Clean Transportation Market and Impact Evaluation: Impact Report

Final Report

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Table of Contents

List of Figures

List of Tables

1 Introduction

This report provides an evaluation of direct and indirect impacts from NYSERDA's Drive Clean Electric Vehicle (EV) Rebate program. The direct impact analysis identifies the number of Battery Electric Vehicles (BEV) and Plug-In Hybrid Electric Vehicles (PHEV) on the road and the associated MMBtu savings that were influenced by the Drive Clean program. These direct impacts include Verified Gross Savings (VGS) brought about by the Drive Clean program. The direct impact analysis also addresses the Estimated Net Savings (ENS) based on participants' counterfactual vehicles (the vehicles that they would have purchased in the absence of the Drive Clean program), identified through participant surveys. The indirect impact analysis assesses the number of additional vehicles that will be on the road by 2030 and beyond as a result of the Drive Clean program. Indirect impact estimates use the VGS estimates to calculate indirect MMBtu savings from these additional vehicles on the road.

The direct impact analysis used survey data to estimate rebated vehicle miles driven, miles per gallon (MPG) for baseline vehicles, and miles per gallon equivalents (MPGe) for rebated vehicles. The analysis also uses survey responses to determine program influence; in other words, to answer the question "Would this vehicle have been purchased in the absence of the program?" VGS estimates of MMBtu savings are based on these evaluation estimates of rebated vehicle miles driven, miles per gallon equivalents (MPGe) for rebated vehicles, and average fleet vehicle MPG. In place of the average fleet vehicle MPG, the ENS include program influence data reflecting what vehicle the participant would have purchased in the absence of the program and the MPG for those vehicles.

The indirect impact analysis provides estimates of savings related to follow-on market activity that results from NYSERDA's investments, outside of vehicles that receive rebates. For this purpose, the Impact Evaluation Team developed vehicle adoption curves for a naturally occurring market adoption (NOMAD), and compared it to total market adoption with the program. The difference between these curves represents the overall program impacts, and indirect impacts are the remaining difference once directly rebated vehicles are accounted for. The analysis employs a range of scenarios that reflect different levels of program influence, different percentages of vehicle markets accessible to EVs and different approaches to modeling adoption trajectory through time.

1.1 COVID Impact

Throughout this section impacts are presented by year and cumulatively for years 2017 through 2020. Due to the extreme disruption of the COVID pandemic on all aspects of life – travel, purchases, commercial supply chains, lockdowns, remote work and more – impacts and results for 2020 may not be generalizable to future years. While it is possible that changes observed in 2020 may show a longer-term market transformation, changes may also be representative of the COVID period, exemplified not only by the pandemic but the lockdowns, multiple rounds of economic stimulus, and other effects. As a result, the evaluation team urges great caution in taking any observations, results, findings, or conclusions as generalizable to future years or trends.

1.2 Direct impact findings

The direct impact analysis estimates VGS of 30.7 MMBtu per vehicle, inclusive of increased electricity use, compared to expected program savings of 42.9 MMBtu. This translates into a realization rate (RR) of 0.72, or 72%. The difference between VGS and expected program savings results from a combination of lower rebated vehicle efficiencies and lower miles driven compared to program assumptions.

Estimated net savings (ENS) per vehicle is 10.4 MMBtu. In addition to the lower rebated vehicle efficiency and the lower mileage driven, this estimate incorporates survey results that indicate that half of the program vehicles would have been purchased in the absence of the Drive Clean program (i.e., BEV and PHEV purchasers would otherwise have purchased more efficient-than-average vehicles), and that replaced vehicles are more efficient than program assumptions.

1.3 Indirect impact findings

The indirect impact analysis takes a scenario-based approach to developing an estimate of indirect impacts. Across most scenarios, the program is expected to motivate the purchase of additional, non-rebated vehicles comparable with the numbers projected in the Clean Energy Fund Plan. Projected vehicle counts are combined with the VGS MMBtu estimates from the direct impact analysis to produce overall indirect savings. Plan indirect impacts are projected through 2030. This analysis produces indirect impact estimates that continue to increase beyond 2030. The MMBtu impacts are comparable to Clean Energy Fund (CEF) Investment Plan projections for most scenarios by the mid-2030s.

2 Direct Impact Evaluation

2.1 Evaluation Metrics

The Drive Clean program EV direct impact metrics are listed in Table 1. These metrics are based on (a) assumptions made during program design, about vehicles purchased and miles driven, and (b) evaluation study results.

Table 1 includes the following:

(1) Program assumptions counterfactual MPGe. These are the Miles per Gallon equivalent of the vehicles that the Program assumed would be purchased instead of the vehicles that were purchased through the Program.

(2) Program participants MPGe (average 2017-2020). These are the average Miles per Gallon equivalent of the vehicles that were purchased through the program between 2017 and 2020. They are obtained directly from Program records.

(3) Program participants counterfactual MPGe (average 2017-2020). These are the NOMAD average Miles per Gallon equivalent, from the vehicles that would have been purchased by Program participants, in the absence of the Program. These are estimated through a sample of Program participants.

(4) Program assumptions average vehicle miles driven per year. These are the program's assumptions of miles driven per year, for all vehicles.

(5) Program participants average vehicle miles driven per year (average 2017-2020).). These are the average miles driven of the vehicles that were purchased through the program between 2017 and 2020. These are estimated through a sample of Program participants.

(6)

Table 1. Drive Clean Impact Program Evaluation Metrics

Metric / Indicator	Vehicle Type	All rebated vehicles	Vehicles with ENS Greater Than or Less Than 0 [F]
(1) Program assumptions counterfactual [A] MPGe [B]	Both	25.2	25.2
(2) Program participants MPGe (average 2017-2020) [C]	BEV	118.0	120.2
	PHEV	45.5	45.2
(3) Program participants counterfactual [A] MPGe (average 2017-2020) [D]	BEV	93.9	46.1
	PHEV	41.2	32.0
(4) Program assumptions average vehicle miles driven per year	Both	15,000	15,000
(5) Program participants average vehicle miles driven per year (average 2017-2020) [E]	BEV	10,628	10,686
	PHEV	11,035	11,750

[A] – The vehicles that program participants would have purchased in the absence of the program.
[B] – Average new car MPG ranged between 24.6 and 25.4 from 2015 to 2020. Source: https://www.epa.gov/automotive-trends/highlights-automotive-trends-report
[C] – Source: year, make, model obtained from program participation list. MPGe obtained from EPA vehicle list
[D] – Source: year, make, model obtained from Sample. MPGe obtained from EPA vehicle list.
[E] – The difference between BEV and PHEV miles driven is statistically significant; PHEV program participants drive more.
[F] – This excludes vehicles with an ENS of zero.

2.2 Direct Impacts

Direct impacts, the energy savings produced by the program, are estimated through a comparison of what participants did compared to what they would have done in the absence of the program (a counterfactual scenario). This report presents two types of direct impacts: Verified Gross Savings (VGS), estimated relative to the average efficiency of new vehicles in the United States, and Estimated Net Savings (ENS), based on survey responses that indicated what vehicle participants would have purchased in the absence of the program. Both types of direct impacts are estimated using some combination of the following data, listed here, shown below in Table 2, and described in the following subsection:

- New vehicle efficiency
- Energy savings – the difference between the energy use of the rebated vehicle and the energy use of the counterfactual vehicle. This estimate includes:
    - The miles-per-gallon equivalent (MPGe) of the rebated vehicle

- o The MPGe of the counterfactual vehicle(s)
- o The vehicle miles traveled

- Statistical weights – calculated as a proportion of program participants to survey respondents, stratified by vehicle technology (BEV or PHEV), and ownership type (purchase or lease)

- Self-reported program influence/action without rebate – the participants' opinion of the impact of the program

- Self-reported counterfactual vehicle – counterfactual vehicles are (a) the vehicle that would have been purchased instead of the rebated vehicle, and (b) the vehicles already owned that would be replaced or driven less as a result of the purchase.

Table 2. Savings Methods Table

<table>
<tr><th>Action Without Rebate</th><th>Household Status</th><th>Counterfactual Vehicle</th><th>Type</th><th>Household Cars - Pre</th><th>Vehicle Miles Traveled</th><th>Action</th><th>Method</th></tr>
<tr><td>Same exact car</td><td colspan="5"></td><td>No savings</td><td rowspan="2"></td></tr>
<tr><td>Same car, different trim/options</td><td colspan="5"></td><td>No savings or negative savings</td></tr>
<tr><td rowspan="5">Different car</td><td></td><td>Known Make and Model - New</td><td colspan="2"></td><td rowspan="5">Vehicle miles traveled</td><td rowspan="7">Savings estimated</td><td rowspan="5">Savings are the difference between Rebated and Counterfactual vehicle</td></tr>
<tr><td></td><td>Known Make and Model - Used</td><td colspan="2"></td></tr>
<tr><td></td><td rowspan="3">Don't Know</td><td>New vs Used</td><td></td></tr>
<tr><td></td><td>BEV, PHEV, Hybrid, ICE</td><td></td></tr>
<tr><td></td><td>Make</td><td></td></tr>
<tr><td rowspan="3">Not purchased a car. Maintain status quo</td><td>Replaced other car</td><td>Replaced Year Make Model Type</td><td></td><td>Yes</td><td rowspan="2">Total household vehicle miles traveled Pre - Post</td><td rowspan="2">Total household vehicle energy consumption Pre - Post</td></tr>
<tr><td>Added to household fleet</td><td colspan="2"></td><td>Yes</td></tr>
<tr><td>Household first car</td><td colspan="3"></td><td>Vehicle miles traveled</td><td>Negative savings</td><td>Total Consumption</td></tr>
</table>

This report presents survey statistics, overall and for two savings levels: "verified gross savings" (all program participants), and "estimated net savings" (which includes estimates of program influence, whether positive or negative.) The occurrence of negative energy savings is common in energy efficiency evaluation, especially for programs like EV Rebates that promote technology improvements, and it is explained in more detail in the following sections.

Throughout this chapter, the term "acquiring" a vehicle refers to purchasing or leasing a vehicle.

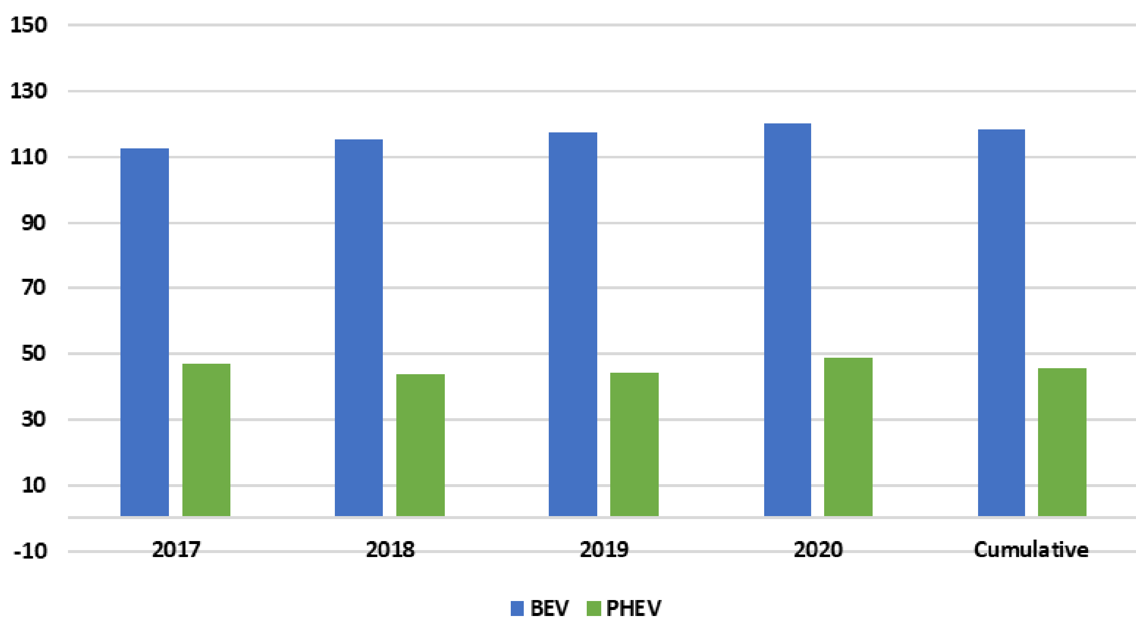
2.2.1 Data used in Direct Impacts estimation

2.2.1.1 Miles per Gallon equivalent (MPGe) for Replacement Vehicles

"Miles per gallon" (MPG) is a well-known vehicle efficiency metric that has been used for decades and is prominently displayed in new gasoline vehicles. In order to have a comparable metric for electric and hybrid vehicles, the EPA introduced MPGe. One MPGe is 33.7 kWh, which results from the conversion of the energy content of a gallon of gasoline (BTU) to kWh. Miles per gallon (MPG) and miles per gallon equivalent (MPGe) are equivalent by definition and can be compared directly.

Vehicles with zero ENS are those where the same model would have been acquired in the absence of the program. Thus, the MPGe of these vehicles is the same as of the program vehicles. For rebated vehicles with positive ENS, there is a very large difference between the MPGe of the program vehicles and their counterfactuals. Most of these program vehicles have counterfactuals that are gasoline or non-plug-in hybrids.

Figure 2. MPGe of Rebated Vehicles by Rebate Year and Type*



*These figures differ slightly from those presented in Table 1. In this figure, estimates are based on the sample. This is necessary to compare to the counterfactual MPGe, which cannot be obtained from program data.

Figure 3. MPGe of Counterfactual Vehicles by Rebate Year and Type

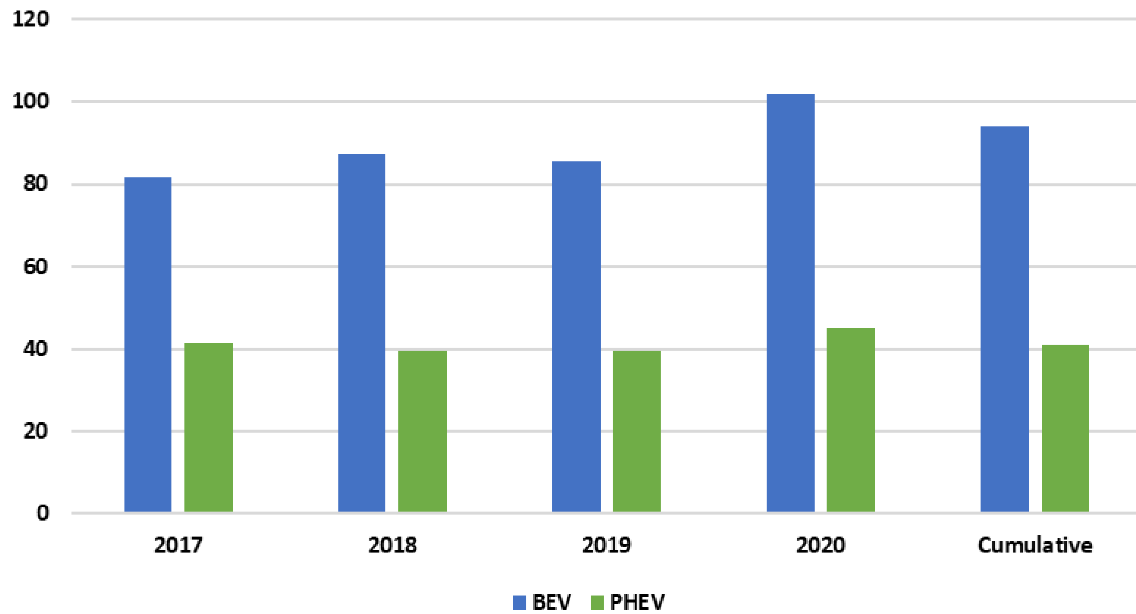
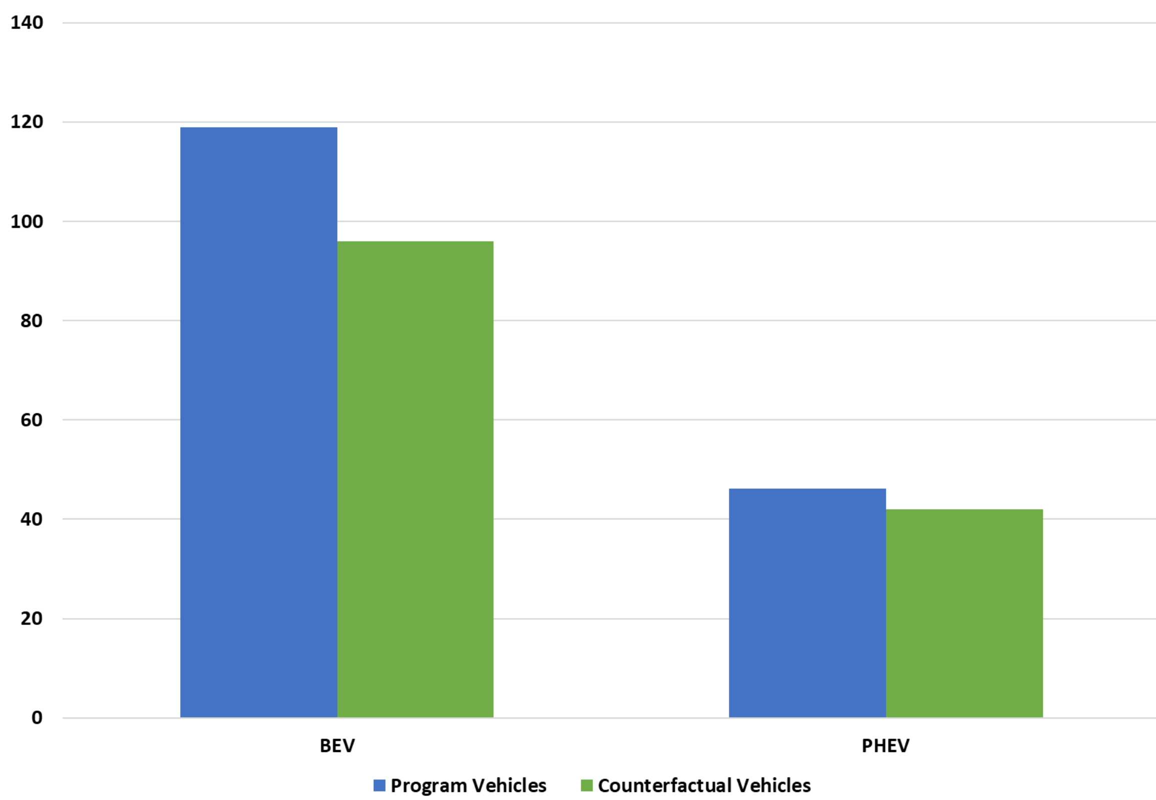


Figure 4. MPGe of Program Vehicles Vs Counterfactual Vehicles



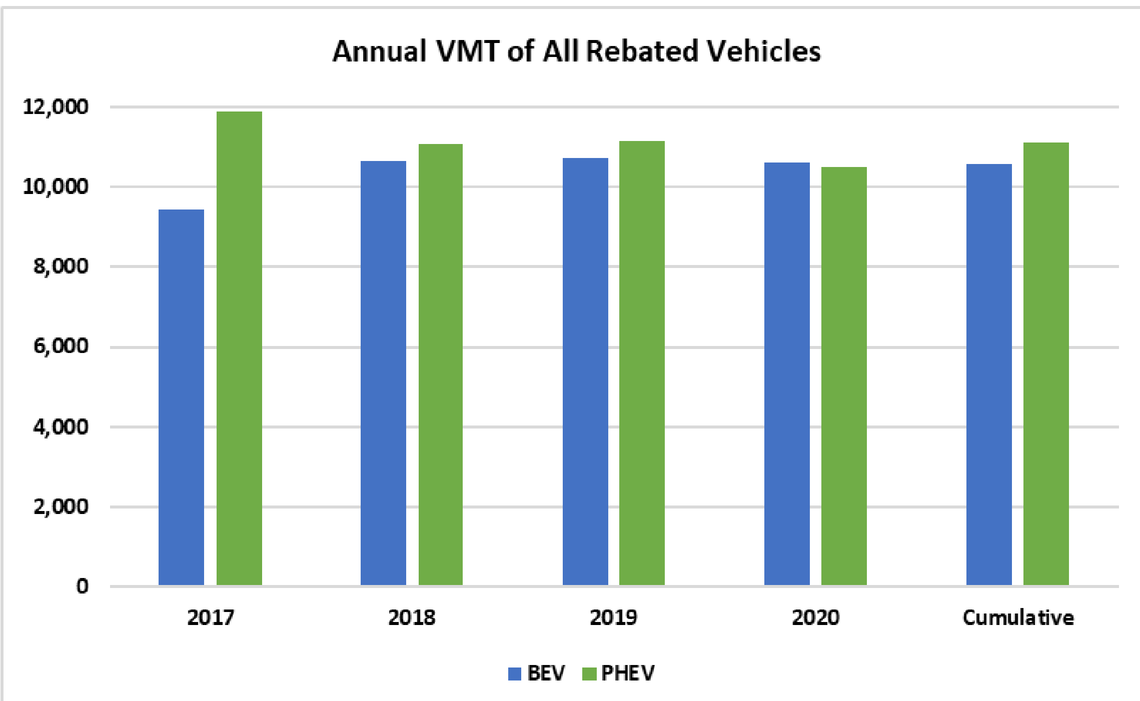
2.2.1.2 Mile per Gallon equivalent for Typical New Vehicles

The VGS estimate uses the typical new vehicle MPGe estimate from program assumptions: 25.2 MPG. Average new car MPGe ranged between 24.6 and 25.4 from 2015 to 2020[1].

2.2.1.3 Vehicle Miles Traveled

The direct impact estimates are dependent on how much the vehicle is driven. Usage levels are assumed to be the same between the counterfactual and the rebated vehicle. The survey asked participants to estimate the annual mileage of the rebated vehicle, and the annual mileage of the vehicle or vehicles that were replaced or that will be driven more or less because of the rebated vehicle. These differences in mileage were used to estimate the program's impact. Estimated average vehicle miles traveled (VMT) are presented in Figure 1.

Figure 1. VMT of Rebated Vehicles by Rebate Year and Type



VMT findings:

- This evaluation estimates the average VMT of Drive Clean participants to be 10,571 miles per year for BEV, and 11,086 for PHEV. These miles driven estimates are 30% and 26% lower than the program assumption of 15,000 VMT per year.

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[1] Source: https://www.epa.gov/automotive-trends/highlights-automotive-trends-report

- Overall, the difference between BEV and PHEV miles traveled is statistically significant. This evaluation estimates that, across all program years, PHEV vehicles are driven about 5% more miles per year than BEV vehicles. However, BEV and PHEV rebated vehicles with no savings have approximately the same miles traveled, whereas there is a substantial difference for rebated vehicles with savings, of approximately 10% more miles driven for PHEV than for BEV.

2.2.1.4 Energy Consumption

The combination of miles traveled and MPGe yields estimates of annual energy usage per vehicle, expressed in gallons equivalent (GALe). The following figures present the estimated annual consumption in GALe per vehicle for rebated and counterfactual vehicles.

Figure 5. Average Annual GALe Consumption of Rebated Vehicles by Rebate Year and Type

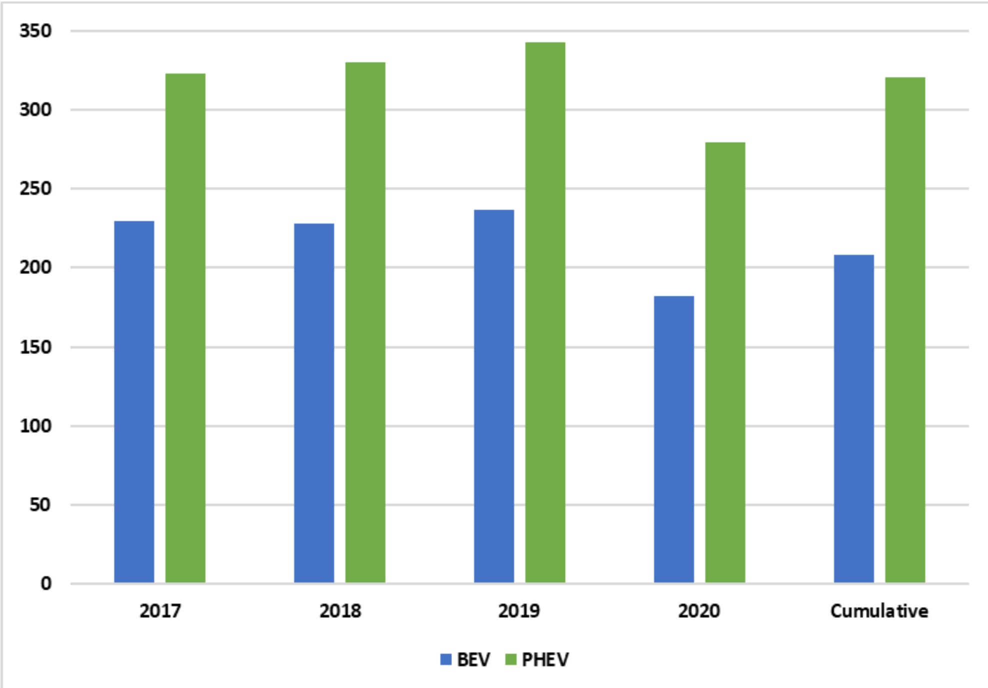
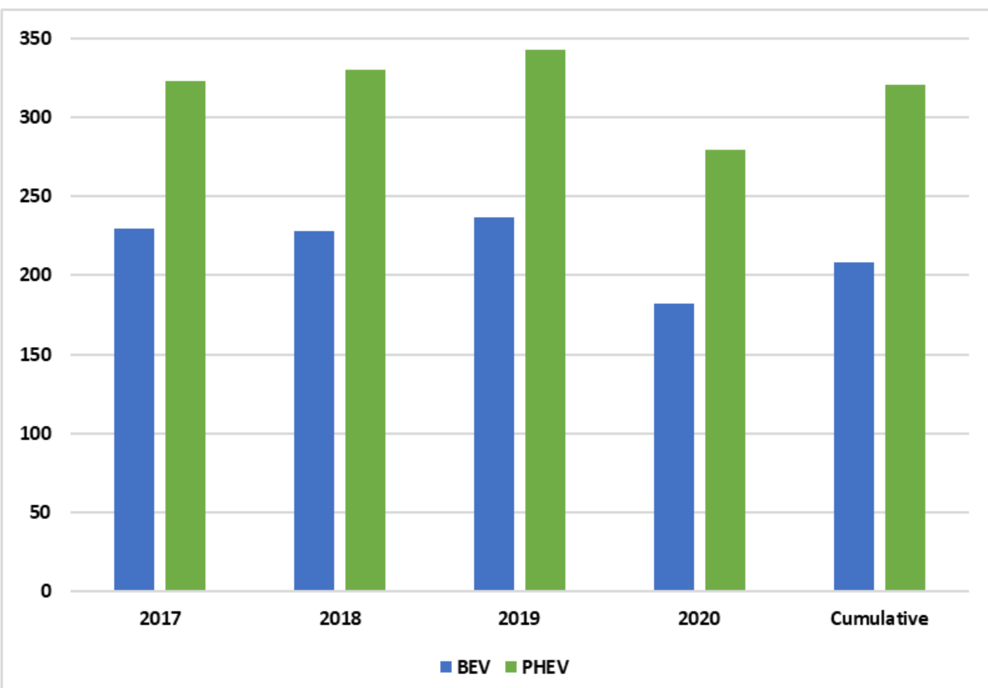


Figure 6. Average Annual GALe Consumption of Counterfactual Vehicles by Rebate Year and Type



2.2.1.5 Program Participants and Survey Respondents

Starting with a list of 34,156 records, the evaluation team identified 27,718 records for private individuals (after cleaning for duplicate individuals, business, government records, and those with no vehicle type assigned). All participants that were identified as individual participants were solicited to participate in the survey. The survey obtained 4,302 responses. Of these, 3,071 responses were used to estimate program impacts. Sample sizes by vehicle type and program year are reported in Table 3.

2.2.1.6 Self-Reported Program Influence and Counterfactual Vehicles

The Survey's program influence question (Question 15: If the Drive Clean Rebate were not available for electric vehicles, which of the following would you most likely have done?) classifies respondents into three groups: customers that would have acquired the same vehicle, customers that would have acquired a different vehicle, and customers that would not have acquired a vehicle. The responses to Question 15 are presented in Table 3.

Table 3. Q15: If the Drive Clean Rebate were not available for electric vehicles, which of the following would you most likely have done?

BEV Participants Q15	Program Influence	Sample Count	Program Estimate *	Percentage of BEV Program Participants	Combined BEV Percentage
BEV					
Not made any vehicle purchase/lease at all	With Savings / Program Influence	307	2,659	16.2	36.5
Purchased/leased a different vehicle		322	3,325	20.3	
Purchased/leased a less expensive version of the same model	No Savings / Program Influence	217	2,123	13.0	63.5
Purchased/leased this exact electric vehicle anyway		842	8,265	50.5	
Total BEV		1,688	16,371	100.0	100.0

PHEV Participants Q15	Program Influence	Sample Count	Program Estimate *	Percentage of PHEV Program Participants	Combined PHEV Percentage
PHEV					
Not made any vehicle purchase/lease at all	With Savings / Program Influence	186	1,979	11.9	44.1
Purchased/leased a different vehicle		429	5,538	33.2	
Purchased/leased a less expensive version of the same model	No Savings / Program Influence	252	3,071	18.4	54.9
Purchased/leased this exact electric vehicle anyway		516	6,094	36.5	
Total PHEV		1,383	16,682	100.0	100.0

*Program estimate – participants from 2017 to 2020

Question 15 was used to classify survey respondents into two groups[2]:

- With savings/program influence: Participants for whom the program influenced actions (not purchased a vehicle at all or purchased a different vehicle). Savings can be positive or negative.

- No savings/program influence: Participants that would have taken the same actions (purchased same model or exact same vehicle) in the absence of the program are zero program influence participants.

Program influence findings:

- Zero program influence participants (those that would have acquired the same vehicle, or the same model with less features) account for an estimated 63.5% of BEV program participants and 54.9% of PHEV program participants (cumulative 2017-2020).

- Over half of both BEV and PHEV participants are likely to have purchased the exact same vehicle without the rebate, but the proportion is higher for BEV than for PHEV. Similarly, the proportion of customers that would have purchased a less expensive version of the same vehicle is higher for PHEV than for BEV.

[2] Figures throughout this section report the estimated total from both groups combined. For tables reporting the difference between groups please refer to Appendix

In prior reports, emissions savings were calculated based on the previously owned and replaced vehicle for all program participants. For this evaluation, the team introduced the counterfactual vehicle as described above. Participants that, in the absence of the program, would have acquired a different vehicle or would not have replaced the vehicle that the rebated vehicle replaced, were asked questions regarding the vehicles that they would have acquired instead, or that they would have not replaced. These vehicles are the counterfactual ("comparison") vehicles that are used to estimate program savings in the ENS approach. For example, a participant that would have acquired a gasoline-only vehicle has more estimated savings than a participant that would have acquired a non-plug-in hybrid. Conversely, a participant that would have acquired a different electric vehicle than what they purchased with the program could possibly have negative savings, if the counterfactual vehicle has a higher MPGe than the rebated vehicle.

If respondents would not have purchased a vehicle in the absence of the rebate, the evaluation team used the replaced vehicle to estimate program savings and emissions benefits. In some instances, there was neither a counterfactual nor a replaced vehicle.

Counterfactual vehicle findings:

- In 40% of the cases where participants would have acquired a different vehicle, the counterfactual is from the same make as the rebated vehicle. The most common counterfactuals from the same make are Toyota, Honda, Ford, and Chevrolet.

- Among participants that would have acquired a different vehicle, the most common rebated vehicle versus counterfactual pairs are: Toyota Prius Prime vs Toyota Prius (9% of program participants), Honda Clarity vs Honda Accord or Honda Accord Hybrid (4%), and Ford Fusion vs Ford Escape (3%).

- Among those that replaced an existing vehicle with a rebated vehicle, 73% did not acquire a vehicle of the same make as the existing vehicle, while 27% did. Of those that acquired a vehicle of a different make, the most common makes are Tesla (27% of replacements) and Toyota (10% of replacements). Of those that acquired a vehicle of the same make as the replaced vehicle, the most common makes are Toyota (9%), Ford (5%), and Honda (3%).

2.2.2 Verified Gross Savings Realization Rate

The savings realization rate (RR) is the ratio of savings (*ex post* estimates) to program assumptions savings (*ex ante* savings). This evaluation includes estimates for two types of savings: verified gross savings, and estimated net savings. Savings of either type use survey data and program tracking data, while program assumptions savings are based on values identified prior to the start of the program (*ex ante* estimates). All programs have *ex ante* estimates, and it is rare that the ex post estimates match the *ex ante* estimates. Some programs change their ex-ante estimates for future program cycles based on the evaluation results of the first years of the programs.

The realization rate ratio is expressed in the simple formula shown below in Equation 3.

Equation 3. Verified Gross Savings Realization Rate

$$VGS\ RR = \frac{Verified\ Savings}{Savings_{Program\ Assumptions}}$$

As a result of the savings presented in prior sections, this evaluation finds a cumulative verified gross savings realization rate (VGS RR) of 0.72, or 72%, inclusive of both fuel savings and increased use of electricity. This rate, along with program estimates and verified gross savings, is presented below in Figure 2. The ENS ratio, calculated as shown in Equation 4, is presented in Table 5.

Equation 4. Estimated Net Savings Ratio

$$ENS\ Ratio = \frac{Estimated\ Net\ Savings}{Savings_{Program\ Assumptions}}$$

Table 4. First Year MMBtu Verified Gross Savings Realization Rate by Rebate Year

Method	2017	2018	2019	2020	Total
Program Assumptions*	168,898	253,199	354,596	639,379	1,416,072
Verified Gross Savings	122,485	184,353	253,680	454,970	1,015,488
VGS Realization Rate	0.73	0.73	0.72	0.71	0.72

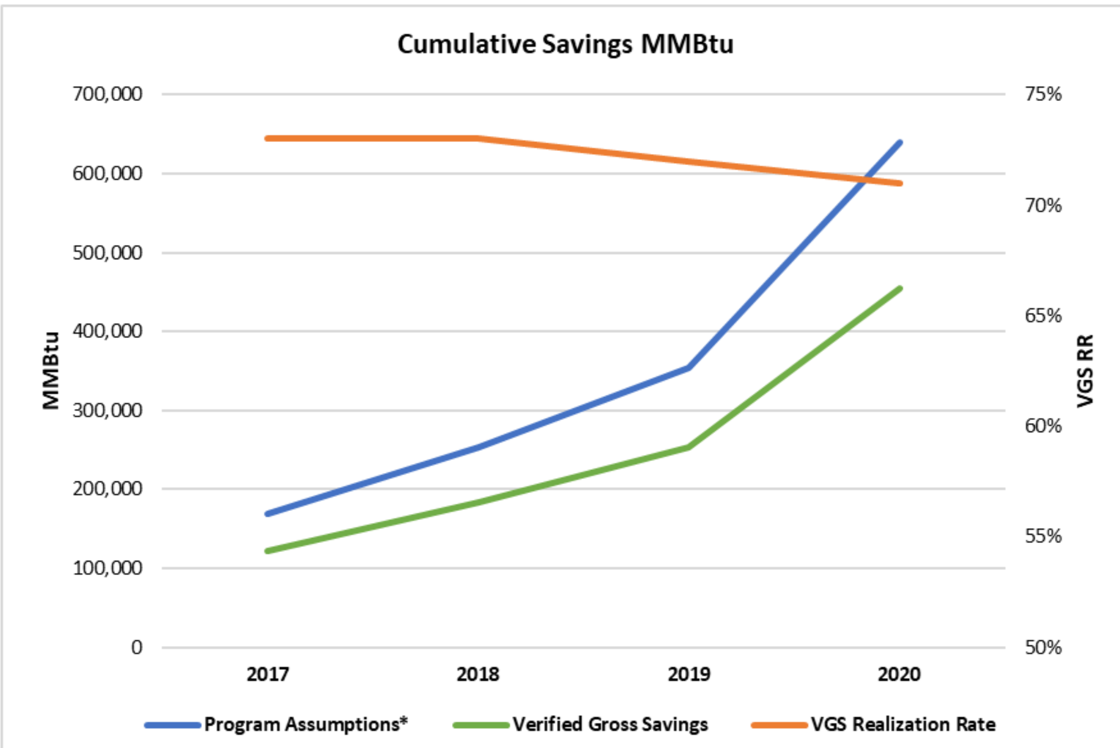
* Savings estimates with rebated vehicle MPGe and program assumptions of 15,000 miles, MPGe=25.2, 100% replacement. These savings values are not from the Investment Plan, as that value also assumed estimates of vehicles by year, this value compares weighted vehicle counts by year against Investment Plan assumptions.

Table 5. First Year MMBtu Estimated Net Savings by Rebate Year

Method	2017	2018	2019	2020	Total
Program Assumptions*	168,898	253,199	354,596	639,379	1,416,072
Verified Gross Savings with Program Influence	38,412	70,549	133,828	101,060	343,848
Estimated Net Savings Ratio	0.23	0.28	0.38	0.16	0.24

* Savings estimates with rebated vehicle MPGe and program assumptions of 15,000 miles, MPGe=25.2, 100% replacement. These savings values are not from the Investment Plan, as that value also assumed estimates of vehicles by year, this value compares weighted vehicle counts by year against Investment Plan assumptions.

Figure 2. Cumulative Savings in MMBtu with VGS RR by Rebate Year



* Savings estimates with rebated vehicle MPGe and program assumptions of 15,000 miles, MPGe=25.2, 100% replacement. These savings values are not from the Investment Plan, as that value also assumed estimates of vehicles by year, this value compares weighted vehicle counts by year against Investment Plan assumptions.

The overall VGS RR of 0.72, or 72%, results from a number of factors. For illustration of the effects, Table 6 shows the variables used to determine verified gross savings and estimated net savings for rebated vehicles in 2017 and 2020. The rebated vehicles' average MPGe is higher than the program's assumptions, which increases savings. Independently, most of these variables would have a limited impact. Combined, they contribute to an VGS realization rate of 0.73 or 73% in 2017 and 0.71 or 71% in 2020. Note the high percent of consumers that would have acquired the same vehicle in 2020, compared to 2017 and to program assumptions.

Table 6. Example of variables affecting savings: 2017 and 2020

Variable	Program Value	2017	2020	Effect on VGS	Effect on ENS
Percent of customers that would have acquired the same vehicle	0%	48%	72%	None	↓
Vehicle miles per year	15,000	11,047	10,503	↓	↓
MPGe of counterfactual vehicle	25.2	81	102	None	↓
MPGe of rebated vehicle		BEV: 113.7 PHEV: 46.7	BEV: 119.8 PHEV: 47.5	↑	↑
Verified gross savings realization rate (VGS RR)	1.0	0.73	0.71		
Estimated net savings (ENS) ratio	1.0	0.23	0.16		

Realization Rate findings:

- The verified gross savings realization rate has remained stable, at 0.71 to 0.73 for the first four years of the program. The reduction compared to program assumptions is proportional to the verified lower vehicle miles per year.

- Consistent with annual savings, the estimated net savings realization rate saw a sharp decrease in 2020 compared to the programs' prior years. This is the result of the sharp increase in the number of participants that would have acquired the same vehicle in the absence of the program. The year 2020 was highly different from other years due to the extreme impacts of COVID. It remains to be seen if changes are strictly due to the pandemic and trends will return or if this marks a more permanent market transformation.

2.2.3 Estimated Net Savings

Savings were calculated separately for each survey respondent. Savings per rebated vehicle in gallons equivalent (MPGe) were calculated by subtracting counterfactual vehicle consumption from rebated EV consumption. Statistical survey weights were applied to each survey respondent to produce estimates at the program level.

Equation 3 shows the general energy savings equation, as applied to this analysis.

Equation 1. Energy savings equation, per rebated vehicle

$$Savings_{Fuel} = \left(\frac{VMT_{CF}}{MPGe_{CF}}\right) - \left(\frac{VMT_{RV}}{MPGe_{RV}}\right)$$

CF: counterfactual vehicle
RV: rebated vehicle

Equation 2. Energy savings equation, per rebated vehicle, in MMBtu EV

$$Savings_{MMBtu} = Savings_{Fuel} * MMBtu_{Factor}$$

Equation 3. Energy savings equation, applied

$$\sum_{T=BEV}^{PHEV} \sum_{S=Yes}^{No} \sum_{Y=2017}^{2020} \left(\left(\left(\left(VMT_{TSY}/MPG_{CF,TSY} \right) - \left(VMT_{TSY}/MPGe_{RV,TSY} \right) \right) * W \right) * N_{TY} \right)$$

Where:
VMT= Vehicle Miles Traveled
MPG= Average efficiency of counterfactual vehicle
MPGe= Average efficiency of rebated electric vehicle
CF = Counterfactual Vehicle
RV = Rebated Vehicle
W = Weight
N=Number of rebated vehicles
T = Type (BEV or PHEV)
S = Savings Applied
Y=Program Year
(TSY=By type, savings applied status, and program year – as used in tables throughout this analysis)

Respondent ENS fall into one of three scenarios:

Positive savings. These are customers that produced energy savings by participating in the program and reducing their MPGe. There were 1,117 survey respondents in this group, representing 10,047 program participants.

Zero savings. These are customers that would have acquired the exact same car, or the same model with less features. There were 1,827 survey respondents in this group, representing 16,258 program participants.

Negative savings. There were 127 survey respondents with negative savings. These respondents represent 1,413 program participants. Negative savings were caused by the following:

- Upward counterfactuals (the counterfactual vehicle is more efficient than the vehicle acquired through the program). We observed two types of upward counterfactuals: (1) the vehicle that the respondent would have acquired in the absence of the program is more efficient than the car that was acquired with the program, and (2) the vehicle that the household already owned (that was replaced or is driven less) is more efficient than the vehicle acquired under the program.
- New vehicle owners that did not have a car prior to this acquisition, that would not have acquired a vehicle in the absence of the program. These are different than new vehicle owners that would have acquired a different vehicle in the absence of the program.
- Snapback (the acquired vehicle is driven more miles than the replaced vehicle).

The program's average per vehicle and total annual estimated net savings are presented below.

Figure 7. Savings: Annual Gallons per Rebated Vehicle by Rebate Year and Type

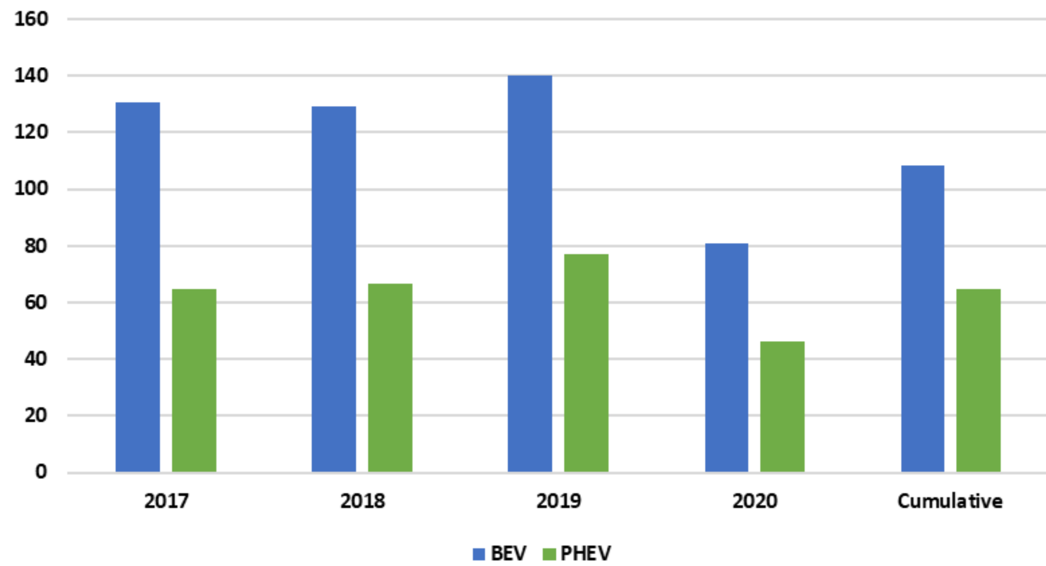


Figure 8. Savings: Annual MMBtu per Rebated Vehicle by Rebate Year and Type

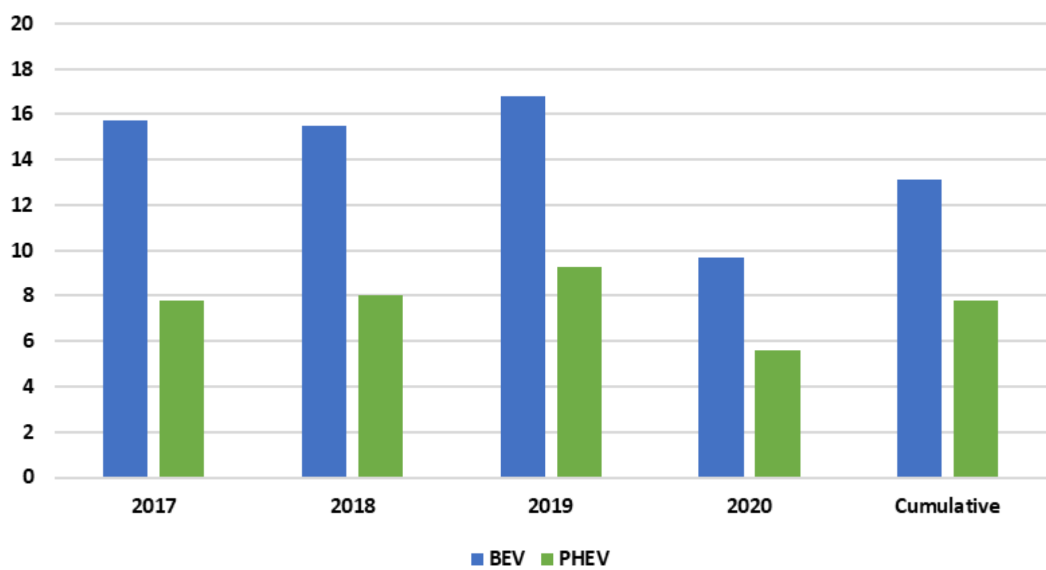
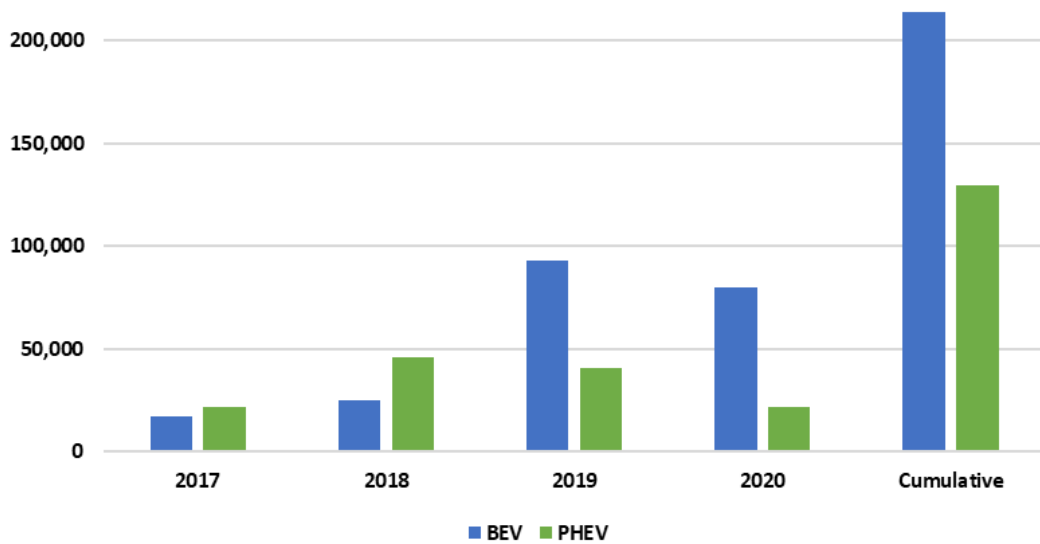


Figure 9. Savings: Annual (1st Year) Total MMBtu by Rebate Year and Type



Annual savings findings:

- Even with greater participation, there was a marked reduction in savings in year 2020. This is due to the large number of zero savings participants (participants that would have acquired the same vehicle in the absence of the program). This may be due to COVID, but may also be the result of a larger market transition indicating a more widespread acceptance of electric vehicles.

2.3 Recommendations

The Impact Evaluation team recommends exploring these potential improvements to the future evaluation methodology.

Program influence is decreasing, with an especially large drop in 2020. This may be due to a variety of factors at play during the COVID period and may also be due to a shift in the market from more consumers willing to adopt electric vehicles on their own.

Recommendation 1. NYSERDA should study future program influence levels to monitor the program influence trend as well as to attempt to better identify reasons behind changes.

There was a slight upward trend in vehicle miles traveled (VMT) for vehicles purchased from 2017 through 2019. Year 2020 ended that trend with a decrease that may not be entirely due to

COVID-related changes, as participants from all program years responded to the survey at the same time. This may be an anomaly, or the start of a downturn in VMT for participating vehicles. Tracking VMT can help NYSERDA's evaluators to better understand and quantify program influence.

NYSERDA Response to Recommendation: Pending. This will be discussed for the next impact evaluation.

Recommendation 2. NYSERDA should include additional VMT questions in future studies, with the objective to determine whether program VMT is changing, why, and in what direction. This may include questions about how the household uses the program vehicle compared to their other vehicles and transportation alternatives.

NYSERDA Response to Recommendation: Rejected. This recommendation seems unlikely to improve data quality.

Whether rebated vehicles continue to be in service in New York is important to gauge the program's long-term benefits. This can be learned from mining NY Department of Motor Vehicles registration data to assess whether rebated vehicles are still active and domiciled in the state. Alternatively, it may be possible to capture this information and other useful data with a very short survey (do you still own this vehicle, is the vehicle still in the state, how many miles per year do you drive it, do you recommend plug-in vehicles).

Recommendation 3. NYSERDA should conduct a persistence study, designed to gauge whether the rebated vehicles are still in New York. This can be used to determine what percent of vehicles continue to benefit the state and what percent may have moved out of the jurisdiction. Such a study could consist of a very short survey (do you still own this vehicle, is the vehicle still in the state, how many miles per year) or, if the Department of Motor Vehicles allows it, it may be possible to submit the list of VINs and have the DMV verify whether the vehicle is still active and domiciled in the state. EValuateNY provides counts of EVs by vehicle age and county or other information that can help the evaluation team assess how many vehicles are purchased outside of the program.

NYSERDA Response to Recommendation: Pending. The program team supports this recommendation, but has not yet discussed how to implement this recommendation.

2.4 Methods

2.4.1 Verified Gross Savings (VGS)

Verified Gross Savings are estimated based on the difference between the vehicle acquired through the program and a hypothetical typical vehicle that is constructed with program design assumptions, and the number of miles driven per year (based on the survey.)

2.4.2 Estimated Net Savings (ENS)

A saving methods tree (illustrated in Table 2) was developed for identifying savings calculations based primarily on what the respondent would have done in a counterfactual case. As stated previously, respondents were asked what they would have done without the program rebate. Those who would have purchased the same vehicle (exact same or same model with different trim) received no savings – the program did not influence the purchase decision. Those who would have purchased a different car were asked to identify the counterfactual vehicle; averages for those who were able to identify the vehicle were used for those who did not know what vehicle they would have purchased. If they would not have purchased a car but for the rebate, respondents were then asked about the household vehicle status – whether this rebated vehicle replaced another car, added to the household fleet, or was the household's first car. For those that this was the first car (and as established, they would not have purchased anything but for the rebate), total consumption was calculated and resulted in negative savings. For those where the rebated vehicle relaced another car or was added to the household fleet was identified both pre and post EV purchase with total household consumption calculated for pre and post EV purchase with the difference resulting in any savings.

2.4.3 Survey Disposition

The starting point for this evaluation is the Program's list of participants. The list of participants includes 34,156 records. Of these, 27,816 are classified as *individual* program participants. Individual participants are the focus of this study. There are 5,737 records that do not have a type (the type is *blank,* or null). These counts are shown in Table 7.

In order to not underestimate program participation and program savings, records with no participant type were randomly assigned to Individual or non-Individual types with a 97% and 3% probability, respectively. This resulted in a final count of 33,052 individual program participants. This participant count was used to develop the sampling weights and the population statistics presented in this report.

Table 7. Rebated vehicles (not individuals) by Rebate Year, Owner, and Type (*)

Type	Owner	2017	2018	2019	2020	Total
BEV	Individual	1,150	2,303	4,275	5,285	13,013
	Government Entity	8	5	14	7	34
	Business	37	40	45	176	298
	Blank	296	254	275	2,716	3,541
BEV Total		1,491	2,602	4,609	8,184	16,886
PHEV	Individual	3,029	5,617	3,288	2,869	14,803
	Government Entity	3	4	2	1	10
	Business	62	98	66	35	261
	Blank	453	555	223	965	2,196
PHEV Total		3,547	6,274	3,579	3,870	17,270
Program List Total		5,038	8,876	8,188	12,054	34,156
Individual Owner Total		4,179	7,920	7,563	8,154	27,816
Duplicates Emails Removed						98
Final List Total						27,718

* This table matches the counts used in the Spring 2021 report

Further refinement of the list (removal of duplicate records) resulted in a final count of 27,718 individual participants. All participants that were identified as individual participants were solicited to participate in the survey. The survey obtained 4,302 responses. Of these, 3,071 responses were used to estimate program impacts. Table 8 shows the disposition of the survey responses and reasons for removal.

Table 8. Survey Disposition

Survey Disposition	Count	Percent of Survey Responses
Number of rebated vehicles (all "Individual" participants that received a rebate and had a valid email address were asked to participate in the survey)	27,718	
Survey responses	4,302	100.0 %
Removals from analysis dataset		
Q1: I did not receive a rebate for a vehicle	587	13.6 %
Q1: I received a different rebate amount	53	1.2 %
Q1: I received a rebate for a different vehicle	23	0.5 %
Q2: This vehicle is primarily for commercial/organizational use	33	0.8 %
Q3: Respondent was not primary decision maker in vehicle purchase	19	0.4 %
Q15: Respondent does not know what Respondent would have done in the absence of the Clean Rebate	503	11.7 %
Respondent does not know any of these: Q18: if alternative car would have been new or used Q19: type of fuel of alternative car Q20: make of alternative car	13	0.3 %
Number of Surveys available for program influence analysis	3,071	71.4 %

We used vehicle make, technology type, and county as factors to weight responses. The comparison of actual program participant counts to estimated participant counts show that, as expected, the difference between total counts and estimated total counts is almost zero, but there is expected variation at the annual level. This variation should be considered when comparing program characteristics that are known for all participants (for example, technology type) and those that are estimated based on survey results (for example, type of counterfactual vehicle.)

Table 9. Survey Final Sample Size by Rebate Year and Type

Type	2017	2018	2019	2020	Total
Sample Size					
BEV	114	203	587	784	1,688
PHEV	226	466	368	323	1,383
Total	340	669	955	1,107	3,071

Table 10. Weighting of Program Participants

Type	2017	2018	2019	2020	Total
Actual Program Participants					
BEV	1,249	1,495	4,399	9,146	16,289
PHEV	3,182	5,944	3,717	3,920	16,763
Total	4,431	7,439	8,116	13,066	33,052
Raked and Weighted Number of Program Participants (Difference)					
BEV	1,065 (184)	1,592 (-97)	5,504 (-1,105)	8,211 (935)	16,371 (-82)
PHEV	2,741 (441)	5,690 (254)	4,412 (-695)	3,839 (81)	16,682 (81)
Total	3,805 (626)	7,282 (157)	9,915 (-1,799)	1,2050 (1,016)	33,053 (-1)

* These counts include 5,334 program participants for which Type=Individual was imputed

2.4.4 Statistical Weights

The survey was administered to all Individual program participants with valid email addresses. In this sense, program participants had an equal probability of selection.

After the surveys were compiled and the exclusions were processed (see Table 8 for the counts of surveys that were excluded from this study), the weights were estimated using an iterative proportional fitting approach ("raking"). This is a widely used approach for estimating sampling weights where some of the population's important characteristics are known. In this case, the rebate tracking data include data for rebated vehicle make/model, transaction type (purchase/lease), and county. The raking process adjusts the statistical weights to approximate the know characteristics in the population.

2.4.5 Main Data Sources: Program Participants List and Survey Sample

The two primary sources of the analysis presented in the Program Impact Evaluation are the list of program participants provided by the Program, and the survey sample, a primary data collection effort conducted by the evaluators. The program participants list was prepared by removing participants classified as Business or Commercial customers, or lacking a classification, and by removing duplicate entries of the same rebate. When data exists or can be directly attached to the program participants list, the list is directly used. For example, rebated vehicle counts are obtained directly from the list, and the MPGe of rebated vehicles was attached to this list. If the data does not exist in the program participants list, then the survey sample is used. For example, the MPGe of counterfactual vehicles is obtained from the sample.

2.4.6 Fuel Efficiency

Fuel efficiency was obtained from fuel efficiency data available through fueleconomy.gov. This was done separately for all rebated vehicles in the program list, and the counterfactual vehicles reported in the sample.

Counterfactual vehicles were matched to the fuel efficiency data by year, make, and model, when sufficient data from the adoption survey was available. The rebated vehicles were matched to the fuel economy data by year, make, model, and EV type. Rebated and counterfactual vehicles that were not directly matched were reviewed individually and matched by the evaluators. Most of these "hand matches" were due to differences in naming conventions between the program list and the fuel economy list (e.g., "Kia Soul EV" Vs "Kia Soul", or "BMW i3s Rex" Vs "BMW i3 with Range Extender").

Table 11. Annual GALe (with 90% CI) Consumption of Rebated Vehicles by Rebate Year

Type	2017	2018	2019	2020	TOTAL
BEV	83.4 (7.6)	93.9 (6.2)	92.8 (3.8)	90.4 (3.2)	91.1 (2.2)
PHEV	255.5 (15.2)	262.7 (12.6)	262.3 (15)	222.3 (12.4)	252.1 (7)

* These figures differ slightly from those presented in Table 1. In this table, these figures are estimated from the sample. This is necessary to compare to the counterfactual MPGe, which cannot be obtained from program data.

Table 12. Annual GALe (with 90% CI) of Counterfactual Vehicles by Rebate Year

Type	2017	2018	2019	2020	TOTAL
BEV	229.4 (32.5)	227.9 (27.7)	237 (15.5)	181.8 (12.2)	207.9 (8.8)
PHEV	323.4 (20.6)	330 (16.8)	343.1 (20.3)	279.2 (17)	320.7 (9.4)

3 Indirect Impact Evaluation

3.1 Indirect Impacts

This section attempts to quantify the possible indirect impacts of the Drive Clean EV Rebate Program. The analysis specifically targets indirect impacts related to the vehicle rebates but provides a framework that could encompass wider NYSERDA efforts in the EV area.

The primary focus of this analysis is the indirect impacts of the additional BEVs and PHEVs on the road as a result of the Drive Clean rebate program. Measure or technology market adoption generally follows predictable patterns and trajectories that have been established in the literature. The additional or more rapid adoption of those measures or technologies early in the market adoption cycle will affect the predicted market adoption trajectory in the long run, even if the changes appear modest. Consistent with this theory, the program logic of a rebate program like Drive Clean is that additional vehicles on the road early in the adoption curve will increase the rate of adoption over the long run, beyond what would have occurred in the absence of the program. For example, word-of-mouth is considered an important driver of new technology adoption. More EVs on the road support more word-of-mouth interaction. There is an implicit causal link between the original rebated vehicles and the multiple generations of additional vehicles on the road later that were motivated by those early, rebated vehicles.

NYSERDA's efforts to support the EV market go well beyond vehicle rebates. NYSERDA is enhancing charging networks, supporting local sustainability efforts, and expanding market awareness of electric passenger vehicles while providing similar support more widely across all aspects of public transit. None of these activities would have occurred in the NOMAD scenario. These additional efforts are not explicitly included in the modeling that supports this analysis because of the difficulty of quantifying these inputs. This does not mean they will not have an essential role in driving adoption and will only have the effect of increasing the indirect impacts that flow from NYSERDA's efforts.

3.1.1 Indirect Impacts Definition

NYSERDA defines indirect impacts as "market effects that are expected to accrue over the longer term from follow-on market activity that results from NYSERDA's investments." The initial workplan from NYSERDA stated that "Indirect impacts from the EV-Rebate program will be calculated in the same manner as the direct impacts; however, they will…only consider EVs purchased in NYS which did not receive a rebate from the program." Indirect impacts estimates will be developed based on NYSERDA's Appendix C: The Indirect Benefits Evaluation Framework (IBEF).

3.1.2 Indirect Impacts Plan

In the CEF Investment Plan[3] Clean Transportation Chapter appendix, indirect impacts are projected annually for the 11 years starting from program year 2020 through 2030. The investment plan provides annual planned direct and indirect impacts (i.e., the number of direct and indirect EV purchases and the associated MMBtu savings) for the Clean Energy Fund.[4] Table 13 summarizes those values. NYSERDA does not provide indirect impact projections in terms of vehicles. This analysis will estimate indirect effects in terms of additional vehicles and then calculate MMBtu savings based on direct impact analysis estimates of savings per rebated vehicle. The inferred number of indirect impact vehicles is provided to put this analysis in context. It is based on the Plan MMBtu indirect impacts projection divided by the Plan MMBtu savings per vehicle.

[3] Clean Energy Fund Investment Plan: Clean Transportation Chapter. Revised May 27, 2021. {8EE2A4C4-2255-4CCC-B073-8A7883450FF8}.pdf

[4] The chapter also provides planned impacts for the combined CEF and Regional Greenhouse Gas Initiative (RGGI) programs. In the 2021 version only the first three years of direct impact values are different across the two reports.

Table 13. CEF Investment Plan EV Program Annual Direct and Indirect Savings and Rebated Vehicles

Primary Metrics	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	TOTAL
Direct Impacts (MMBtu)	189,782	316,456	353,363	540,000	72,000										1,471,601
Indirect Impacts (MMBtu)				590,625	738,281	922,852	1,153,564	1,441,956	1,802,444	1,802,444	1,802,444	1,802,444	1,802,444	1,802,444	15,661,942
Rebated Vehicles (Direct)	3,213	5,475	5,603	9,000	1,200										24,491
Indirect Impact Vehicles (inferred)				9,844	12,305	15,381	19,226	24,033	30,041	30,041	30,041	30,041	30,041	30,041	261,032
Actual Rebated Vehicles	5,038	8,876	8,188	12,054											34,156
CEF/RGGI direct impacts report same number of participants and indirect impacts but additional direct impacts during the first three years															

Figure 3 plots the planned direct and indirect MMBtu savings. Also included are the numbers of participants—planned and actual for program rebates (direct) and inferred participant equivalents for indirect savings.[5] The Investment Plan numbers indicate that the program expects the indirect impacts to show a lagged effect that starts as direct EV rebates are phased out in 2020 and increases year to year until 2025 before becoming constant.

[5] Counts of customer equivalents in this plot use average savings per customer from the plan.

Figure 3. CEF Investment Plan EV Program Annual Direct and Indirect Savings and Rebated Vehicles

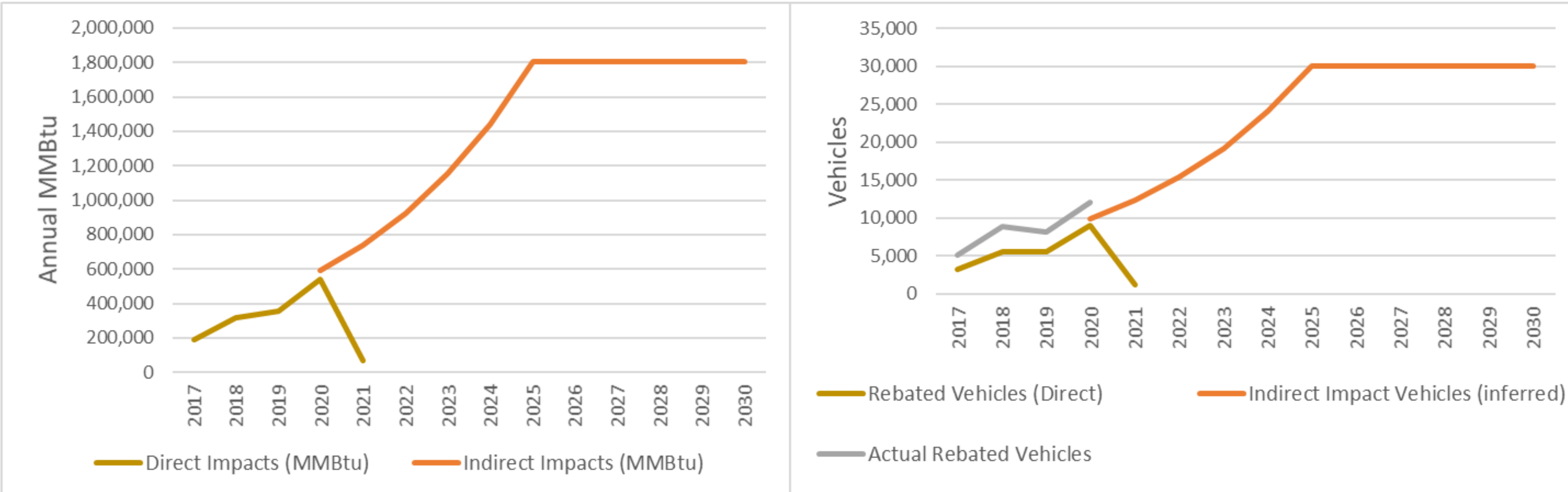
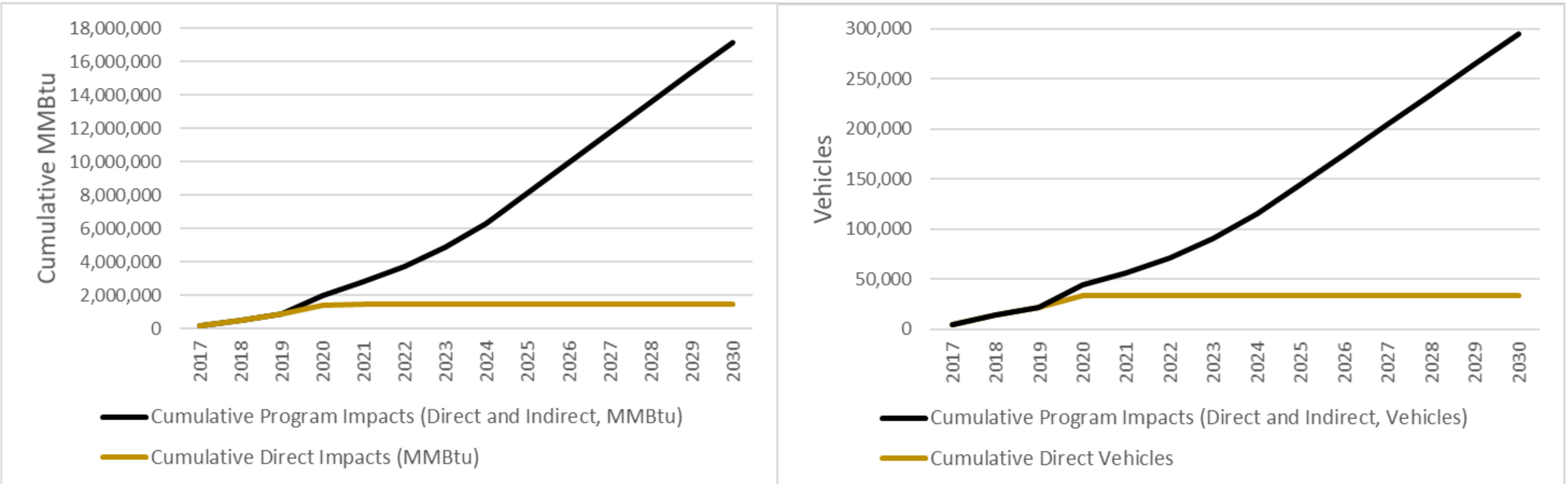


Figure 4 shows the same values plotted cumulatively. As discussed, direct impacts reach their final level at the end of the program and remain constant from that point forward. Indirect impacts develop during or immediately after the program and will continue to grow for multiple years determined by the overall shape of the adoption curves with and without the program.

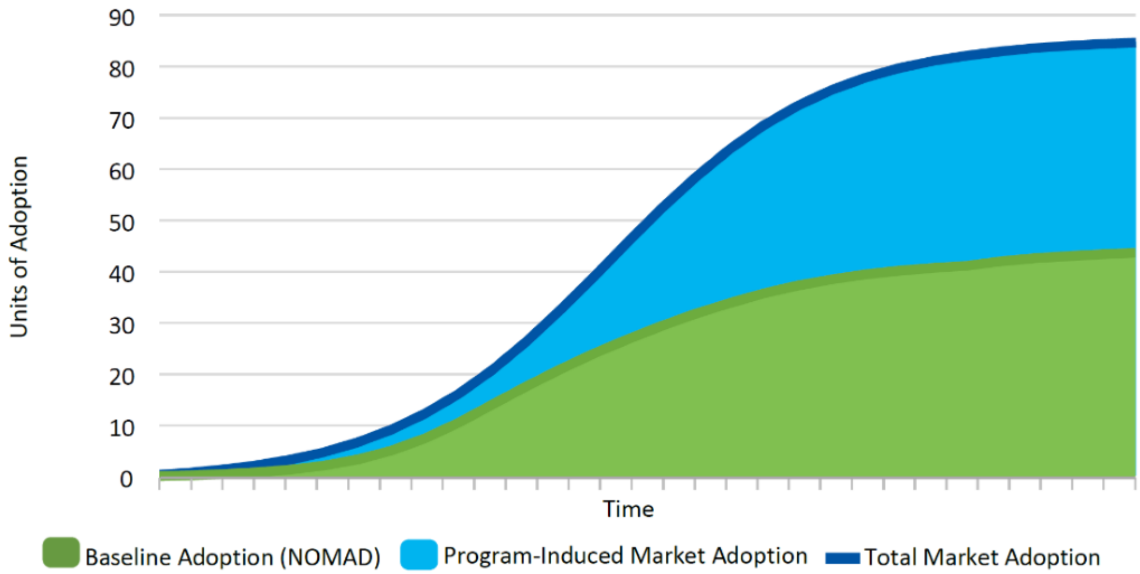
Figure 4 CEF Investment Plan EV Program Cumulative Direct and Indirect



3.1.2.1 Indirect Impact Framework

Figure 5 illustrates the IBEF framework, taken from the IBEF Appendix C document. The plot shows a classic adoption curve for total market adoption (vehicles purchased) divided into program-induced adoption (blue) and naturally-occurring market adoption (NOMAD, green). Baseline or natural adopters are EV acquirers who would have purchased an EV even if there had never been an EV rebate program. The program-induced adopters are EV acquirers that were motivated either directly or indirectly by the rebate program to purchase an EV. Both direct and indirect impacts are included in the program-induced market adoption (the blue area). The CEF Investment Plan version of these impacts is expressed above by the cumulative program impacts in Figure 4. Indirect impacts are the program-induced adopters excluding direct program participants. Direct program participants are addressed in the direct impact analysis.

Figure 5. Total, Program-Induced, and NOMAD Adoption Over Time



To accommodate the distinction between direct and indirect impacts required for this analysis, Figure 5 could have a third curve that would fall between NOMAD and Total Market Adoption that would represent direct program-induced adoption. The blue portion of the figure would look like Figure 4. The direct program adoption line would closely parallel the NOMAD line. The difference between the direct program adoption line and NOMAD reflects the number of program-induced rebated vehicles and the difference would be fixed as of the end of the rebate program. Because the total number of rebated vehicles represent a miniscule percentage of the overall population of vehicles in New York (roughly .4%), the direct program adoption line will always be indistinguishable from the NOMAD when looking at a figure that covers the the full adoption curve.

Indirect impacts are defined as the remainder of Total Market Adoption after the removal of NOMAD and direct impacts. As the figure illustrates, the removal of NOMAD is most important, and most challenging, step in this process. Removal of direct impacts is essential to avoid a kind of double counting. However, ultimately, it amounts to the removal of a fixed value of vehicles that represesnt the final program-induced vehicles. The direct program adoption line is included in the one plot that is sufficient zoomed-in to be able to see it. Otherwise, it is not included so as to maintain the focus on the removal of the NOMAD portion of adoption.

The IBEF offers the conceptual top-down approach to estimating indirect benefits in equation form:

Equation 5 Indirect Benefits

$$Indirect\ benefits = \sum (TMA - DPA - NOMAD)_t * UEB$$

Where:

TMA = Total market adoption

DPA= Direct participant adoption

NOMAD = Naturally-occurring market adoption

UEB = Unit energy benefits, in this case the MMBtu savings from the direct impact analysis

This approach starts with the top-down total market adoption of EVs and removes the direct effects of the program and NOMAD adoption to isolate the remaining EV sales. Indirect effects do not receive direct monetary support from the program but are still influenced by program efforts. Indirect effects can be positive, in this case, additional vehicles and savings, or negative. A benefit of this approach is that all components on the righthand side of the equation are known, with the exception of NOMAD. With the estimation of the New York EV NOMAD baseline, it is straightforward to estimate indirect benefits.

Unit energy benefits are based on the number of additional vehicles purchased as a result of the program. Vehicles are transformed to energy benefits based on the savings per vehicle calculated in the direct impact analysis. Final evaluation indirect impacts may differ from plan indirect impacts for either of two reasons – a different number of projected additional vehicles and/or a different MMBtu per vehicle assigned to those additional vehicles. In this case, prior to assessing the number of additional vehicles, we know from the direct impact analysis that MMBtu per vehicle will be well below those with which plan projections were made. The analysis follows this approach because IBEF states that indirect impacts should be "calculated in the same manner as the direct impacts" We acknowledge that is a conservative assumption for the projection of indirect impacts given the effects of COVID and the likely increase in VMT as levels of adoption increase.

3.1.2.2 Technical Approach

The framework offers three options for baseline forecasting methods: industry forecasts, econometric modeling, and structured expert judgment. The evaluation team proposed an econometric modeling approach. This approach is based on data related to historical EV adoption as a share of the market from New York and multiple other states with variation across the presence, level, and timing of EV rebates. Such a state-level model uses fixed effects to control for non-time-varying state characteristics along with time-fixed effects to control for non-state-varying trends that are consistent at the national level. Additional explanatory variables might control for vehicle cost, energy savings, and state-level demographics.

Such models can have a variety of structures. A common one is the difference-in-difference structure. This structure looks at changes over time and changes across states while minimizing imposed modeling. For this project, it would produce New York-specific estimates of NOMAD only for program years with existing historical data. Results would support an estimate of indirect benefits, during program years, that would be consistent with the IBEF, the rebate program's direct impacts, and the overall EV adoption in New York.

This econometric modeling approach was desirable due to its relative lack of structural assumptions and the use of other states' data to support the counterfactual. Unfortunately, the approach was not possible due to a lack of viable data from other states. Further, a key part of the indirect impact analysis is projecting vehicle adoption until 2030 and beyond. It is the structural assumptions of a model that allow results to be projected into the future, providing a forecast of EV adoption with and without rebates. Even if the state-level data had been available for this modeling approach, the results would have had to be projected forward, requiring the use of an additional model like the one we ultimately chose to use.

The approach pursued here is fundamentally an econometric one that incorporates aspects of other approaches. To combine the required forecasting functionality into an econometric approach, we use a Bass diffusion curve (the function underlying the indirect benefits framework discussed above). This approach grounds the modeling process in a widely accepted framework for understanding how a population adopts a new technology. The underlying equation follows a roughly logistic shape, indicating slow and gradual adoption by the first innovators and then the early adopters before the adoption rate increases as the technology takes hold in the wider population. Adoption then slows again as the market reaches saturation, with remaining laggards very gradually taking part.

This modeling approach assumes that adoption will take a trajectory with this rough shape and ultimately reach full adoption among the portion of the population willing to adopt the product (this can be expressed as 100 percent of the specific market, or some percentage of a broader market, but the adoption curve is the same). The model increases monotonically but is flexible about how early the increase begins and the maximum rate of increase when adoption is its highest. For this analysis, it is most important to be able to apply a consistent modeling process to the data, producing both the total market adoption curve and the NOMAD. Rather than making arbitrary decisions about how the trajectory of adoption would change due to the Drive Clean program, this approach allows the data to determine the different curves within a set of reasonable assumptions.

A key driver of the final indirect impact estimate is the program-induced direct impact of each rebate. The direct impact result provides a program inducement rate of 0.41, or 41%, indicating that, on average across the four years, 41 out of 100 of the rebated vehicles were purchased as a result of the rebates. That is, 59 of 100 rebated vehicles would have been purchased without the program and thus fall under the NOMAD curve.[6] This represents the percentage of vehicles on the market for which the rebate program can claim direct responsibility. We develop our analysis across a range of input values.

The modeling approach is based on program-induced vehicles and does not explicitly account for other CEF-funded programs NYSERDA is implementing in the EV space. A fully conservative approach would assume that those additional efforts are required as support for the vehicle-based indirect impact results produced here. More likely, those efforts represent further positive inputs that should increase the differential between NOMAD and Total Market Adoption, increasing the indirect impacts.

[6] Strictly speaking, in later program years, vehicles that would have been purchased without a rebate could have been motivated by earlier, program-influenced vehicle purchases, or by non-rebate NYSERDA programmatic efforts (e.g., installation of EVSE). That is, the indirect effects specific to the rebate, and broader changes from NOMAD, could start materializing shortly after the first direct effects. In actuality, the CEF Investment Plan only starts claiming indirect impacts associated with rebates in 2020 and the simplifying assumptions required for modeling mean this analysis starts measuring indirect impacts after the close of the program.

3.2 Data

The indirect impacts analysis required additional data beyond what was required for the direct impact analysis.

New York maintains a public vehicle registration database that includes unique Vehicle Identification Numbers (VIN) for all registered vehicles. This makes it possible to identify the total number of BEV and PHEV vehicles registered in New York as well as the total number of private vehicles.

Such tractable data were not available for other states. The evaluation team looked at historic vehicle registration datasets used for developing Atlas Public Policy's EV Hub. The hope for these data was to create a state-by-state time series analysis that would identify variation of EV purchasing behavior in the face of different incentive structures. These datasets varied in structure from state to state, and furthermore only included the publicly facing, anonymized data after Atlas has processed the files originally provided by the states. These datasets left us with 3 main unknowns for which credible analysis of EV market shares could not be completed:

1. All datasets, except that from EValuateNY, only included BEV/PHEV registration data. This means it is impossible to get an accurate and consistent market share from these data for BEV/PHEV purchasing habits in relation to standard combustion vehicles (ICE)
2. All state registration datasets have multiple DMV snapshots stacked on top of each other, meaning a vehicle can show up multiple times either from re-registration, or from showing up in consecutive snapshots for the same instance of registration. Because provided vehicle IDs are not unique to the actual vehicle themselves, it's not possible to identify and remove these types of duplicates.
3. Lastly, after internal investigation and a conversation with staff at Atlas Public Policy, the only way to get a time-series dataset would be to calculate the difference in registrations between datasets. For example, if snapshot 45 has 39,000 registrations and snapshot 44 had 38,000 registrations, it could be assumed there were 1,000 new BEV/PHEVs registered during that time period. Variation of snapshot occurrences and limited historic data make this analysis not possible.

3.3 Methods

This analysis uses a Bass diffusion curve approach. This approach is consistent with the IBEF. It is also consistent with the scope and nature of the current analysis. While diffusion (or adoption) curves have well enumerated limitations, they also have, by their ubiquity, a level of conceptual understanding. The Bass diffusion curve incorporates coefficients that can be understood to reflect the processes of innovation and imitation within the adopting population. In the context of indirect benefits that require some form of forecast, a Bass diffusion curve approach provides a useful structure for forecasting while incorporating available observed market share data. Finally, this analysis focuses on the difference between two forecasts rather than relying on the accuracy of a single forecast. The use of a consistent function to develop the two adoption curves is essential and focusing on the difference places a limit on how inaccurate the results can be.

3.3.3 Theoretical Approach

Massiani and Gohs provide a useful but cautionary summary of the use of Bass diffusion models, both in general and in the context of EVs.[7] The Bass model is driven by three parameters. The parameters *p* and *q* capture the actions of two kinds of people. Massiani describes the two kinds of people this way:

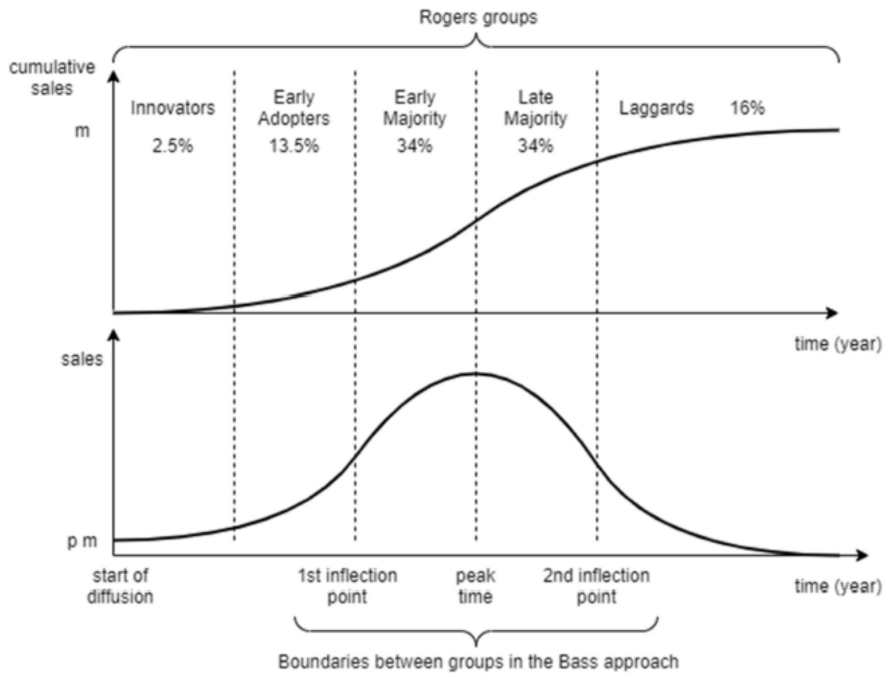
Innovators (*p*)—people who buy the product first and are influenced only by "external communication" (e.g., mass media or advertisements), and Imitators (*q*)—people who, in contrast, buy the product if others have already bought the product, since they are influenced by word-of-mouth or so-called "internal communication."

The third parameter, usually referred to as *M*, represents market saturation, or the portion of the population that will ultimately adopt the measure. Because this parameter is far more difficult to estimate empirically, it is frequently included in modeling and tested as a range of fixed values.

Figure 6 copies a popular visual reference used in the Massiani paper to explain how Bass diffusion curves work.

[7] Massiani, J.; Gohs, A. The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. Res. Transp. Econ. 2015, 50, 17–28. [CrossRef]

Figure 6. Bass diffusion curve explanation



Sales are specified as:

$$f(t) = Mp + (q - p)F(t) - \frac{q}{M}F(t)^2$$

where sales at any point (*f(t)*) are a function of cumulative sales to that point (*F(t)*). The parameter of imitation (q) operates on the level of cumulative sales in the prior period whereas the parameter of innovation (p) enters primarily as a constant operating on the potential population and secondarily as a dampening effect on q in the second component of the equation.

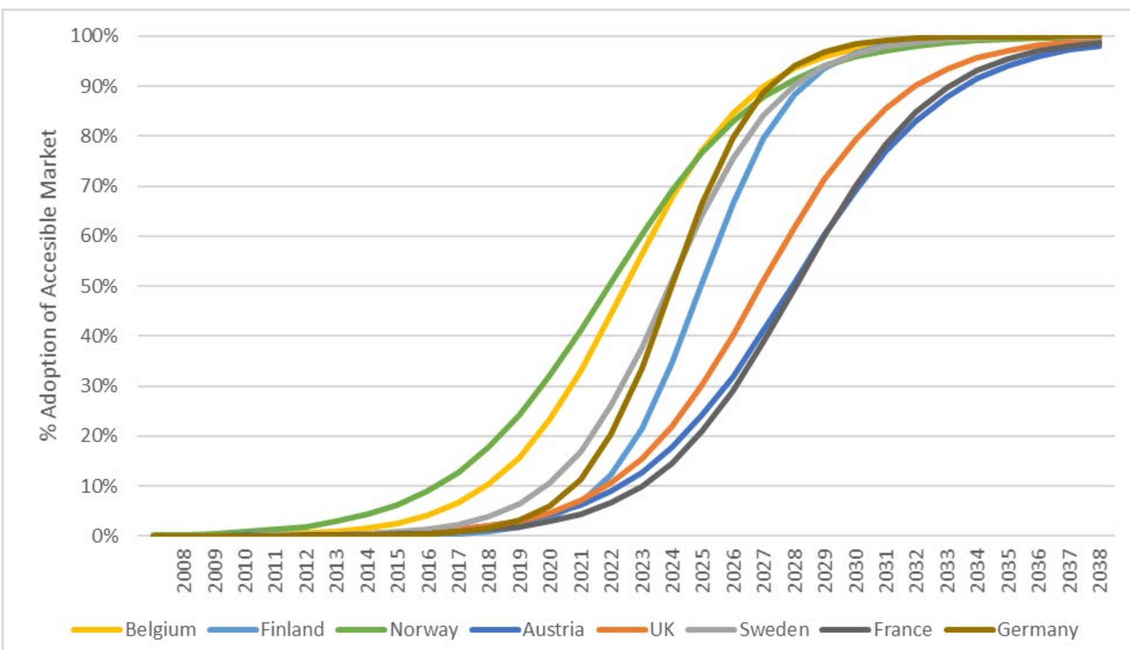
These parameters enter the following equation to estimate the total fraction that is adopted by time t:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 - \frac{p}{q}e^{-(p+q)t}}$$

Because of the way they enter the equation, the p parameter drives the speed of early adoption while the q parameter determines the speed of increase. A higher p parameter with a fixed q parameter will flatten the adoption curve into a straighter line between starting and end points. An increasing q parameter with a fixed p parameter will increase the steepness of the climb at the point of greatest adoption.

A recent article in *Energies* Journal explores the heterogeneity of alternative fuel vehicle adoption in European countries using a Bass diffusion curve approach.[8] Like the analysis pursued here, the goal of the analysis focuses on the difference between curves all estimated in a consistent fashion. The article provides estimated adoption curve coefficients for European countries considered leaders in the adoption of alternative fuel vehicles (AFVs). Figure 7 provides a plot of those curves. Each line represents a different combination of innovation and imitation parameters. Also, the Y-axis represents adoption percentage of the accessible market, which varies between 70 and 100% percent of the full vehicle market in each country. Due to other technologies, some countries are expected to reach their maximum EV adoption at 70% of the market whereas others will reach full adoption at 100% of the market.

Figure 7. Example adoption curves from "BASS Model Analysis in 'Crossing the Chasm' in E-Cars Innovation Diffusion Scenarios"



[8] Brdulak, A.; Chaberek, G.; Jagodzinski, J. BASS Model Analysis in "Crossing the Chasm" in E-Cars Innovation Diffusion Scenarios. Energies 2021, 14, 3216. https://doi.org/10.3390/en14113216

The plot offers an illustration of the different adoption trajectories of a subset of more active European countries. The different curves illustrate a range of combinations of p and q parameters. Comparing any of the two curves over the x-axis timeframe, it's possible to see the implications of two divergent policy paths.

For our analysis, the rebates will be the driver of different trajectories, accelerating the adoption of EVs. The two lines, representing Total Market Adoption and NOMAD will diverge up to a point and that divergence, excluding the direct rebates themselves (an interim line, as illustrated in Figure 4), will represent the indirect impact of the rebates. Because the assumed end point is the same for both Total Market Adoption and NOMAD—the accessible portion of the market—the range of possible differences between the two lines is reduced. This assumption that the program does not increase the ultimate percentage of the market that is accessible to EV adoption is an important conservative assumption in this analysis.

A key finding from the Massiani paper is that the percentage of the population that will ultimately adopt is both difficult to estimate and can lead to widely varying estimates of p and q. The solution it offers, which we follow, is to make this an exogenous input into the model.[9] For this analysis, we test scenarios across a range of population levels to understand the implications for the difference between Total Market Adoption and NOMAD (net of the direct impacts). We estimate indirect impacts, or the difference between the two curves, under different assumptions about the population. The difference in estimated impacts across population percentage levels is not substantial (a range of 15%) and is not directly correlated with the change in population level (increasing or decreasing as the population moves in one direction).

3.3.4 Technical Methods

The data available for this analysis are limited to the span of 10 years—6 before the start of the Drive Clean program and 4 since the start. It was not practical to estimate curve parameters using a full-blown non-linear regression approach. Instead, we mimicked a regression approach by identifying the curve and associated set of parameters that minimized the error with respect to actual adoption data. We developed adoption curves reflecting the full range of feasible model parameters and compared them to the annual market share data. This grid-search approach

[9] Follows a similar approach to that used in the report to NYSERDA by IEc, ETAC and Advanced Buildings Solid State Lighting and Controls Market Adoption Curve Analysis, May 2017 .

identifies the set of parameters that minimize the squared error. The accuracy of the approach is limited only by the fineness of the grid search.

Two general approaches were considered. The most intuitive approach develops the NOMAD adoption curve using the available pre-program data while the second, total market adoption curve is estimated using all 10 years of data including the four program years. All else being equal, if the program increases the adoption of EVs, then the total market adoption curve should increase more quickly than the NOMAD curve.

In fact, when we applied this approach, the estimated NOMAD curve indicated that adoption would proceed more quickly without the program than it did with the program. This highlights the shortcomings of modeling without comparison states to account for changes in vehicle adoption not otherwise accounted for in the model. An approach like this, which compares pre-rebate data to program-period data, assumes that all variables not accounted for in the model that could affect EV sales do not change. This model does not control for the pandemic or any other external drivers of EV adoption. The assumption of no change over time is unreasonable and the results from this approach illustrate that.

In the absence of other states' data, an alternative, direct way to estimate the two curves addresses the challenge of time-varying effects by including all 10 years in the estimation of both the NOMAD and total market adoption curves. For this approach, the total market adoption curve is estimated using the existing market-share data from 2011 through 2020. These data include the additional vehicles on the road as a result of the Drive Clean rebate program.

The NOMAD curve is produced by using the same data but removing the program-induced portion of rebate participants from each of the 4 years of market share data during the timeframe of the program. The NOMAD data series is a recreation of the market share data that would have existed had the Drive Clean program not existed. The direct impact analysis provides an estimate of program influence. This allows the difference between the two adoption curves to represent only those rebated vehicles that would not have been purchased had the program not existed. The remainder, those vehicles that do receive program-induced savings are removed from the Total Market Adoption to NOMAD difference for the final estimate of indirect impacts. Because this approach implicitly assumes indirect impacts do not begin until after the program ends, this is a further conservative assumption built into the method.

We estimate total market adoption curves in two different ways. The first identifies the adoption curve, allowing both p and q to vary, that minimizes squared error over the 4 program years. The second approach fixes the total market adoption imitation coefficient, q, at the same level as the NOMAD but allows p to vary. The second approach limits the change to the parameter that is designed to track external effects.

Using either estimation approach, the calculation of indirect impacts is the same. Because the market data represents adoption across the whole population, the cumulative impact of an intervention is represented by the difference between the lines at each year. The Drive Clean program claims indirect benefits through 2030. Maximum indirect impacts will be the maximum difference between the two curves through 2030. Because of the early intervention in the market, for all results, the curves continue to diverge at year 2030. This means indirect impacts are calculated as the difference as of 2030 (with directly rebated vehicles removed). The estimate of indirect impacts as of 2030 is a conservative estimate, as they will continue to expand beyond 2030.[10]

Finally, the estimate of additional vehicles due to the program is put on MMBtu terms using the direct impact VGS estimate for MMBtu savings for program vehicles. As discussed there, this value is lower than program claimed values. This is, in part, due to lower actual miles driven than assumed for plan direct impacts. For these results, this potentially conservative assumption is maintained throughout the adoption curve despite the fact that miles driven will assuredly increase as larger share of cars on the road are EVs. We report indirect impacts in vehicle and MMBtu terms so that it is possible to view the implications of the indirect impact analysis separately as well as combined with direct impact analysis MMBtu values.

3.4 Results

This section provides results for the two analysis approaches across ranges of program influence and percentage of market. First, we provide examples of the two analysis approaches for a set program influence and percentage of market to clarify the differences between the two

[10] Indirects impacts can be reported annually as the marginal indirect impacts that accrue each year. Those annual indirect savings will increase at an increasing rate, then increase at a decreasing rate before starting to decrease. Because all visual representations of adoption are cumulative, we believe it is easier to picture total indirect impacts at any point as the difference between curves at that point.

approaches. Next, we illustrate how curves differ across market percentages. Finally, we provide tabular indirect impact estimates for all scenarios illustrating the range of possible outcomes.

Figure 8 provides an example of the fully independent total market adoption curve where both p and q are allowed to vary. The plot overlays the total market adoption and NOMAD curves for the scenario where EVs ultimately take over 70% of the vehicle market shortly after 2050 and the program has 0.45 program influence. The impacts are cumulative and, in this plot, primarily direct impacts. The difference between the Actual EV% and the NOMAD EV% represents the program induced vehicles from the Drive Clean program.

Figure 8. Total Market vs NOMAD with underlying data, varying p and q

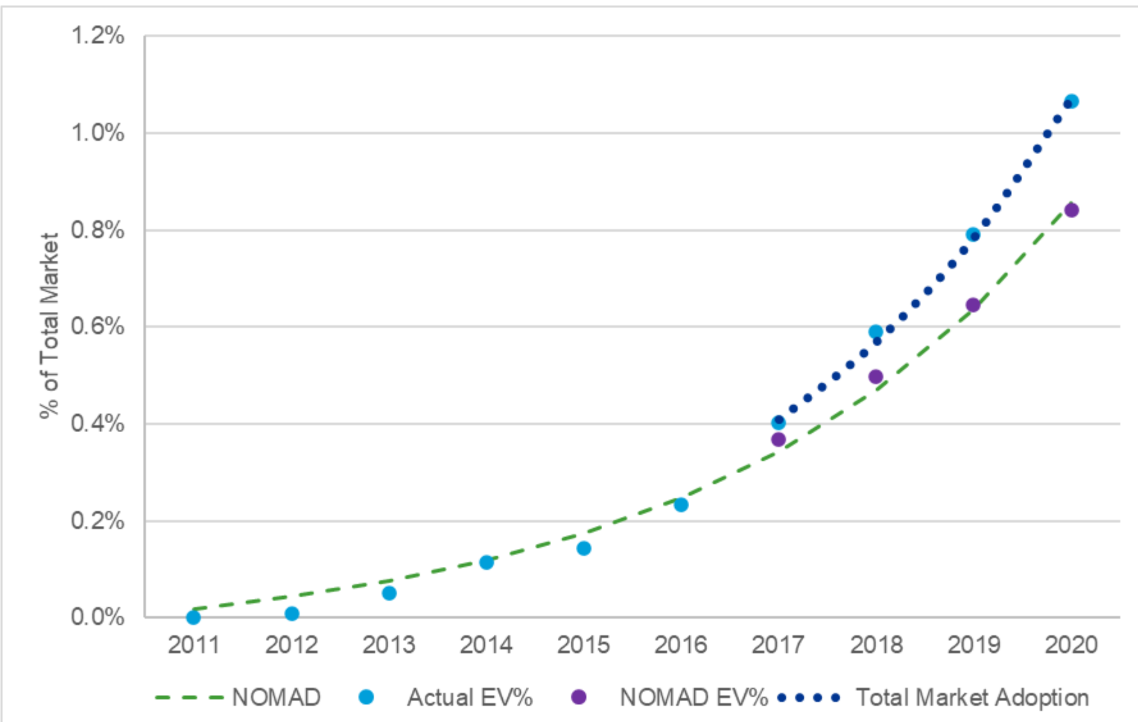


Figure 9 plots the same data as Figure 8 but through the year 2030. The difference between the curves in the year 2030, excluding the direct impacts, represents the indirect impacts through 2030. Because the full market is illustrated each year, indirect impacts are not the area under the curve. To be consistent with how the indirect impacts were claimed in the plan, the indirect impacts could be calculated as the marginal additional distance between the two curves each year.

They would still sum to the difference between the two lines in 2030. The indirect impacts continue to grow after 2030.

Figure 9. Total Market vs NOMAD, varying p and q, through 2030

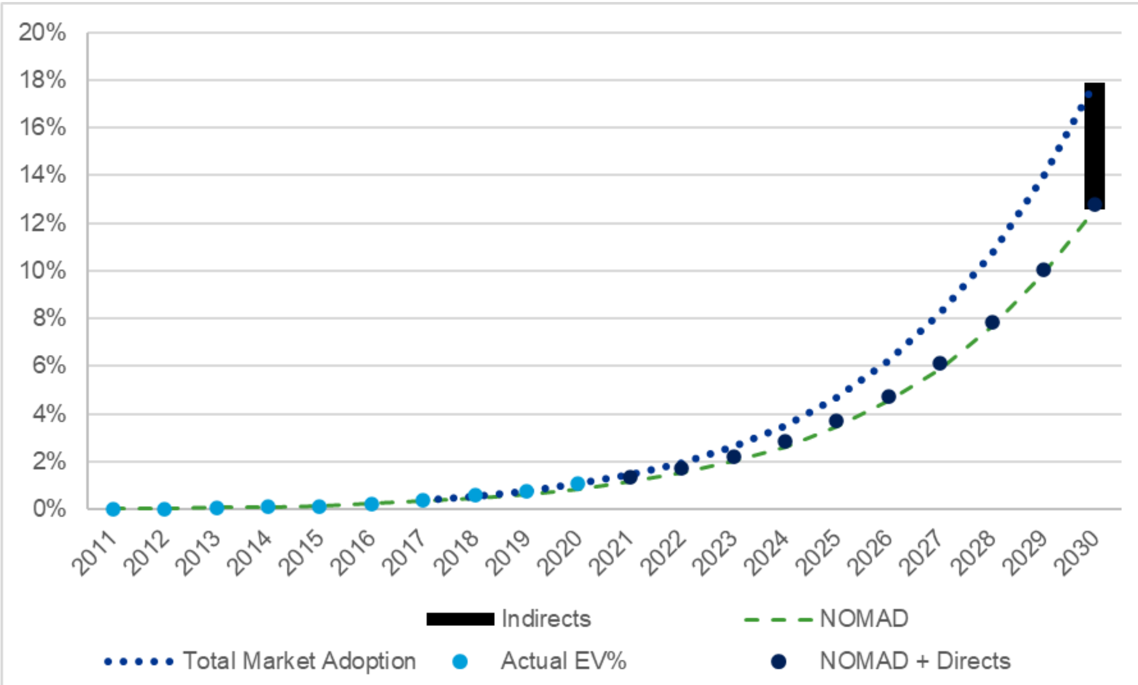


Figure 10 and Figure 11 provide the same plots with the Total Market adoption curve only varying with respect to p, the innovation coefficient. This second set of plots assumes that the program cannot affect the imitation coefficient, q. While the distinction is subtle through 2020, by 2030 there is a marked reduction in the curves' divergence, lowering the implied indirect impacts.

Figure 10. Total Market vs NOMAD with underlying data, varying only p

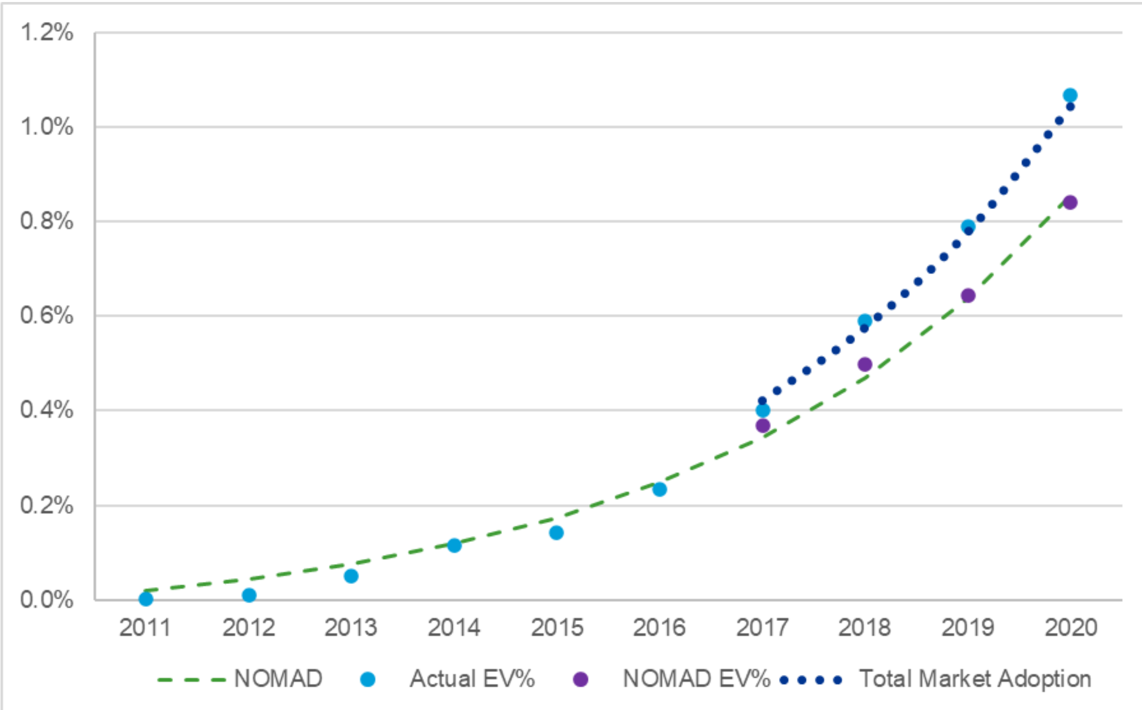


Figure 11. Total Market vs NOMAD, varying only p, through 2030

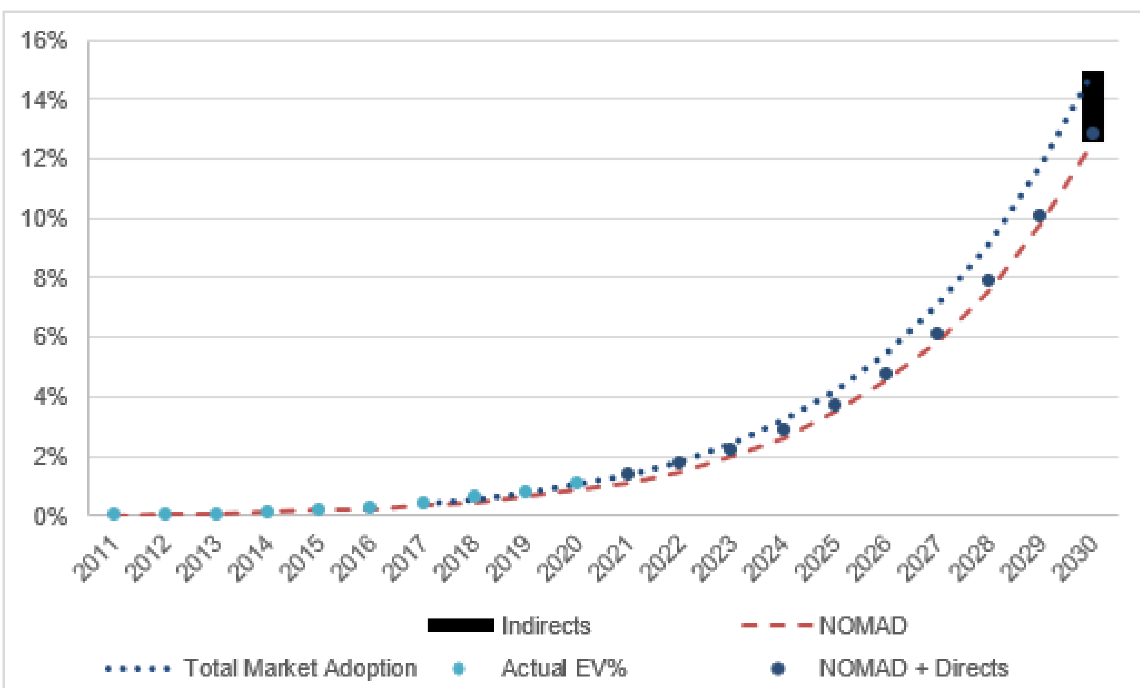


Figure 12 shows the estimated market adoption curves for EVs given a program influence of 0.41 and allowing total market adoption to vary in both p and q. The four curves represent scenarios where EVs take over 70, 80, 90 or 100% of the non-commercial passenger vehicle market. The curves all approach 100% adoption in 2050. By 2030, the adoption curves have reached 12 and 18% of their respective markets. The plot illustrates the assumption that the size of the potential market is outside of the control of this program; the program cannot increase the portion of the vehicle market accessible to EVs.

Figure 12. Market and NOMAD, 70 through 100% of New York market, 0.41 program inducement, p and q varying

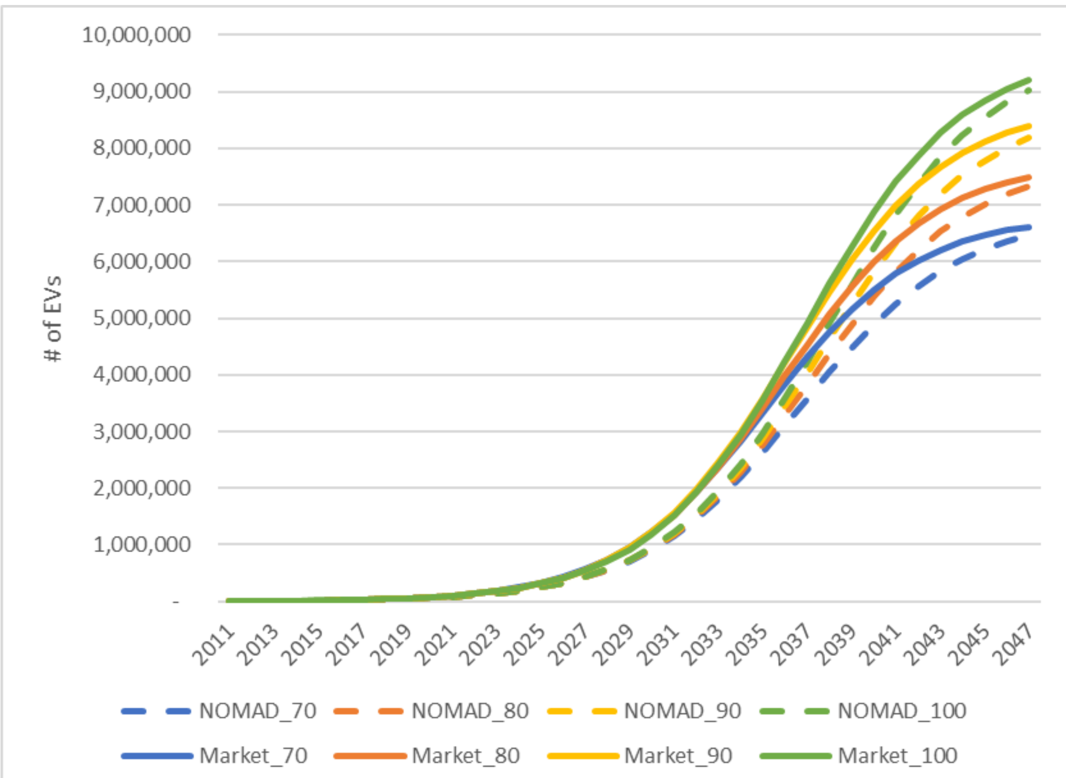


Figure 13 provides the same set of curves for the other analysis approach where the total market adoption curve can only vary in p. It is clear that the divergence for this approach is reduced.

Figure 13. Market and NOMAD, 70 through 100% of New York market, 0.41 program inducement, p only varying

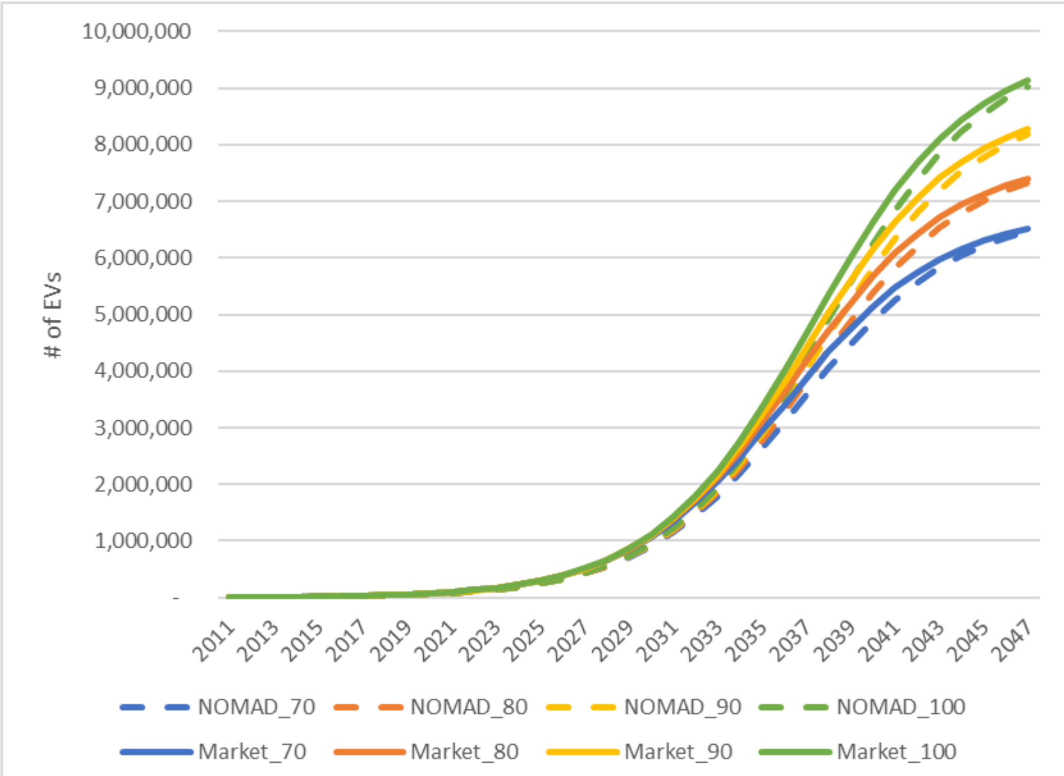


Table 14 and Table 15 provide the estimates of indirect impacts, in terms of additional vehicles, across a range of assumed market percentages and program inducements. The results in Table 14 are based on the total market adoption curve that is free to vary across p and q, while the results in Table 15 are based on the total market adoption curve that only varies across p. The first set of results where q can vary is substantially more sensitive with respect to program inducement rate. The variation across market percentage within any program inducement level is much more limited but impacts generally increase as market percentage decreases.

Table 14. Additional vehicles due to indirect impacts by percent of market and program inducement, p and q varying

Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	395,501	342,808	241,081	218,283	104,457	36,717
80%	372,525	309,199	208,575	134,112	69,026	0
90%	383,498	318,768	206,057	144,387	63,122	0
100%	335,344	230,502	213,442	95,196	11,922	0

By contrast, when the imitation coefficient, q, is held constant, there is less variation across NOMAD and total market adoption. Table 15 is shaded on the same color gradation as Table 14. All of the results with the fixed imitation coefficient are in the range of the 0.35 program inducement results when both coefficients are allowed to vary.

Table 15. Additional vehicles due to Indirect impacts by percent of market and program inducement, p only varying

Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	152,112	143,845	134,132	111,334	93,022	86,224
80%	162,915	141,593	138,723	121,358	101,656	78,282
90%	167,594	154,078	135,483	129,536	105,653	95,559
100%	166,126	162,030	144,971	133,462	105,574	93,275

The CEF Investment Plan indirect impacts forecast represents approximately 260,000 additional vehicles from 2020 through 2030. Given a program inducement in the 0.40 and 0.45 range, the results range from approximately 50% to 132% of the expected level (a low-end value of 134,132 vehicles in Table 15 at 70 percent market adoption, to a high-end value of 342,808 vehicles in Table 14 at 70 percent market value). A single, best estimate of the additional vehicles that will be on the road in 2030 due to the program is 253,597 which is calculated at 0.41 program inducement with EVs capturing 80% of the market. The value is based on the more flexible model (p and q varying) and falls in the middle of the range of estimates across different market percentages. This evaluation estimate of indirect vehicles represents 0.97% relative to CEF Investment Plan projections.

It is worth noting that across both approaches and all combinations of percentage of market and program inducement, indirect impacts continue to increase after 2030. By 2035, both approaches produce indirect impacts estimates at 100% to over 200% of CEF Investment Plan expectations. That is, 2030 is an arbitrary deadline when considering indirect impacts in an adoption context.

Table 16 and Table 17 provide the same two sets of results in MMBtu terms. These impacts are calculated using the direct impact VGS estimate of 30.7 MMBtu savings per program-induced vehicle. The best single estimate of program indirect impacts, calculated at 0.41 program inducement with EVs capturing 80% of the market, is 7.8 million MMBtu. For a realization rate, these estimates can be compared to the CEF Plan projections of 15.6 million MMBtu or 11.1 million MMBtu which is the CEF Plan projected vehicles updated to Program expected per-vehicle savings[11]. As mentioned above, the vehicle estimate is 97% of those projected in the CEF Plan. The indirect MMBtu impacts are 70% of CEF Plan projections that is consistent with the direct VGS RR combined with the slightly reduced expected vehicles. As discussed above, this is in part driven by lower miles driven for current program-induced vehicles which is likely a conservative assumption for future vehicles as market adoption reaches a greater share of the market.

[11] The CEF Investment Plan values are the only projected indirect impact values and were created in advance of program implementation and actual program claimed savings. Program claimed savings are roughly 70% of those used in the CEF Investment Plan. In combination, this means the current indirect impact results appear to have a roughly 0.50 realization rate (71% * 71%) relative to CEF Investment Plan projections.

Table 16. MMBtu savings due to Indirect impacts by Percent of Market and Program inducement, p and q varying

Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	12,141,871	10,524,215	7,401,198	6,701,301	3,206,841	1,127,209
80%	11,436,525	9,492,403	6,403,243	4,117,242	2,119,109	0
90%	11,773,377	9,786,183	6,325,951	4,432,684	1,937,846	0
100%	10,295,062	7,076,401	6,552,681	2,922,509	366,020	0

Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	12,275,036	10,639,639	7,482,370	6,774,797	3,242,012	1,139,571
80%	11,561,954	9,596,510	6,473,470	4,162,397	2,142,350	0
90%	11,902,501	9,893,513	6,395,331	4,481,299	1,959,099	0
100%	10,407,972	7,154,011	6,624,547	2,954,562	370,034	0

Table 17. MMBtu savings due to Indirect impacts by Percent of Market and Program inducement, p only varying

Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	4,669,832	4,416,034	4,117,841	3,417,943	2,855,780	2,647,071
80%	5,001,484	4,346,893	4,258,783	3,725,705	3,120,838	2,403,253
90%	5,145,141	4,730,185	4,159,320	3,976,746	3,243,545	2,933,670
100%	5,100,061	4,974,314	4,450,595	4,097,275	3,241,114	2,863,529

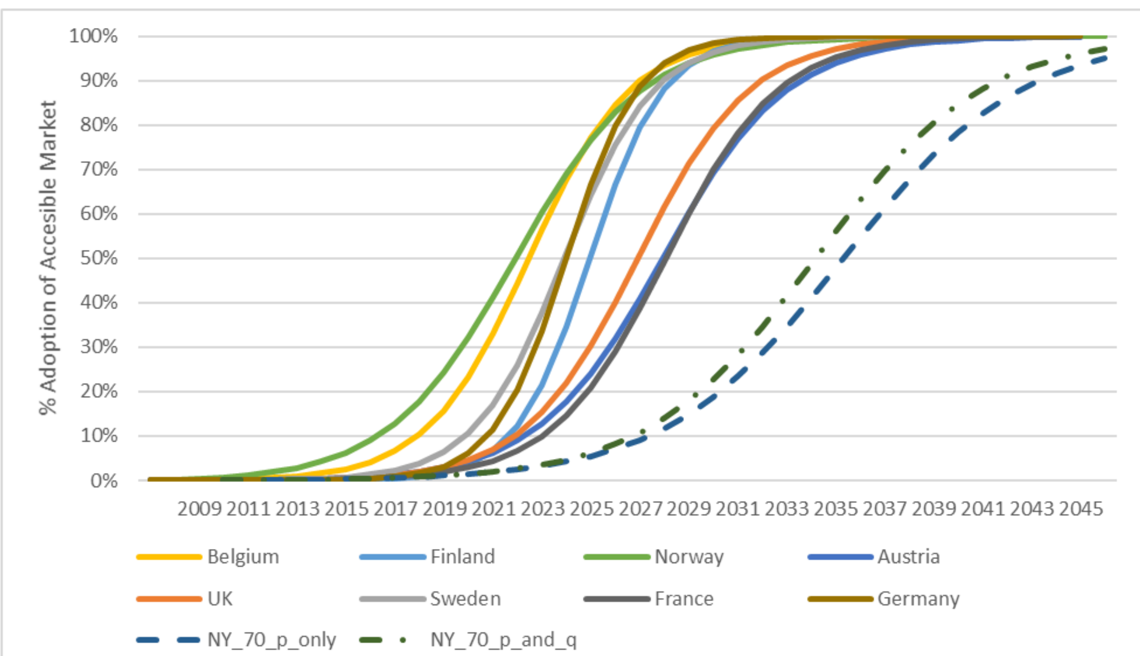
Percent of Market	Attribution					
	0.5	0.45	0.40	0.35	0.30	0.25
70%	4,721,048	4,464,466	4,163,003	3,455,429	2,887,100	2,676,103
80%	5,056,337	4,394,567	4,305,491	3,766,566	3,155,066	2,429,610
90%	5,201,570	4,782,063	4,204,937	4,020,361	3,279,118	2,965,845
100%	5,155,995	5,028,870	4,499,407	4,142,212	3,276,660	2,894,935

3.4.5 Discussion

An estimate of the indirect impacts of a rebate program in the decade following the program is an exercise in forecasting market development and accounting for program inducement. As discussed in the methods section, the NYSERDA indirect impact framework describes the appropriate conceptual framework with which to estimate the indirect impacts. Indirect impacts are the difference between the NOMAD and total market adoption net of direct impacts. These two adoption curves can be reasonably described mathematically using the Bass diffusion curve. The Bass diffusion curve offers a consistent mathematical formula that provides substantial flexibility of form around the classic S-shaped adoption path. We chose the basic, widely used Bass diffusion curve because it has proven to be descriptive of adoption across a range of products. The assumption is that adoption of EVs, under total market and NOMAD conditions, will increase to some market percentage following a path described by this formula.

To put the results from this analysis in context, it is worth putting the total market adoption curves in the context of the European adoption curves provided earlier. Figure 14 adds New York total market adoption curves to the examples of empirically estimated adoption curves for the European countries with the highest current EV adoption. The two added New York adoption curves depict a 70% market adoption for the two estimation approaches. The total market adoption curves estimated for New York indicate slower adoption than any of the European countries but still reach 100% adoption by 2050. Both of the New York total market adoption curves are paired with the same NOMAD.

Figure 14. New York Adoption curves relative to Top European Countries



If, in reality, the New York Total Market Adoption curves prove to be closer to even the least aggressive European countries, the indirect impacts will be higher than those calculated by this analysis. Conversely, if adoption, particularly in the early years, is slower than as modeled, then the indirect impacts will be lessened. However, because the indirect impacts estimate is a function of the difference between two curves estimated from the same underlying data, the difference in indirect impacts will change more slowly than any change in actual adoption rate.

Table 18 shows the innovation and imitation coefficients for the leading European EV adopting countries compared to the two New York adoption curves presented. The two New York innovation coefficient are greater than all countries other than Norway. In contrast, the New York imitation coefficients are well below all of the other countries. These comparisons are somewhat counterintuitive. On the one hand, we would expect New York's externally oriented factors, the innovation coefficients, to be similar to or below most European countries. On the other hand, it is unexpected that New York's imitation coefficient would be so much lower than all of the European countries. As partial explanation of this, it is worth remembering that these models do not control for other independent variables such as gas and electricity prices, income, miles driven, etc. Given this, the two Bass diffusion model coefficients account for these differences. That is, Europeans are not necessarily more prone to word-of-mouth dissemination of the measure (high imitation coefficient, q) but under their overarching market conditions, a higher rate of the imitation coefficient is required to fit the data.

Table 18. Innovation (p) and Imitation (q) coefficients for New York and Leading European countries

Country	P	q
Austria	0.000050	0.391
Belgium	0.000169	0.483
Finland	0.000002	0.663
Norway	0.000807	0.387
UK	0.000031	0.436
Sweden	0.000018	0.544
France	0.000019	0.436
Germany	0.000002	0.686
NY_70_p_only	0.000198	0.275
NY_70_p_and_q	0.000176	0.295

There are two takeaways from this comparison that have implications for indirect impacts in New York. First, while it might be reasonable to assume that all else equal, the imitation coefficient should not vary (the assumption under which the more conservative approach is estimated, with only p varying), if those independent variables change and move closer to European levels, it appears likely that the imitation coefficient would increase. An increased imitation coefficient would lead to greater indirect impacts.

Second, in either case, if NYSERDA wanted to incorporate improvements to charging infrastructure and other enhancements into the models, the approach is straightforward, and implications easily assessed. Improved charging structure should be understood as an external input into the model, thus affecting the innovation coefficient, p. Increases in this parameter, with a fixed imitation coefficient, will increase indirect impacts but will have more modest implications with respect to indirect impacts as reflected in the approach that only varies in p. Despite this, any increase in the innovation coefficient will have a clear multiplier effect in subsequent years. It is also worth noting that, while the theoretical underpinnings of the model point to an increase in p only, the recognition that both coefficients incorporate effects of unaccounted-for inputs could also support an increase in the imitation coefficient. This would only increase the downstream indirect impacts of the charging infrastructure improvements.

This indirect impact analysis demonstrates that the NYSERDA Drive Clean EV rebate program indirect impact projections are reasonable. The indirect impacts estimate of additional vehicles as of 2030 is similar to projections in some scenarios and goes well beyond projections in most scenarios shortly after 2030. Because MMBtu savings per vehicle expectations were too high, projected indirect MMBtu impacts are proportionally lower. Again, shortly after 2030, the number of estimated additional vehicles makes up for the decrease in per vehicle MMBtus.

The analysis incorporates stringent program inducement findings from the direct impact analysis as well as numerous assumptions that are likely to lead to conservative estimates of impacts – no changes in the imitation parameter, no increase in accessible market percentage, etc. While indirect impact forecasts are, by definition, highly contingent, this analysis demonstrates that projected impacts were reasonable given a set of reasonable assumptions and scenarios.

Appendix A: Direct Impact Tables

Table A-1. Rebated Vehicle Counts by Vehicle Type, Acquisition Type, and Program Year

Vehicle Type	Acquisition Type	_2017	_2018	_2019	_2020	Cumulative
BEV	Lease	801	393	1,061	2,708	4,963
BEV	Purchase	456.0	1103.0	3344.0	6451.0	11354.0
BEV	**Total**	**1,257**	**1,496**	**4,405**	**9,159**	**16,317**
PHEV	Lease	1,404	3,001	1,772	1,881	8,058
PHEV	Purchase	1,791	2,951	1,949	2,030	8,721
PHEV	**Total**	**3,195**	**5,952**	**3,721**	**3,911**	**16,779**
Both	**TOTAL**	**4,452**	**7,448**	**8,126**	**13,070**	**33,096**

Table A-2. Rebated Vehicle Counts by Vehicle Type, Vehicle Make, and Program Year

Vehicle Type	Vehicle Make	_2017	_2018	_2019	_2020	Cumulative
BEV	Audi			28	24	52
BEV	BMW	5	10	11		26
BEV	Chevrolet	539	383	298	460	1,680
BEV	Ford	18	6			24
BEV	Hyundai			442	469	911
BEV	Jaguar			25	19	44
BEV	Kia	396	69	44	86	595
BEV	MINI				20	20
BEV	Mercedes-Benz	2	1			3
BEV	Nissan	169	215	273	129	786
BEV	Porsche				8	8
BEV	Tesla	113	742	3,197	7,926	11,978
BEV	Volkswagen	4	29	59	18	110
BEV	smart	11	41	28		80
BEV	**Total**	**1,257**	**1,496**	**4,405**	**9,159**	**16,317**
PHEV	Audi	1	1		7	9
PHEV	BMW	273	489	234	172	1,168
PHEV	Chevrolet	430	733	397	9	1,569
PHEV	Chrysler	27	96	67	42	232
PHEV	Ford	577	355	725	349	2,006
PHEV	Honda	8	1,547	481	29	2,065
PHEV	Hyundai	4	16	117	1,089	1,226
PHEV	Kia	136	207	94	49	486
PHEV	Lincoln				3	3
PHEV	MINI	1	5	11	1	18
PHEV	Mercedes-Benz		9	18		27
PHEV	Mitsubishi		285	168	94	547
PHEV	Porsche	3	3	3	2	11
PHEV	Subaru			102	126	228
PHEV	Toyota	1,729	2,202	1,298	1,932	7,161
PHEV	Volvo	6	4	6	7	23
PHEV	**Total**	**3,195**	**5,952**	**3,721**	**3,911**	**16,779**
PROGRAM TOTAL		**4,452**	**7,448**	**8,126**	**13,070**	**33,096**

Table A-3. Average Vehicle Miles Traveled by Vehicle Type and Program Year

Vehicle Type	_2017	_2018	_2019	_2020	Average
BEV	9,462	10,667	10,726	10,599	10,628
PHEV	11,872	11,079	11,128	10,509	11,035

Table A-4. Average Rated MPGe of Rebated Vehicles by Vehicle Type and Program Year

Vehicle Type	_2017	_2018	_2019	_2020	Average
BEV	112	114	117	120	118
PHEV	46.7	44.3	44.4	47.5	45.5

Table A-5. Annual Gasoline Savings by Vehicle Type, Program Year, and Savings Type

Vehicle Type	Savings Estimate	Statistic	_2017	_2018	_2019	_2020	Average over all years
BEV	*Ex ante*	Average per rebated vehicle	460	462	466	468	466
PHEV	*Ex ante*		258	238	241	262	248
							Cumulative
BEV	*Ex ante*	Sum for all rebated vehicles	578,534	690,500	2,052,077	4,290,265	7,611,376
PHEV	*Ex ante*		825,607	1,414,479	895,868	1,025,240	4,161,194
Both	*Ex ante*		1,404,141	2,104,979	2,947,945	5,315,505	11,772,570
							Average over all years
BEV	VGS	Average per rebated vehicle	324	325	328	330	329
PHEV	VGS		191	176	178	194	183
							Cumulative
BEV	VGS	Sum for all rebated vehicles	407,828	486,756	1,446,578	3,024,351	5,365,513
PHEV	VGS		610,454	1,045,866	662,405	758,063	3,076,787
Both	VGS		1,018,282	1,532,622	2,108,983	3,782,413	8,442,300
							Average over all years
BEV	ENS	Average per rebated vehicle	131	129	140	81	109
PHEV	ENS		66	67	77	46	64
							Cumulative
BEV	ENS	Sum for all rebated vehicles	139,547	206,176	773,935	662,542	1,782,201
PHEV	ENS		179,790	380,334	338,645	177,624	1,076,392
Both	ENS		319,337	586,510	1,112,580	840,165	2,858,593
							Average over all years
BEV	ENS	90% conf. interval of the mean +/-	30.8	27.0	14.9	11.5	8.4
PHEV	ENS		16.3	11.9	15.4	14.7	7.2

Table A-6. Annual MMBtu Savings by Vehicle Type, Program Year, and Savings Type

Vehicle Type	Savings Estimate	Statistic	_2017	_2018	_2019	_2020	Average over all years
BEV	*Ex ante*	Average per rebated vehicle	55	56	56	56	56
PHEV	*Ex ante*		31	29	29	32	30
							Cumulative
BEV	*Ex ante*	Sum of rebated vehicles	69,589	83,057	246,836	516,058	915,540
PHEV	*Ex ante*		99,309	170,142	107,760	123,322	500,532
Both	*Ex ante*		168,898	253,199	354,596	639,379	1,416,072
							Average over all years
BEV	VGS	Average per rebated vehicle	39	39	40	40	40
PHEV	VGS		23	21	21	23	22
							Cumulative
BEV	VGS	Sum of rebated vehicles	49,056	58,550	174,003	363,786	645,395
PHEV	VGS		73,429	125,803	79,678	91,184	370,094
Both	VGS		122,485	184,353	253,680	454,970	1,015,488
							Average over all years
BEV	ENS	Average per rebated vehicle	16	16	17	10	13
PHEV	ENS		8	8	9	6	8
							Cumulative
BEV	ENS	Sum of rebated vehicles	16,786	24,800	93,093	79,694	214,373
PHEV	ENS		21,626	45,749	40,734	21,366	129,475
Both	ENS		38,412	70,549	133,828	101,060	343,848
							Average over all years
BEV	ENS	90% conf. interval of the mean +/-	3.7	3.2	1.8	1.4	1.0
PHEV	ENS		2.0	1.4	1.9	1.8	0.9