to have a completely definitive analysis of the full importance of the HVIP in this context, but over time more can be learned and a better understanding can be gained.

Finally, as new and existing regulations such as Advanced Clean Fleets, Advanced Clean Trucks, and the Innovative Clean Transit rule become more binding in the future, CARB should clarify the future role of HVIP in the context of these programs. Current CARB rules only allow the use of HVIP vouchers for pre-compliance or excess compliance for these regulations. But in the future, when more and more fleet purchasers of HDZEVs are for compliance, what is the role of HVIP in helping fleets to comply with these challenging regulations?

Conclusion

In conclusion, a full understanding of the overall impact of HVIP is not feasible. However, a combination of historical analysis and improved survey methods and strategies can help to shed better light into the importance of the program to the fleets have that used HVIP vouchers. Forward looking analysis using diffusion curve theory can help to assess the potential future impact of the program, including variations in potential future voucher value, impacts on different vehicle categories (e.g., trucks versus buses), impacts by ZEV fuel type (battery electric versus hydrogen fuel cell), and disentangling the impact of the HVIP relative to other incentive programs.

Fundamental concepts highlighted here include:

- Understanding and quantifying the impact of the HVIP on fleet purchases of HDZEVs requires a more complete knowledge of *all* incentives from all sources and how they combine to impact fleet purchases, and requires the program to be implemented in a different way to test for experimental controls and variables that would be operationally impractical to achieve the program's objective;
- More stringent collection of mandatory surveys for voucher recipients could give a better sense of HVIP "importance" for vehicle purchases, but surveys will always have some limitations;
- Imperfect alignment of fleet database and HVIP vehicle categories creates analysis challenges with regard to analysis of historical program distribution of vouchers; and
- Well-established diffusion curve concepts could allow for future market forecasting, including the impact of the HVIP in a broader market context, that includes other market factors such as other applicable incentives and more general economic conditions such as future fuel cost and California GDP forecasts. However, developing such curves will require significantly more years of data after HVIP funds electric trucks, and such data will not be available in the near term.

Overall, based on observable market development and the latest voucher recipient survey in 2022, HVIP is clearly an important program for further developing the market for HDZEVs in California. The continued and expanded adoption of these vehicles is critical to achieving the state's environmental goals.

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Appendix A: HVIMPACT Code

Access the HVIMPACT Code here

1type_fuel_num.py

```
#remove everything other then the vechile type (B,BS, and so on till T7),
Fuel type, and Number of the vechiles

import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Create a list to store the modified rows
        modified_rows = []
        # Open the file and read its contents as a CSV file
        with open(file_path, "r", encoding="utf-8-sig", newline="") as
csv_file:
            csv_reader = csv.reader(csv_file)
            # Loop through each row in the CSV file
            for row in csv_reader:
                # Remove all values in the row other than the first,
third, and eighth column
                modified_row = [row[0], "", row[2], "", "", "", "",
row[7]]
                modified_rows.append(modified_row)
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="", encoding="utf-8") as
csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(modified_rows)
```

This code snippet is designed to process multiple CSV files located in a folder and modify each file by removing all values except for specific columns. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

3. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

4. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

5. A list called `modified_rows` is created to store the modified rows of the CSV file.

6. The file is opened using `open(file_path, "r", encoding="utf-8-sig", newline="")` to read its contents as a CSV file.

7. The `csv.reader` is used to iterate over each row in the CSV file.

8. For each row, the code creates a modified row by selecting specific columns. In this case, only the first, third, and eighth columns are retained, while the rest are replaced with empty strings. The modified row is then appended to the `modified_rows` list.

9. After processing all rows in the CSV file, the file is closed.

10. The code then opens the file again, this time in write mode using `open(file_path, "w", newline="", encoding="utf-8")`.

11. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(modified_rows)`.

12. Finally, the file is closed, and the loop continues to the next file in the folder.

This code essentially reads each CSV file, modifies the rows by selecting specific columns, and writes the modified rows back to the same file, effectively removing all other values except for the desired columns.

2change.py

```
import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Create a list to store the modified rows
        modified_rows = []
        # Open the file and read its contents as a CSV file
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            # Loop through each row in the CSV file
            for row in csv_reader:
                # Replace ",," with ","
                modified_row = [cell.replace(",,", ",") for cell in row]
                # Replace ",,,,," with ","
                modified_row = [cell.replace(",,,,,", ",") for cell in
modified_row]
                modified_rows.append(modified_row)
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(modified_rows)
```

This code snippet is designed to process multiple CSV files located in a folder and modify each file by replacing specific patterns of consecutive commas with a single comma. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

3. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

4. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

5. A list called `modified_rows` is created to store the modified rows of the CSV file.

6. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

7. The `csv.reader` is used to iterate over each row in the CSV file.

8. For each row, the code replaces consecutive occurrences of two or more commas with a single comma. This is done by using a list comprehension with the `replace()` method on each cell in the row. The modified row is then appended to the `modified_rows` list.

9. After processing all rows in the CSV file, the file is closed.

10. The code then opens the file again, this time in write mode using `open(file_path, "w", newline="")`.

11. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(modified_rows)`.

12. Finally, the file is closed, and the loop continues to the next file in the folder.

This code essentially reads each CSV file, replaces consecutive commas in each row with a single comma, and writes the modified rows back to the same file. This can be useful for cleaning up CSV files where there may be extra commas due to formatting issues or data inconsistencies.

3.removeunused.py

```
#remove all the rows (vechile types) that are not used : "MC", "MH", "P",
"T1", "T2"

import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Define the rows to remove
rows_to_remove = ["MC", "MH", "P", "T1", "T2"]

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Create a list to store the modified rows
        modified_rows = []
        # Open the file and read its contents as a CSV file
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            # Loop through each row in the CSV file
            for row in csv_reader:
                # Check if the row starts with any of the rows to remove
                if not row or not any(row[0].startswith(x) for x in
rows_to_remove):
                    # If the row doesn't start with any of the rows to
remove, append it to the modified rows list
                    modified_rows.append(row)
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(modified_rows)
```

This code snippet is designed to process multiple CSV files located in a folder and remove rows (vehicle types) that are not included in a predefined list. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The rows to remove are defined in the `rows_to_remove` list. In this case, the list contains the vehicle types "MC", "MH", "P", "T1", and "T2".

3. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

4. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

5. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

6. A list called `modified_rows` is created to store the modified rows of the CSV file.

7. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

8. The `csv.reader` is used to iterate over each row in the CSV file.

9. For each row, the code checks if the first column value (vehicle type) starts with any of the rows to remove. It uses a list comprehension with the `startswith()` method and the `any()` function to check if any of the rows in `rows_to_remove` match the beginning of the vehicle type in the current row.

10. If the row doesn't start with any of the rows to remove, it is appended to the `modified_rows` list.

11. After processing all rows in the CSV file, the file is closed.

12. The code then opens the file again, this time in write mode using `open(file_path, "w", newline="")`.

13. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(modified_rows)`.

14. Finally, the file is closed, and the loop continues to the next file in the folder.

This code essentially reads each CSV file, checks the vehicle type in each row, and removes rows that have vehicle types not included in the predefined list. The modified rows are then written back to the same file.

4combine.py

```
#combine the vechile based on the same type, and fuel type

import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Create a dictionary to store the rows
        rows_dict = {}
        # Open the file and read its contents as a CSV file
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            # Loop through each row in the CSV file
            for i, row in enumerate(csv_reader):
                # Check if this is the first row
                if i == 0:
                    # Store the header row in the dictionary
                    header_row = row
                else:
                    # Get the values for the first and third column
                    key = (row[0], row[2])
                    # Check if this key already exists in the dictionary
                    if key in rows_dict:
                        # If it does, add the 8th column value to the
existing row's 8th column value
                        rows_dict[key][7] = str(float(rows_dict[key][7]) +
float(row[7]))
                    else:
                        # If it doesn't, add the row to the dictionary
                        rows_dict[key] = row
        # Create a list to store the modified rows
        modified_rows = [header_row]
```

```
        # Loop through the dictionary and append the modified rows to the
list
        for row in rows_dict.values():
            modified_row = [row[0], row[2], "", "", "", "", "", row[7]]
            modified_rows.append(modified_row)
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(modified_rows)
```

This code snippet is designed to process multiple CSV files located in a folder and combine rows (vehicles) based on the same vehicle type and fuel type. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

3. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

4. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

5. A dictionary called `rows_dict` is created to store the rows. The dictionary keys will be a combination of the vehicle type (first column) and fuel type (third column).

6. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

7. The `csv.reader` is used to iterate over each row in the CSV file.

8. For each row, it checks if it's the first row (header row) by checking if the loop variable `i` is 0.

9. If it's the first row, it stores the header row in the `header_row` variable.

10. If it's not the first row, it creates a key by combining the values of the first and third columns (`key = (row[0], row[2])`).

11. It then checks if this key already exists in the `rows_dict` dictionary.

12. If the key exists, it means there is already a row with the same vehicle type and fuel type combination. In this case, it adds the value of the 8th column from the current row to the existing row's 8th column value.

13. If the key doesn't exist, it means it's a new vehicle type and fuel type combination. In this case, it adds the entire row to the `rows_dict` dictionary.

14. After processing all rows in the CSV file, the file is closed.

15. A list called `modified_rows` is created to store the modified rows. The first element of this list is the `header_row` obtained from the first row of the CSV file.

16. The code then loops through the values in the `rows_dict` dictionary and appends modified rows to the `modified_rows` list. The modified rows contain the vehicle type, fuel type, and the sum of the 8th column values for rows with the same vehicle type and fuel type combination.

17. The `modified_rows` list is then written back to the CSV file, effectively replacing the original rows.

This code essentially reads each CSV file, combines rows with the same vehicle type and fuel type, and writes the modified rows back to the same file. The modification involves summing the 8th column values for rows with the same vehicle type and fuel type combination, while retaining the other columns from the first occurrence of each combination.

5add.py

```
#add the first row of all csv files because they are output as:
#B,,Diesel,,,,,32
#B,Diesel,,,,,,241.0
import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Open the file and read its contents as a list of lists
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            rows = list(csv_reader)
        # Get the last value of the first row and the last value of the
second row
        first_row_last_value = rows[0][-1]
        second_row_last_value = rows[1][-1]
        # Add the values together
        new_last_value = str(float(first_row_last_value) +
float(second_row_last_value))
        # Remove the first row
        modified_rows = rows[1:]
        # Set the last value of the new first row to the sum of the
original last values
        modified_rows[0][-1] = new_last_value
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(modified_rows)
```

This code snippet is designed to process multiple CSV files located in a folder and add the first row of each file to the second row by summing their last values. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

3. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

4. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

5. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

6. The `csv.reader` is used to read the CSV file and convert it into a list of lists called `rows`.

7. The last value of the first row and the last value of the second row are obtained using indexing (`rows[0][-1]` and `rows[1][-1]`, respectively).

8. The code adds the two values together and stores the result in `new_last_value`.

9. The first row is removed from the `rows` list using slicing (`rows[1:]`), and the modified rows are stored in `modified_rows`.

10. The last value of the new first row (`modified_rows[0][-1]`) is updated to the sum of the original last values (`new_last_value`).

11. The file is opened again, this time in write mode using `open(file_path, "w", newline="")`.

12. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(modified_rows)`.

13. Finally, the file is closed, and the loop continues to the next file in the folder.

This code essentially reads each CSV file, combines the first and second rows by summing their last values, removes the original first row, and writes the modified rows back to the same file. This allows for the addition of the first row to the second row while updating the necessary values.

6addtittle.py

```
#add tittles to the first row
import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Get the filename without the extension
        title = os.path.splitext(filename)[0]
        # Open the file and read its contents as a list of lists
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            rows = list(csv_reader)
        # Add the filename to the first row
        rows[0].append(title)
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(rows)
```

This code snippet is designed to add titles to the first row of each CSV file in a folder. The titles are derived from the filenames of the CSV files. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

3. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

4. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

5. The filename without the extension is obtained using `os.path.splitext(filename)[0]` and stored in the `title` variable.

6. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

7. The `csv.reader` is used to read the CSV file and convert it into a list of lists called `rows`.

8. The code appends the `title` to the first row (`rows[0]`) using the `append()` method. This adds the title derived from the filename as an additional column to the first row.

9. The file is opened again, this time in write mode using `open(file_path, "w", newline="")`.

10. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(rows)`.

11. Finally, the file is closed, and the loop continues to the next file in the folder.

This code essentially reads each CSV file, adds a title derived from the filename as an additional column to the first row, and writes the modified rows back to the same file. This allows for the inclusion of a title that corresponds to the specific CSV file in each first row.

7.numtypes.py

```
#so sometimes the number of vechiles are 0 fora fuel type, we don't want
to erase that we want that to appear as 0,
#so here we are going to format our data like that
import os
import csv

# Define the folder path containing the CSV files
folder_path = "datas_all"

# Define the car types to repeat
car_types = ["B", "BS", "BT", "T3", "T4", "T5", "T6", "T7"]

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)
        # Open the file and read its contents as a list of lists
        with open(file_path, "r", newline="") as csv_file:
            csv_reader = csv.reader(csv_file)
            rows = list(csv_reader)
        # Create a list of repeated car types
        repeated_car_types = []
        for car_type in car_types:
            repeated_car_types += [car_type] * 4
        # Add rows for any missing car types
        for car_type in set(car_types) - set(row[0] for row in rows[1:]):
            new_rows = [[car_type] * 4] * 4
            rows += new_rows
        # Reorder the rows to match the repeated car types
        reordered_rows = [rows[0]] + [row for car_type in
repeated_car_types for row in rows[1:] if row[0] == car_type]
        # Write the modified rows back to the CSV file
        with open(file_path, "w", newline="") as csv_file:
            csv_writer = csv.writer(csv_file)
            csv_writer.writerows(reordered_rows)
```

This updated code snippet aims to format the data by ensuring that all car types appear in the CSV files, even if the number of vehicles for a fuel type is 0. Here's an explanation of the code:

1. The folder path containing the CSV files is specified using the `folder_path` variable.

2. The car types that need to be repeated are defined in the `car_types` list. In this case, it includes the car types "B", "BS", "BT", "T3", "T4", "T5", "T6", and "T7".

3. The code then loops through each file in the specified folder using `os.listdir(folder_path)`.

4. For each file, it checks if the file ends with the `.csv` extension using `filename.endswith(".csv")`.

5. If the file is a CSV file, the file path is constructed by joining the folder path and the file name using `os.path.join(folder_path, filename)`.

6. The file is opened using `open(file_path, "r", newline="")` to read its contents as a CSV file.

7. The `csv.reader` is used to read the CSV file and convert it into a list of lists called `rows`.

8. The code creates a list called `repeated_car_types` by repeating each car type in the `car_types` list four times. This ensures that each car type appears four times in the final data.

9. The code then checks for any missing car types in the CSV file by comparing the car types in `rows[1:]` (excluding the header row) with the set of car types defined in the `car_types` list. If a car type is missing, it adds four new rows with the missing car type to the `rows` list.

10. Next, the code reorders the rows to match the repeated car types. It starts by keeping the header row (`rows[0]`), and then adds rows from the original `rows[1:]` list for each car type in `repeated_car_types`. It filters out rows that don't match the car type in the current iteration.

11. The modified rows are stored in the `reordered_rows` list.

12. The file is opened again, this time in write mode using `open(file_path, "w", newline="")`.

13. A `csv.writer` is created to write the modified rows back to the CSV file using `csv_writer.writerows(reordered_rows)`.

14. Finally, the file is closed, and the loop continues to the next file in the folder.

This code ensures that all car types appear in the CSV files, even if the number of vehicles for a fuel type is 0. It repeats the car types and adds rows with missing car types to the CSV file. The rows are then reordered to match the repeated car types, and the modified rows are written back to the same file.

Appendix B: HVIMPACT Detailed Results

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
California	Bus	Natural Gas	0	0	0	0	285	704
California	Truck/Van	Natural Gas	0	0	25	81	216	375
California	Misc/Other	Natural Gas	0	0	244	527	740	975
California	Bus	ZEV-BEV	33	60	121	155	347	677
California	Truck/Van	ZEV-BEV	5	10	17	73	143	219
California	Misc/Other	ZEV-BEV	1	1	1	1	3	16
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
California	Bus	Natural Gas	8,672	9,101	9,602	10,829	10,139	10,106
California	Truck/Van	Natural Gas	7,987	8,543	9,739	10,954	11,697	13,682
California	Misc/Other	Natural Gas	2,723	2,365	2,843	2,570	2,767	2,487
California	Bus	ZEV-BEV	569	640	558	712	896	1,115
California	Truck/Van	ZEV-BEV	214	254	229	323	773	622
California	Misc/Other	ZEV-BEV	627	619	609	578	349	3636
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
California	Bus	Natural Gas	0	0	0	0	2.81	6.97
California	Truck/Van	Natural Gas	0	0	0.88	3.15	7.81	15.08
California	Misc/Other	Natural Gas	0	0	8.58	20.51	26.74	39.20
California	Bus	ZEV-BEV	5.80	9.38	21.68	21.77	38.73	60.72
California	Truck/Van	ZEV-BEV	2.34	3.94	7.42	22.60	18.50	35.21
California	Misc/Other	ZEV-BEV	0.16	0.16	0.16	0.17	0.86	0.44

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
AlamedaSF	Bus	Natural Gas	0	0	0	0	0	0
AlamedaSF	Truck/Van	Natural Gas	0	0	0	0	2	2
AlamedaSF	Misc/Other	Natural Gas	0	0	0	0	0	43
AlamedaSF	Bus	ZEV-BEV	0	0	0	0	11	25
AlamedaSF	Truck/Van	ZEV-BEV	0	1	1	7	12	15
AlamedaSF	Misc/Other	ZEV-BEV	0	0	0	0	0	2
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
AlamedaSF	Bus	Natural Gas	0	0	0	0	0	0
AlamedaSF	Truck/Van	Natural Gas	21	20	20	21	20	20
AlamedaSF	Misc/Other	Natural Gas	33	31	52	45	36	28
AlamedaSF	Bus	ZEV-BEV	8	8	8	8	9	27
AlamedaSF	Truck/Van	ZEV-BEV	0	0	0	0	6	6
AlamedaSF	Misc/Other	ZEV-BEV	0	0	0	2	1	7
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
AlamedaSF	Bus	Natural Gas	0	0	0	0	0	0
AlamedaSF	Truck/Van	Natural Gas	0	0	0	0	10	10
AlamedaSF	Misc/Other	Natural Gas	0	0	0	0	0	153.57
AlamedaSF	Bus	ZEV-BEV	0	0	0	0	122.22	92.59
AlamedaSF	Truck/Van	ZEV-BEV	0	0	0	0	200	250
AlamedaSF	Misc/Other	ZEV-BEV	0	0	0	0	0	28.57

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
ButteSV	Bus	Natural Gas	0	0	0	0	0	0
ButteSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ButteSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ButteSV	Bus	ZEV-BEV	0	0	0	0	0	1
ButteSV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ButteSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ButteSV	Bus	Natural Gas	0	0	0	0	0	0
ButteSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ButteSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ButteSV	Bus	ZEV-BEV	0	0	0	2	3	13
ButteSV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ButteSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ButteSV	Bus	Natural Gas	0	0	0	0	0	0
ButteSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ButteSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ButteSV	Bus	ZEV-BEV	0	0	0	0	0	7.69
ButteSV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ButteSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
ContraCostaSF	Bus	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Truck/Van	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Misc/Other	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Bus	ZEV-BEV	0	1	1	7	10	11
ContraCostaSF	Truck/Van	ZEV-BEV	1	1	1	1	2	5
ContraCostaSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ContraCostaSF	Bus	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Truck/Van	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Misc/Other	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Bus	ZEV-BEV	0	0	0	4	6	9
ContraCostaSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ContraCostaSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ContraCostaSF	Bus	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Truck/Van	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Misc/Other	Natural Gas	0	0	0	0	0	0
ContraCostaSF	Bus	ZEV-BEV	0	0	0	175	166.67	122.22
ContraCostaSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ContraCostaSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
ElDoradoLT	Bus	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Truck/Van	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Misc/Other	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Bus	ZEV-BEV	0	0	0	0	0	2
ElDoradoLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ElDoradoLT	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ElDoradoLT	Bus	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Truck/Van	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Misc/Other	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Bus	ZEV-BEV	0	0	0	0	0	2
ElDoradoLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ElDoradoLT	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ElDoradoLT	Bus	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Truck/Van	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Misc/Other	Natural Gas	0	0	0	0	0	0
ElDoradoLT	Bus	ZEV-BEV	0	0	0	0	0	100
ElDoradoLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ElDoradoLT	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
FresnoSJV	Bus	Natural Gas	0	0	0	0	0	0
FresnoSJV	Truck/Van	Natural Gas	0	0	0	0	9	9
FresnoSJV	Misc/Other	Natural Gas	0	0	0	0	0	1
FresnoSJV	Bus	ZEV-BEV	0	0	6	8	14	19
FresnoSJV	Truck/Van	ZEV-BEV	0	0	0	2	2	2
FresnoSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
FresnoSJV	Bus	Natural Gas	0	0	0	0	0	0
FresnoSJV	Truck/Van	Natural Gas	2	2	2	3	3	4
FresnoSJV	Misc/Other	Natural Gas	121	146	201	203	243	255
FresnoSJV	Bus	ZEV-BEV	0	0	0	0	12	22
FresnoSJV	Truck/Van	ZEV-BEV	0	0	0	0	1	0
FresnoSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
FresnoSJV	Bus	Natural Gas	0	0	0	0	0	0
FresnoSJV	Truck/Van	Natural Gas	0	0	0	0	300	225
FresnoSJV	Misc/Other	Natural Gas	0	0	0	0	0	0.39
FresnoSJV	Bus	ZEV-BEV	0	0	0	0	116.67	86.36
FresnoSJV	Truck/Van	ZEV-BEV	0	0	0	0	200	0
FresnoSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
HumboldtNC	Bus	Natural Gas	0	0	0	0	0	0
HumboldtNC	Truck/Van	Natural Gas	0	0	0	0	0	0
HumboldtNC	Misc/Other	Natural Gas	0	0	0	0	0	0
HumboldtNC	Bus	ZEV-BEV	0	0	0	0	1	1
HumboldtNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
HumboldtNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
HumboldtNC	Bus	Natural Gas	0	0	0	0	0	0
HumboldtNC	Truck/Van	Natural Gas	0	0	0	0	0	0
HumboldtNC	Misc/Other	Natural Gas	0	0	0	0	0	0
HumboldtNC	Bus	ZEV-BEV	0	0	0	0	1	1
HumboldtNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
HumboldtNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
HumboldtNC	Bus	Natural Gas	0	0	0	0	0	0
HumboldtNC	Truck/Van	Natural Gas	0	0	0	0	0	0
HumboldtNC	Misc/Other	Natural Gas	0	0	0	0	0	0
HumboldtNC	Bus	ZEV-BEV	0	0	0	0	100	100
HumboldtNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
HumboldtNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
KernMD	Bus	Natural Gas	0	0	0	0	0	0
KernMD	Truck/Van	Natural Gas	0	0	0	0	4	25
KernMD	Misc/Other	Natural Gas	0	0	0	0	4	4
KernMD	Bus	ZEV-BEV	3	4	4	4	4	9
KernMD	Truck/Van	ZEV-BEV	1	1	1	4	4	6
KernMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
KernMD	Bus	Natural Gas	0	0	0	0	0	0
KernMD	Truck/Van	Natural Gas	0	0	0	0	0	1
KernMD	Misc/Other	Natural Gas	9	3	0	8	0	14
KernMD	Bus	ZEV-BEV	3	1	1	0	1	4
KernMD	Truck/Van	ZEV-BEV	0	0	0	0	2	2
KernMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
KernMD	Bus	Natural Gas	0	0	0	0	0	0
KernMD	Truck/Van	Natural Gas	0	0	0	0	0	2500
KernMD	Misc/Other	Natural Gas	0	0	0	0	0	28.57
KernMD	Bus	ZEV-BEV	100	400	400	0	400	225
KernMD	Truck/Van	ZEV-BEV	0	0	0	0	200	300
KernMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
LosAngelesMD	Bus	Natural Gas	0	0	0	0	253	631
LosAngelesMD	Truck/Van	Natural Gas	0	0	0	31	95	189
LosAngelesMD	Misc/Other	Natural Gas	0	0	136	386	508	671
LosAngelesMD	Bus	ZEV-BEV	18	32	66	81	116	286
LosAngelesMD	Truck/Van	ZEV-BEV	1	3	8	25	38	43
LosAngelesMD	Misc/Other	ZEV-BEV	0	0	0	0	0	3
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
LosAngelesMD	Bus	Natural Gas	41	41	41	41	41	48
LosAngelesMD	Truck/Van	Natural Gas	1	2	1	3	3	6
LosAngelesMD	Misc/Other	Natural Gas	51	48	93	78	100	367
LosAngelesMD	Bus	ZEV-BEV	2	2	5	26	49	54
LosAngelesMD	Truck/Van	ZEV-BEV	0	0	0	0	0	0
LosAngelesMD	Misc/Other	ZEV-BEV	0	0	0	0	2	1
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
LosAngelesMD	Bus	Natural Gas	0	0	0	0	617.07	1314.58
LosAngelesMD	Truck/Van	Natural Gas	0	0	0	1033.33	3166.67	3150
LosAngelesMD	Misc/Other	Natural Gas	0	0	146.24	494.87	508	182.83
LosAngelesMD	Bus	ZEV-BEV	900	1600	1320	311.54	236.73	529.63
LosAngelesMD	Truck/Van	ZEV-BEV	0	0	0	0	0	0
LosAngelesMD	Misc/Other	ZEV-BEV	0	0	0	0	0	300

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
MarinSF	Bus	Natural Gas	0	0	0	0	0	0
MarinSF	Truck/Van	Natural Gas	0	0	0	0	0	0
MarinSF	Misc/Other	Natural Gas	0	0	0	0	0	0
MarinSF	Bus	ZEV-BEV	0	0	0	0	1	2
MarinSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MarinSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MarinSF	Bus	Natural Gas	0	0	0	0	0	0
MarinSF	Truck/Van	Natural Gas	0	0	0	0	0	0
MarinSF	Misc/Other	Natural Gas	0	0	0	0	0	0
MarinSF	Bus	ZEV-BEV	0	0	0	0	2	2
MarinSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MarinSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MarinSF	Bus	Natural Gas	0	0	0	0	0	0
MarinSF	Truck/Van	Natural Gas	0	0	0	0	0	0
MarinSF	Misc/Other	Natural Gas	0	0	0	0	0	0
MarinSF	Bus	ZEV-BEV	0	0	0	0	50	100
MarinSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MarinSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
MariposaMC	Bus	Natural Gas	0	0	0	0	0	0
MariposaMC	Truck/Van	Natural Gas	0	0	0	0	0	0
MariposaMC	Misc/Other	Natural Gas	0	0	0	0	0	0
MariposaMC	Bus	ZEV-BEV	0	0	0	0	2	2
MariposaMC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MariposaMC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MariposaMC	Bus	Natural Gas	0	0	0	0	0	0
MariposaMC	Truck/Van	Natural Gas	0	0	0	0	0	0
MariposaMC	Misc/Other	Natural Gas	0	0	0	0	0	0
MariposaMC	Bus	ZEV-BEV	0	0	0	0	0	0
MariposaMC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MariposaMC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MariposaMC	Bus	Natural Gas	0	0	0	0	0	0
MariposaMC	Truck/Van	Natural Gas	0	0	0	0	0	0
MariposaMC	Misc/Other	Natural Gas	0	0	0	0	0	0
MariposaMC	Bus	ZEV-BEV	0	0	0	0	100	100
MariposaMC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MariposaMC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
MendocinoNC	Bus	Natural Gas	0	0	0	0	0	0
MendocinoNC	Truck/Van	Natural Gas	0	0	0	0	0	0
MendocinoNC	Misc/Other	Natural Gas	0	0	0	0	0	0
MendocinoNC	Bus	ZEV-BEV	0	0	0	0	0	0
MendocinoNC	Truck/Van	ZEV-BEV	0	0	0	0	0	2
MendocinoNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MendocinoNC	Bus	Natural Gas	0	0	0	0	0	0
MendocinoNC	Truck/Van	Natural Gas	0	0	0	0	0	0
MendocinoNC	Misc/Other	Natural Gas	0	0	0	0	0	0
MendocinoNC	Bus	ZEV-BEV	0	0	0	0	0	0
MendocinoNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MendocinoNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MendocinoNC	Bus	Natural Gas	0	0	0	0	0	0
MendocinoNC	Truck/Van	Natural Gas	0	0	0	0	0	0
MendocinoNC	Misc/Other	Natural Gas	0	0	0	0	0	0
MendocinoNC	Bus	ZEV-BEV	0	0	0	0	0	0
MendocinoNC	Truck/Van	ZEV-BEV	0	0	0	0	0	100
MendocinoNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
MontereyNCC	Bus	Natural Gas	0	0	0	0	0	0
MontereyNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
MontereyNCC	Misc/Other	Natural Gas	0	0	0	0	0	0
MontereyNCC	Bus	ZEV-BEV	0	0	0	2	4	9
MontereyNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MontereyNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MontereyNCC	Bus	Natural Gas	0	0	0	0	0	0
MontereyNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
MontereyNCC	Misc/Other	Natural Gas	0	0	0	0	0	0
MontereyNCC	Bus	ZEV-BEV	0	0	0	2	4	7
MontereyNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MontereyNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
MontereyNCC	Bus	Natural Gas	0	0	0	0	0	0
MontereyNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
MontereyNCC	Misc/Other	Natural Gas	0	0	0	0	0	0
MontereyNCC	Bus	ZEV-BEV	0	0	0	100	100	128.57
MontereyNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
MontereyNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
OrangeSC	Bus	Natural Gas	0	0	0	0	0	21
OrangeSC	Truck/Van	Natural Gas	0	0	25	36	65	66
OrangeSC	Misc/Other	Natural Gas	0	0	0	0	1	2
OrangeSC	Bus	ZEV-BEV	0	4	4	4	35	40
OrangeSC	Truck/Van	ZEV-BEV	0	1	1	5	11	13
OrangeSC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

DMV Data	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
OrangeSC	Bus	Natural Gas	135	141	192	199	276	300
OrangeSC	Truck/Van	Natural Gas	39	40	62	63	62	62
OrangeSC	Misc/Other	Natural Gas	932	944	1098	1130	1094	1052
OrangeSC	Bus	ZEV-BEV	1	1	6	27	31	36
OrangeSC	Truck/Van	ZEV-BEV	4	4	4	6	38	18
OrangeSC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Impact (%)	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
OrangeSC	Bus	Natural Gas	0	0	0	0	0	7
OrangeSC	Truck/Van	Natural Gas	0	0	40.32	57.14	104.84	106.45
OrangeSC	Misc/Other	Natural Gas	0	0	0	0	0.09	0.19
OrangeSC	Bus	ZEV-BEV	0	400	66.67	14.81	112.90	111.11
OrangeSC	Truck/Van	ZEV-BEV	0	25	25	83.33	28.95	72.22
OrangeSC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
PlacerLT	Bus	Natural Gas	0	0	0	0	0	0
PlacerLT	Truck/Van	Natural Gas	0	0	0	0	0	0
PlacerLT	Misc/Other	Natural Gas	0	0	0	0	0	0
PlacerLT	Bus	ZEV-BEV	0	0	0	0	2	5
PlacerLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
PlacerLT	Misc/Other	ZEV-BEV	0	0	0	0	0	1
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
PlacerLT	Bus	Natural Gas	0	0	0	0	0	0
PlacerLT	Truck/Van	Natural Gas	0	0	0	0	0	0
PlacerLT	Misc/Other	Natural Gas	0	0	0	0	0	0
PlacerLT	Bus	ZEV-BEV	0	0	0	0	0	0
PlacerLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
PlacerLT	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
PlacerLT	Bus	Natural Gas	0	0	0	0	0	0
PlacerLT	Truck/Van	Natural Gas	0	0	0	0	0	0
PlacerLT	Misc/Other	Natural Gas	0	0	0	0	0	0
PlacerLT	Bus	ZEV-BEV	0	0	0	0	100	100
PlacerLT	Truck/Van	ZEV-BEV	0	0	0	0	0	0
PlacerLT	Misc/Other	ZEV-BEV	0	0	0	0	0	100

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
RiversideMD	Bus	Natural Gas	0	0	0	0	0	0
RiversideMD	Truck/Van	Natural Gas	0	0	0	0	0	14
RiversideMD	Misc/Other	Natural Gas	0	0	0	3	3	7
RiversideMD	Bus	ZEV-BEV	0	0	0	4	8	11
RiversideMD	Truck/Van	ZEV-BEV	0	0	0	3	5	24
RiversideMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
RiversideMD	Bus	Natural Gas	0	0	0	0	0	0
RiversideMD	Truck/Van	Natural Gas	0	0	0	0	0	0
RiversideMD	Misc/Other	Natural Gas	5	5	0	14	14	44
RiversideMD	Bus	ZEV-BEV	0	0	0	0	0	0
RiversideMD	Truck/Van	ZEV-BEV	0	0	0	0	0	0
RiversideMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
RiversideMD	Bus	Natural Gas	0	0	0	0	0	0
RiversideMD	Truck/Van	Natural Gas	0	0	0	0	0	100
RiversideMD	Misc/Other	Natural Gas	0	0	0	21.43	21.43	15.91
RiversideMD	Bus	ZEV-BEV	0	0	0	100	100	100
RiversideMD	Truck/Van	ZEV-BEV	0	0	0	100	100	100
RiversideMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SacramentoSV	Bus	Natural Gas	0	0	0	0	1	1
SacramentoSV	Truck/Van	Natural Gas	0	0	0	0	5	5
SacramentoSV	Misc/Other	Natural Gas	0	0	0	8	17	31
SacramentoSV	Bus	ZEV-BEV	0	0	0	0	18	29
SacramentoSV	Truck/Van	ZEV-BEV	0	0	0	0	2	11
SacramentoSV	Misc/Other	ZEV-BEV	0	0	0	0	0	1
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SacramentoSV	Bus	Natural Gas	379	339	344	399	282	276
SacramentoSV	Truck/Van	Natural Gas	4	4	8	12	16	18
SacramentoSV	Misc/Other	Natural Gas	357	370	405	447	528	578
SacramentoSV	Bus	ZEV-BEV	6	6	13	21	39	46
SacramentoSV	Truck/Van	ZEV-BEV	0	0	0	0	2	4
SacramentoSV	Misc/Other	ZEV-BEV	0	0	0	0	0	2
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SacramentoSV	Bus	Natural Gas	0	0	0	0	0.35	0.36
SacramentoSV	Truck/Van	Natural Gas	0	0	0	0	31.25	27.78
SacramentoSV	Misc/Other	Natural Gas	0	0	0	1.79	3.22	5.36
SacramentoSV	Bus	ZEV-BEV	0	0	0	0	46.15	63.04
SacramentoSV	Truck/Van	ZEV-BEV	0	0	0	0	100	275
SacramentoSV	Misc/Other	ZEV-BEV	0	0	0	0	0	50

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanBenitoNCC	Bus	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	Natural Gas	0	0	0	0	0	1
SanBenitoNCC	Bus	ZEV-BEV	0	0	0	0	0	0
SanBenitoNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanBenitoNCC	Bus	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Bus	ZEV-BEV	0	0	0	0	0	1
SanBenitoNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanBenitoNCC	Bus	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SanBenitoNCC	Bus	ZEV-BEV	0	0	0	0	0	100
SanBenitoNCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanBenitoNCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanBernardinoMD	Bus	Natural Gas	0	0	0	0	17	23
SanBernardinoMD	Truck/Van	Natural Gas	0	0	0	1	18	51
SanBernardinoMD	Misc/Other	Natural Gas	0	0	86	91	142	143
SanBernardinoMD	Bus	ZEV-BEV	0	0	1	1	4	17
SanBernardinoMD	Truck/Van	ZEV-BEV	0	0	0	5	16	35
SanBernardinoMD	Misc/Other	ZEV-BEV	0	0	0	0	1	2
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanBernardinoMD	Bus	Natural Gas	15	15	14	13	13	13
SanBernardinoMD	Truck/Van	Natural Gas	0	0	0	0	0	0
SanBernardinoMD	Misc/Other	Natural Gas	1	0	1	0	0	2
SanBernardinoMD	Bus	ZEV-BEV	0	0	0	0	0	1
SanBernardinoMD	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanBernardinoMD	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanBernardinoMD	Bus	Natural Gas	0	0	0	0	130.77	176.92
SanBernardinoMD	Truck/Van	Natural Gas	0	0	0	0	0	0
SanBernardinoMD	Misc/Other	Natural Gas	0	0	100	100	100	100
SanBernardinoMD	Bus	ZEV-BEV	0	0	100	100	100	100
SanBernardinoMD	Truck/Van	ZEV-BEV	0	0	0	100	100	100
SanBernardinoMD	Misc/Other	ZEV-BEV	0	0	0	0	100	100

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanDiegoSD	Bus	Natural Gas	0	0	0	0	14	14
SanDiegoSD	Truck/Van	Natural Gas	0	0	0	4	4	6
SanDiegoSD	Misc/Other	Natural Gas	0	0	19	30	33	33
SanDiegoSD	Bus	ZEV-BEV	2	3	3	3	10	33
SanDiegoSD	Truck/Van	ZEV-BEV	0	0	1	3	13	18
SanDiegoSD	Misc/Other	ZEV-BEV	0	0	0	0	0	0

DMV Data	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanDiegoSD	Bus	Natural Gas	536	496	532	769	626	636
SanDiegoSD	Truck/Van	Natural Gas	3	3	6	10	16	31
SanDiegoSD	Misc/Other	Natural Gas	333	265	286	276	248	41
SanDiegoSD	Bus	ZEV-BEV	2	2	1	1	6	13
SanDiegoSD	Truck/Van	ZEV-BEV	0	0	0	0	2	1
SanDiegoSD	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Impact (%)	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanDiegoSD	Bus	Natural Gas	0	0	0	0	2.24	2.20
SanDiegoSD	Truck/Van	Natural Gas	0	0	0	40	25	19.35
SanDiegoSD	Misc/Other	Natural Gas	0	0	6.64	10.87	13.31	80.49
SanDiegoSD	Bus	ZEV-BEV	100	150	300	300	166.67	253.85
SanDiegoSD	Truck/Van	ZEV-BEV	0	0	100	100	100	100
SanDiegoSD	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanFranciscoSF	Bus	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Bus	ZEV-BEV	0	2	2	2	19	19
SanFranciscoSF	Truck/Van	ZEV-BEV	0	0	0	3	4	4
SanFranciscoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

DMV Data	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanFranciscoSF	Bus	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Bus	ZEV-BEV	431	491	363	371	422	402
SanFranciscoSF	Truck/Van	ZEV-BEV	2	2	0	0	4	6
SanFranciscoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Impact (%)	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanFranciscoSF	Bus	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SanFranciscoSF	Bus	ZEV-BEV	0	0.41	0.55	0.54	4.50	4.73
SanFranciscoSF	Truck/Van	ZEV-BEV	0	0	0	100	100	66.67
SanFranciscoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanJoaquinSJV	Bus	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Bus	ZEV-BEV	0	0	8	8	13	13
SanJoaquinSJV	Truck/Van	ZEV-BEV	0	0	0	1	13	13
SanJoaquinSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanJoaquinSJV	Bus	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Bus	ZEV-BEV	2	2	12	16	17	17
SanJoaquinSJV	Truck/Van	ZEV-BEV	0	0	0	0	2	0
SanJoaquinSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SanJoaquinSJV	Bus	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
SanJoaquinSJV	Bus	ZEV-BEV	0	0	66.67	50	76.47	76.47
SanJoaquinSJV	Truck/Van	ZEV-BEV	0	0	0	100	100	100
SanJoaquinSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanLuisObispoSCC	Bus	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Bus	ZEV-BEV	0	0	0	0	0	1
SanLuisObispoSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	ZEV-BEV	0	0	0	0	1	4

DMV Data	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanLuisObispoSCC	Bus	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Bus	ZEV-BEV	0	0	0	0	0	1
SanLuisObispoSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	ZEV-BEV	32	36	45	47	48	61

HVIP Impact (%)	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanLuisObispoSCC	Bus	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SanLuisObispoSCC	Bus	ZEV-BEV	0	0	0	0	0	100
SanLuisObispoSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SanLuisObispoSCC	Misc/Other	ZEV-BEV	0	0	0	0	2.08	6.56

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanMateoSF	Bus	Natural Gas	0	0	0	0	0	0
SanMateoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanMateoSF	Misc/Other	Natural Gas	0	0	0	0	4	8
SanMateoSF	Bus	ZEV-BEV	3	3	3	5	8	42
SanMateoSF	Truck/Van	ZEV-BEV	1	1	1	1	3	3
SanMateoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

DMV Data	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanMateoSF	Bus	Natural Gas	0	0	0	0	0	0
SanMateoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanMateoSF	Misc/Other	Natural Gas	57	59	76	77	80	144
SanMateoSF	Bus	ZEV-BEV	0	9	13	23	32	32
SanMateoSF	Truck/Van	ZEV-BEV	0	0	0	1	1	1
SanMateoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Impact (%)	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SanMateoSF	Bus	Natural Gas	0	0	0	0	0	0
SanMateoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SanMateoSF	Misc/Other	Natural Gas	0	0	0	0	5	5.56
SanMateoSF	Bus	ZEV-BEV	100	33.33	23.08	21.74	25	131.25
SanMateoSF	Truck/Van	ZEV-BEV	100	100	100	100	300	300
SanMateoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SantaBarbaraSCC	Bus	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Bus	ZEV-BEV	0	0	0	1	1	15
SantaBarbaraSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SantaBarbaraSCC	Bus	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Bus	ZEV-BEV	19	19	19	31	24	20
SantaBarbaraSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SantaBarbaraSCC	Bus	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	Natural Gas	0	0	0	0	0	0
SantaBarbaraSCC	Bus	ZEV-BEV	0	0	0	3.23	4.17	75
SantaBarbaraSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SantaBarbaraSCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SantaClaraSF	Bus	Natural Gas	0	0	0	0	0	0
SantaClaraSF	Truck/Van	Natural Gas	0	0	0	0	6	12
SantaClaraSF	Misc/Other	Natural Gas	0	0	0	6	11	13
SantaClaraSF	Bus	ZEV-BEV	10	14	24	28	57	74
SantaClaraSF	Truck/Van	ZEV-BEV	0	0	0	5	6	6
SantaClaraSF	Misc/Other	ZEV-BEV	0	0	0	0	0	3
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SantaClaraSF	Bus	Natural Gas	0	0	0	0	0	0
SantaClaraSF	Truck/Van	Natural Gas	1	1	1	2	6	2
SantaClaraSF	Misc/Other	Natural Gas	335	335	386	453	490	483
SantaClaraSF	Bus	ZEV-BEV	18	27	26	47	58	69
SantaClaraSF	Truck/Van	ZEV-BEV	0	0	0	0	10	4
SantaClaraSF	Misc/Other	ZEV-BEV	0	1	1	1	2	2
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SantaClaraSF	Bus	Natural Gas	0	0	0	0	0	0
SantaClaraSF	Truck/Van	Natural Gas	0	0	0	0	100	600
SantaClaraSF	Misc/Other	Natural Gas	0	0	0	1.32	2.24	2.69
SantaClaraSF	Bus	ZEV-BEV	55.56	51.85	92.31	59.57	98.28	107.25
SantaClaraSF	Truck/Van	ZEV-BEV	0	0	0	100	60	150
SantaClaraSF	Misc/Other	ZEV-BEV	0	0	0	0	0	150

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
ShastaSV	Bus	Natural Gas	0	0	0	0	0	0
ShastaSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ShastaSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ShastaSV	Bus	ZEV-BEV	0	0	0	0	1	3
ShastaSV	Truck/Van	ZEV-BEV	0	0	1	1	1	1
ShastaSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ShastaSV	Bus	Natural Gas	0	0	0	0	0	0
ShastaSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ShastaSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ShastaSV	Bus	ZEV-BEV	0	0	0	1	4	8
ShastaSV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
ShastaSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ShastaSV	Bus	Natural Gas	0	0	0	0	0	0
ShastaSV	Truck/Van	Natural Gas	0	0	0	0	0	0
ShastaSV	Misc/Other	Natural Gas	0	0	0	0	0	0
ShastaSV	Bus	ZEV-BEV	0	0	0	0	25	37.5
ShastaSV	Truck/Van	ZEV-BEV	0	0	100	100	100	100
ShastaSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SolanoSF	Bus	Natural Gas	0	0	0	0	0	0
SolanoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SolanoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SolanoSF	Bus	ZEV-BEV	0	0	2	2	2	10
SolanoSF	Truck/Van	ZEV-BEV	0	0	0	1	1	1
SolanoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SolanoSF	Bus	Natural Gas	0	0	0	0	0	0
SolanoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SolanoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SolanoSF	Bus	ZEV-BEV	0	0	2	2	2	9
SolanoSF	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SolanoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SolanoSF	Bus	Natural Gas	0	0	0	0	0	0
SolanoSF	Truck/Van	Natural Gas	0	0	0	0	0	0
SolanoSF	Misc/Other	Natural Gas	0	0	0	0	0	0
SolanoSF	Bus	ZEV-BEV	0	0	100	100	100	111.11
SolanoSF	Truck/Van	ZEV-BEV	0	0	0	100	100	100
SolanoSF	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SonomaNC	Bus	Natural Gas	0	0	0	0	0	0
SonomaNC	Truck/Van	Natural Gas	0	0	0	0	0	0
SonomaNC	Misc/Other	Natural Gas	0	0	0	0	0	0
SonomaNC	Bus	ZEV-BEV	0	0	0	0	3	7
SonomaNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SonomaNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SonomaNC	Bus	Natural Gas	0	0	0	0	0	0
SonomaNC	Truck/Van	Natural Gas	0	0	0	0	0	0
SonomaNC	Misc/Other	Natural Gas	0	0	0	0	0	0
SonomaNC	Bus	ZEV-BEV	0	0	0	1	1	3
SonomaNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SonomaNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SonomaNC	Bus	Natural Gas	0	0	0	0	0	0
SonomaNC	Truck/Van	Natural Gas	0	0	0	0	0	0
SonomaNC	Misc/Other	Natural Gas	0	0	0	0	0	0
SonomaNC	Bus	ZEV-BEV	0	0	0	0	300	233.33
SonomaNC	Truck/Van	ZEV-BEV	0	0	0	0	0	0
SonomaNC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
StanislausSJV	Bus	Natural Gas	0	0	0	0	0	0
StanislausSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
StanislausSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
StanislausSJV	Bus	ZEV-BEV	0	0	0	0	0	0
StanislausSJV	Truck/Van	ZEV-BEV	0	1	1	2	4	10
StanislausSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
StanislausSJV	Bus	Natural Gas	0	0	0	0	0	0
StanislausSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
StanislausSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
StanislausSJV	Bus	ZEV-BEV	0	0	0	0	0	0
StanislausSJV	Truck/Van	ZEV-BEV	10	2	2	2	2	10
StanislausSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
StanislausSJV	Bus	Natural Gas	0	0	0	0	0	0
StanislausSJV	Truck/Van	Natural Gas	0	0	0	0	0	0
StanislausSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
StanislausSJV	Bus	ZEV-BEV	0	0	0	0	0	0
StanislausSJV	Truck/Van	ZEV-BEV	0	50	50	100	200	100
StanislausSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
SutterSV	Bus	Natural Gas	0	0	0	0	0	0
SutterSV	Truck/Van	Natural Gas	0	0	0	0	0	0
SutterSV	Misc/Other	Natural Gas	0	0	0	0	0	0
SutterSV	Bus	ZEV-BEV	0	0	0	0	0	0
SutterSV	Truck/Van	ZEV-BEV	0	0	0	0	1	1
SutterSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SutterSV	Bus	Natural Gas	0	0	0	0	0	0
SutterSV	Truck/Van	Natural Gas	0	0	0	0	0	0
SutterSV	Misc/Other	Natural Gas	0	0	0	0	0	0
SutterSV	Bus	ZEV-BEV	0	0	0	0	0	0
SutterSV	Truck/Van	ZEV-BEV	0	0	0	0	1	1
SutterSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
SutterSV	Bus	Natural Gas	0	0	0	0	0	0
SutterSV	Truck/Van	Natural Gas	0	0	0	0	0	0
SutterSV	Misc/Other	Natural Gas	0	0	0	0	0	0
SutterSV	Bus	ZEV-BEV	0	0	0	0	0	0
SutterSV	Truck/Van	ZEV-BEV	0	0	0	0	100	100
SutterSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
TulareSJV	Bus	Natural Gas	0	0	0	0	0	0
TulareSJV	Truck/Van	Natural Gas	0	0	0	0	0	2
TulareSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
TulareSJV	Bus	ZEV-BEV	0	0	0	0	3	11
TulareSJV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
TulareSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
TulareSJV	Bus	Natural Gas	0	0	0	0	0	0
TulareSJV	Truck/Van	Natural Gas	1	1	1	1	1	1
TulareSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
TulareSJV	Bus	ZEV-BEV	0	0	0	0	2	9
TulareSJV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
TulareSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
TulareSJV	Bus	Natural Gas	0	0	0	0	0	0
TulareSJV	Truck/Van	Natural Gas	0	0	0	0	0	200
TulareSJV	Misc/Other	Natural Gas	0	0	0	0	0	0
TulareSJV	Bus	ZEV-BEV	0	0	0	0	150	122.22
TulareSJV	Truck/Van	ZEV-BEV	0	0	0	0	0	0
TulareSJV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
VenturaSCC	Bus	Natural Gas	0	0	0	0	0	14
VenturaSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
VenturaSCC	Misc/Other	Natural Gas	0	0	3	3	17	19
VenturaSCC	Bus	ZEV-BEV	0	0	0	0	0	0
VenturaSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	1
VenturaSCC	Misc/Other	ZEV-BEV	1	1	1	1	1	1
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
VenturaSCC	Bus	Natural Gas	7	6	8	8	8	8
VenturaSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
VenturaSCC	Misc/Other	Natural Gas	71	72	74	76	94	90
VenturaSCC	Bus	ZEV-BEV	0	0	0	0	0	0
VenturaSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	1
VenturaSCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
VenturaSCC	Bus	Natural Gas	0	0	0	0	0	175
VenturaSCC	Truck/Van	Natural Gas	0	0	0	0	0	0
VenturaSCC	Misc/Other	Natural Gas	0	0	4.05	3.95	18.09	21.11
VenturaSCC	Bus	ZEV-BEV	0	0	0	0	0	0
VenturaSCC	Truck/Van	ZEV-BEV	0	0	0	0	0	100
VenturaSCC	Misc/Other	ZEV-BEV	0	0	0	0	0	0

HVIP Funded	Vehicle Category	Fuel Type	2015	2016	2017	2018	2019	2020
YoloSV	Bus	Natural Gas	0	0	0	0	0	0
YoloSV	Truck/Van	Natural Gas	0	0	0	0	0	0
YoloSV	Misc/Other	Natural Gas	0	0	0	0	0	0
YoloSV	Bus	ZEV-BEV	0	0	0	0	4	13
YoloSV	Truck/Van	ZEV-BEV	1	1	1	4	5	5
YoloSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
DMV Data	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
YoloSV	Bus	Natural Gas	0	0	0	0	0	0
YoloSV	Truck/Van	Natural Gas	0	0	0	0	0	0
YoloSV	Misc/Other	Natural Gas	0	0	0	0	0	0
YoloSV	Bus	ZEV-BEV	0	0	0	0	4	12
YoloSV	Truck/Van	ZEV-BEV	0	0	0	0	2	2
YoloSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0
HVIP Impact (%)	**Vehicle Category**	**Fuel Type**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
YoloSV	Bus	Natural Gas	0	0	0	0	0	0
YoloSV	Truck/Van	Natural Gas	0	0	0	0	0	0
YoloSV	Misc/Other	Natural Gas	0	0	0	0	0	0
YoloSV	Bus	ZEV-BEV	0	0	0	0	100	108.3333
YoloSV	Truck/Van	ZEV-BEV	0	0	0	0	250	250
YoloSV	Misc/Other	ZEV-BEV	0	0	0	0	0	0

Appendix C: Specific Survey Question Recommendations

(No recommended improvements)
G5. [READ ONCE FOR EACH TYPE OF VEHICLE LISTED AS GREATER THAN 0 FROM SQ1-SQ2] Would you have purchased/leased your [type of vehicle] if HVIP funding was not available?

a. Yes
b. No
c. Don't know

(New Question – Read once for each type of vehicle listed)
GX. What vehicle would you have purchased/leased your [type of vehicle] if HVIP funding was not available?

a. Vehicle description:

(New Question – Read once for each type of vehicle listed)
GX. Please list the full retail price for *each vehicle* in your fleet that received HVIP support.

a. Vehicle description:
b. Full retail price:

(New Question – Read once for each type of vehicle listed)
GX. Please list all sources of incentive funding for *each vehicle* in your fleet that received HVIP support

a. Vehicle description:
b. HVIP voucher amount:
c. Federal Lo-No incentive amount:
d. Local air district incentive support:
e. Other incentive support:

(Add impact statements to help anchor the number values)
G7. [READ ONCE FOR EACH TYPE OF VEHICLE LISTED AS GREATER THAN 0 FROM SQ1-SQ2] How important was the HVIP voucher in making your purchase decision on a scale of 1 to 5, where 1 means "The HVIP voucher program had no impact on my purchase decision" and 5 means "The HVIP voucher program had a great deal of impact on my purchase decision"?

a. 1 – no impact
b. 2 – small impact
c. 3 – neutral
d. 4 – significant impact
e. 5 – great deal of impact
f. Don't know