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Analyzing the Impacts of a Biogas-to-Electricity Purchase Incentive on Electric Vehicle Deployment with the MA^{3}T Vehicle Choice Model

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Energy and Transportation Science Division

ANALYZING THE IMPACTS OF A BIOGAS-TO-ELECTRICITY PURCHASE INCENTIVE ON ELECTRIC VEHICLE DEPLOYMENT WITH THE MA3T VEHICLE CHOICE MODEL

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ACRONYMS

BEV	Battery electric vehicle
CARB	California Air Resources Board
DOE	Department of Energy
eVMT	Electric vehicle miles traveled
EV	Electric vehicle
eRIN	Electricity Renewable Identification Number
EPA	Environmental Protection Agency
ICCT	International Council on Clean Transportation
LDV	Light duty vehicle
LCFS	Low Carbon Fuel Standard
MA3T	Market Acceptance of Advanced Automotive Technologies
NHTSA	National Highway Traffic Safety Administration
PHEV	Plug-in hybrid electric vehicle
REGS	Renewable Enhancement and Growth Support
RFS	Renewable Fuel Standard
RIN	Renewable Identification Number
VMT	Vehicle miles traveled

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ABSTRACT

In 2014, the EPA approved a biogas-to-electricity pathway under the Renewable Fuel Standard (RFS). However, no specific applications for this pathway have been approved to date (EPA, 2017). This analysis helps understand the impact of the pathway by representing the biogas-to-electricity pathway as a point of purchase incentive and tests the impact of this incentive on EV deployment using a vehicle consumer choice model. To show the potential impact on vehicles sold, the full or partial credit value is modeled as a point of purchase incentive for EVs using the Market Acceptance of Advanced Automotive Technologies (MA^3T) vehicle choice model, which tracks annual sales, overall vehicle fleet size and energy use on a yearly basis. The resulting analysis shows several of the drivers that will impact electricity Renewable Identification Number (eRIN) generation and credit value. While these eRINs can accelerate the deployment of EVs when used to reduce vehicle purchase prices, the ultimate impact will be determined by future RIN prices, the extent to which eRIN credit value is passed on to the consumer to reduce purchase price and the equivalence value.

A series of scenarios were constructed to assess the potential impact of credit parameters, including the biogas-derived electricity availability and the electricity equivalence value, which determines the frequency of eRIN generation. In addition, market dynamics can affect how the credit value is split among eRIN supply chain participants. In an efficient market, greater value would likely go towards EV deployment when biogas-derived electricity exceeds electricity demand and to producers when demand for electricity outstrips biogas-derived electricity supply. This behavior was represented in the model though a series of scenarios that altered the percent of credit value that was passed on to the consumer in the form of a purchase incentive.

Today, biogas-derived electricity generation exceeds transportation electricity demand. In the scenario modeled to represent the existing biogas electricity generation (15 TWh/year) with a 5.24 kWh/RIN equivalence value, when the full value of the credit is passed on to the consumer, the policy leads to an additional 1.4 million plug-in hybrid electric vehicles (PHEVs) and 3.5 million battery electric vehicles (BEVs) in 2025 beyond the no-policy case of 1.3 million PHEVs and 2.1 million BEVs. In 2030, this increases to 2.4 million PHEVs and 7.3 million BEVs beyond the baseline. This larger impact on BEVs relative to PHEVs is due in part to the larger credit that BEVs receive in the model based on the greater percentage of electric vehicle miles traveled by BEVs relative to PHEVs.

This policy could also incent additional biogas-derived electricity production if some of the credit value is shared with biogas electricity producers. A recent study estimated the biogas-derived electricity potential at 41 TWh/year. Using that biogas-derived electricity availability to represent an expanded capacity the impacts of greater eRIN generation is modeled. When 75% of the credit is directed towards reducing vehicle purchase prices (reserving 25% of the credit value to bring additional biogas-electricity production online) under the 5.24 kWh/RIN equivalence value, this high biogas scenario results in 2.7 million additional PHEVs and 8.8 million additional BEVs on the road in 2030 beyond the baseline of 2.5 million PHEVs and 6.1 million BEVs. Under this expanded biogas capacity, biogas-derived electricity generation is able to fully supply electricity demand for a fleet of over 20 million EVs (5.2 million PHEVs and 14.9 million BEVs) on a yearly basis. In this optimistic scenario, eRIN generation would

constitute at most 8% of the 16 billion gallon cellulosic RFS target in 2022 and 43% in 2030, leaving room for other cellulosic fuels.

In addition to assessing the scenarios described above, multiple scenarios were analyzed examining the impact of the policy if only a fraction of the credit value was passed on to the consumer. In all of these cases, EV deployment is scaled back as that fraction is reduced. Similarly, since a higher equivalence value means that a smaller number of credits are generated for a given amount of electricity, the credit value calculated using the current (22.6 kWh/RIN) equivalence value results in lower EV deployment relative to the proposed (5.24 kWh/RIN) equivalence value.

Overall the impact of the incentive on EV deployment scales with the magnitude of the point of purchase incentive. The greater the value that is created and passed on to the consumer, the greater the acceleration of EV deployment is observed.

1. INTRODUCTION

As part of the recently proposed Renewable Enhancement and Growth Support (REGS) rule, EPA is considering four proposed program structures for the biogas-to-electricity pathway under the Renewable Fuel Standard (RFS). The potential impact of this pathway, in terms of an increased use of low carbon fuels and displacement of petroleum, will depend upon the additional electric vehicle (EV) deployment, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), that occurs as a result of the policy as well as the extent to which the policy drives new biogas-to-electricity production.

The following provides a background on the biogas-to-electricity pathway under the RFS, a description of the scenarios evaluated, and an overview of the MA^3T model used to investigate the impact of one potential program structure and the equivalence value on EV deployment.

1.1 BACKGROUND ON THE RENEWABLE FUEL STANDARD AND THE BIOGAS-TO-ELECTRICITY PATHWAY

The Renewable Fuel Standard (RFS), authorized by the Energy Policy Act (EPAct) of 2005 and expanded under the Energy Independence and Security Act (EISA) of 2007, is a federal program that supports the deployment of renewable fuels to reduce greenhouse gas emissions and displace petroleum. Compliance with the RFS is tracked through Renewable Identification Numbers (RINs), which are tradable certificates whose value is determined in part by market forces, which include compliance targets for specific fuel categories. Current RIN market prices range from $0.84-2.70/RIN across all fuel categories, with cellulosic RINs trading at the higher end of that range (Progressive Fuels Limited, 2016).

An update to RFS regulations set forth under the RFS Pathways II, Final Rule (EPA, 2014) allowed electricity produced from biogas and used as a transportation fuel to qualify for cellulosic (D3) RINs. These biogas-derived electricity credits are here described as eRINs.

While established as a qualifying pathway, the EPA has yet to approve any registration requests for biogas-to-electricity eRIN generation under the existing guidelines. In an effort to gather additional information about the benefits and drawbacks of the potential configurations, the EPA has proposed four program structures for renewable electricity pathway in the proposed Renewable Enhancement and Growth Support (REGS) rule. Each structure outlined by EPA in the proposed REGS rule would designate a different entity as the eRIN generator including: vehicle owners, public charging stations, electric utilities and vehicle manufacturers, as well as the possibility for third parties to generate eRINs using the available data sources (EPA, 2016). Figure 1 shows the key participants in the biogas-to-electricity pathway and the potential flow of eRIN credit value under efficient market conditions.

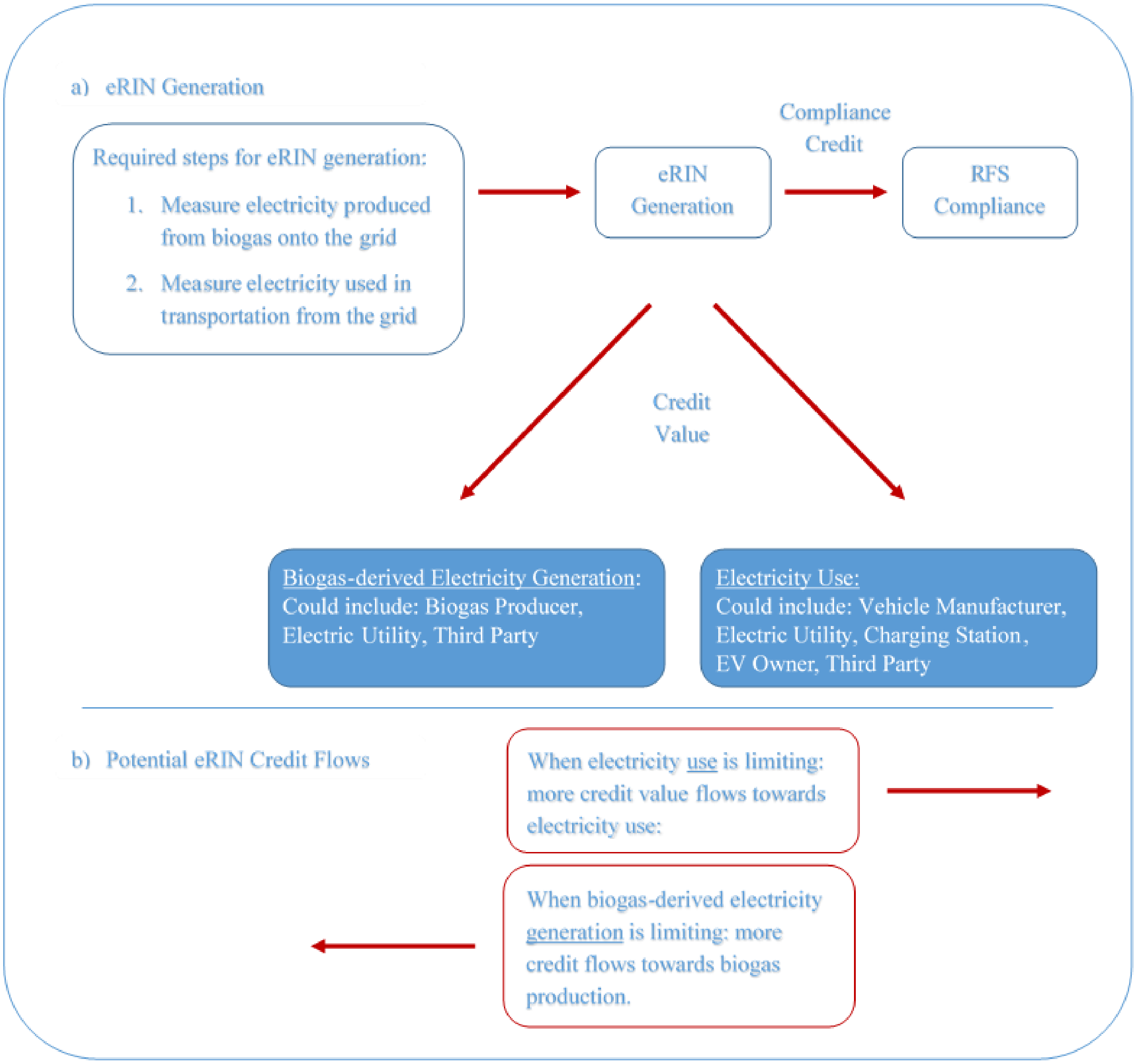

Figure 1. Participants in the biogas-to-electricity pathway and credit allocation. a) The biogas-to-electricity pathway allows eRIN generation when biogas is used to produce electricity that is supplied to the grid and that the same volume of electricity is used in the transportation sector. The electricity use could be verified by several entities along the supply chain – those parties that play a role in the biogas-derived electricity generation, distribution and use, as well as the party that verifies the data for eRIN generation including the electric utility, vehicle manufacturer, charging station, vehicle owner or third party. This party would register with EPA as the eRIN producer. The ability to verify both the biogas-to-electricity production and the electricity use data is necessary for any entity seeking to be registered as an eRIN producer by the EPA. Key to the policy is ensuring that each kWh is only counted once – thus only one of the parties listed can generate an eRIN for a given kWh. b) Under efficient market conditions, the value of eRINs generated by the registered eRIN producer could be split among the entities who contribute to eRIN generation, with the split determined by market forces. For example, if the supply of eligible biogas-derived electricity exceeds the demand for electricity in transportation, the consumers of transportation energy likely capture most of the eRIN value. If demand eventually outstrips the capacity of supply, the producers of biogas-electricity could capture a greater share of the eRIN value.

One policy parameter used in determining the value of eRINs is the electricity equivalence value. The equivalence value is a conversion factor that determines the basis for which RINs are generated for each fuel. Prior regulations set the electricity equivalence value to 22.6 kWh/RIN, based on the energy content of one gallon of ethanol, which serves as the basis for RFS compliance volumes. However, to promote fuel parity based on petroleum displacement, some stakeholders have proposed that the equivalence value should be calculated to reflect the petroleum displacement rather than just the energy displacement alone (ICCT, 2015). In addition to proposing program structures for eRIN generation, in the proposed REGS rule EPA is also taking comment on the equivalence value for electricity.

1.2 USE OF VEHICLE CHOICE MODELS IN POLICY MAKING

In the 2016 Draft Technical Assessment Report, *Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025*, EPA, NHTSA and CARB noted that vehicle choice models can be used for policy analysis, but do not represent macroeconomic shifts or changes in demographic factors. Due to these limitations, the results presented herein are intended to represent the impact of a price reduction on consumer vehicle choice assuming all other conditions remain the same, but should not be interpreted as a prediction of future sales or fleet mix. It is important to recognize these model limitations when interpreting the results of this analysis.

1.3 PAPER OBJECTIVES AND ORGANIZATION

The intent of this project is to provide an analytical assessment of EV deployment as a function of an incentive provided at the point of purchase, with the value of that incentive determined by policy parameters. As many aspects of this program remain uncertain, this analysis is designed to show a broad range of scenarios that provide bounds for the potential impact, an assessment of the key drivers and a framework to assess the likely impacts. The method of this study is explained in the next section, including the MA^3T model, the representation of the policy, the selection of the sensitivity parameters, and the construction of scenarios to reflect uncertainty. Calculation of the upfront purchase incentive is also illustrated. It is then followed by modeling results showing the impact of biogas capacity, allocation of credit to consumers, equivalence value of the credit and fuel use. The policy impacts are then discussed and key conclusions are drawn.

2. METHOD

The impact of this policy on EV deployment will depend on the credit value and the extent to which that value is passed on to consumers. In order to test the impact of the credit value on EV deployment we relied on a vehicle choice model that represents the range of vehicle consumers and the factors that impact their choice among vehicles available on the market. Using key policy and model parameters, the value of the eRIN is represented as a point of purchase incentive to test the impact on EV sales and fleet mix over time.

2.1 MA^{3}T MODEL

Multiple vehicle consumer choice models (Brooker et al., 2015; Lin, 2012; TA Engineering, 2012), each with their own focus, are available that could be used for such analysis. The Market Acceptance of Advanced Automotive Technologies (MA^{3}T) model (Lin, 2012) was used here to represent the biogas-to-electricity policy and test its impact on EV deployment.

The MA^{3}T model is a demand-side vehicle choice model developed and run by Oak Ridge National Laboratory. The core of the model is a nested multinomial logit (MNL) discrete choice model that estimates market shares of various light duty vehicle (LDV) technologies in the United States. With up to 300 vehicle powertrain choices and 9,180 consumer segments, the model has a detailed representation of the U.S. LDV market. Different from other vehicle choice models, the MA^{3}T exogenously takes a calibrated baseline or user-defined assumptions on a wide range of technology, infrastructure, behavior and policy factors (see Figure 2) and, endogenously, the model also integrates technological learning by doing, changes in consumers' willingness to accept technology innovation, etc. Note that the MA^{3}T model is intended for use in policy analyses. It does not take into account macroeconomic shifts or changes in demographic factors, and thus cannot be used to predict future sales or to set precise standard such as the Corporate Average Fuel Efficiency (CAFE) or Greenhouse Gas (GHG) emissions standards (EPA, NHSTA and CARB, 2016). Instead, policy analysis with MA^{3}T can inform policy making, to assess the relative impact of specific policy designs, assuming that all other conditions remain the same, indicating the direction and magnitude of a policy intervention.

All model assumptions, except for the biogas-to-electricity policy, are based on the MA^{3}T baseline scenario[1], which uses the DOE's Vehicle Technology Office's "low technology progress" case and is simulated by the Argonne National Laboratory (ANL)'s Autonomie Model (Rousseau, 2009). For additional detailed descriptions of the MA^{3}T model, interested readers are referred to (Lin and Greene, 2010; Lin and Li, 2014; Liu and Lin, 2016). Figure 2 shows the overall framework of the MA^{3}T model in this study. As shown in Figure 3, inputs to MA^{3}T are altered to form different scenarios and result in different simulated EV sales and changes in energy consumption. Details of the altered inputs will be demonstrated in Section 2.2.

[1] MA^{3}T model inputs are available for download at the TEEM website: http://teem.ornl.gov/

2.2 POLICY REPRESENTATION IN THE MA^{3}T MODEL

In order to represent the biogas-to-electricity policy here in MA^{3}T, the value of an upfront credit is calculated on an annual basis to represent the parameters that define the policy. This credit value calculation also uses several of the model assumptions (described below) including the average annual electric vehicle miles traveled (eVMT) and electricity use profiles by vehicle class and vehicle lifetimes for EVs. The model also accounts for the capacity limitations of this pathway, which is restricted by the amount of biogas-derived electricity that can be produced. In the current analysis, the biogas-derived electricity capacity is limited to two cases: the currently produced biogas-derived electricity and a future potential, representing an expanded capability. With both caps, the available eRINs are shared evenly among EVs as the electricity use reaches that biogas availability cap. The value of future eRIN credits is discounted to represent the time value of money as well as the uncertainty of recovering future eRIN credits. This total discounted value is then offered as an upfront incentive provided at the point of purchase for each class of EVs, allowing the model to select vehicle purchases based upon consumer preferences.

The upfront incentive modeled here is a proxy for examining the potential impact of the biogas-to-electricity pathway on consumer vehicle choice. While the policy allows eRIN generation on a kWh basis, the administrative burden of issuing and collecting a low value credit for every kWh over the course of a vehicle lifetime would be large. One way to implement this structure would be for the credit value to be bundled and offered upfront as a onetime price reduction on the vehicle purchase price. Subsequently the actual value can then be collected by a small number of entities over time as the renewable fuel is used and verified and eRINs are generated. However, there are also risks associated with this approach. The eRIN credit depends upon future eVMT and RIN prices, as well as associated policy risk. In offering an upfront credit, the eRIN generator must assume and quantify these risks, with one approach shown here. Other possible mechanisms for distributing eRIN value to support EV sales have been used or proposed, including an approach by California under the Low Carbon Fuel Standard (LCFS), whereby utilities offer an upfront incentive based on the electricity use of their customers (CARB, 2014). While the mechanisms of the approach may vary, the impact of a given credit value on EV deployment will hold across multiple credit determination schemes.

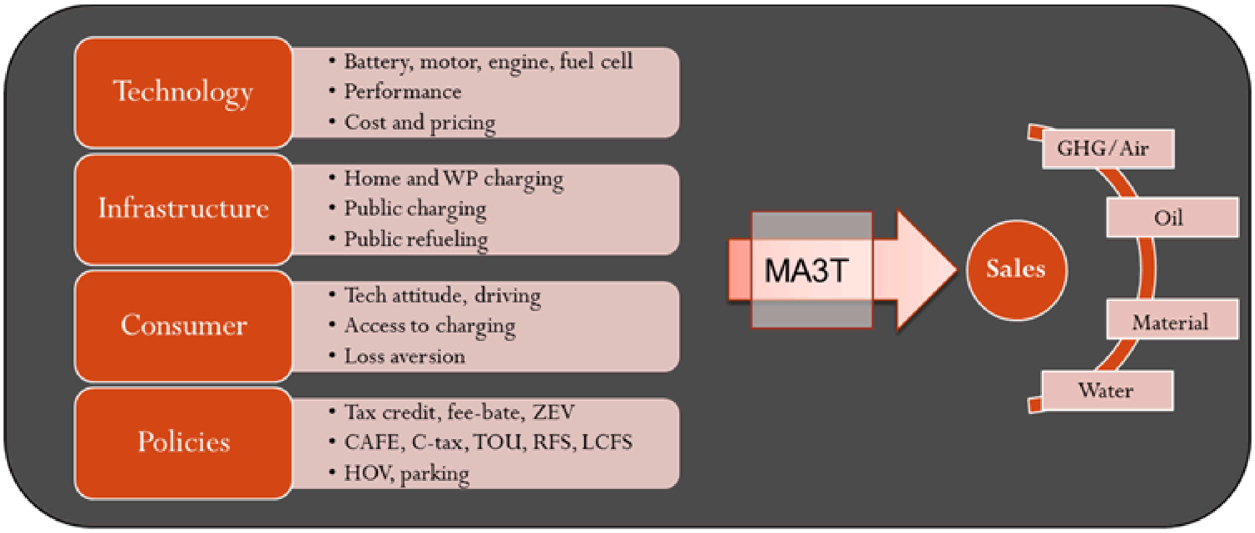

Figure 2. The MA³T model. The MA³T model covers technology, infrastructure, consumer choice and policy impacts to determine yearly sales and fleet size and can be used to determine GHG/air impacts, petroleum displacement, and material and water use. (Source: http://teem.ornl.gov/ma3t.shtml)

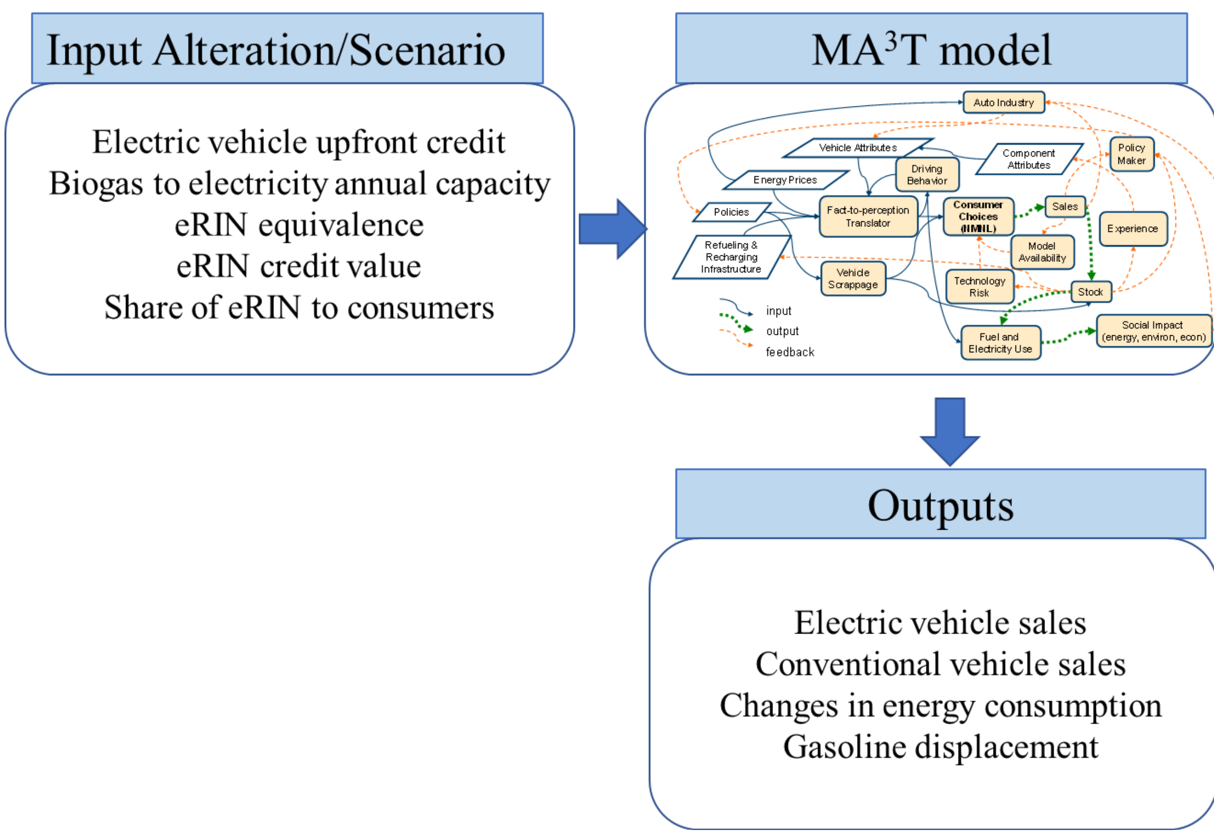

Figure 3. Alteration of MA³T model for eRIN policy analysis. To model the biogas-to-electricity pathway, a number of scenarios were constructed that impact the upfront EV credit and the share of that credit that is passed on to the consumer. These credit values are fed into the MA³T model, which solves for EV sales, conventional vehicle sales, changes in energy consumption and gasoline displacement over time.

For this analysis, all of the factors that impact eRIN generation (discussed below) are used to calculate an upfront incentive provided to consumers at the point of purchase for PHEVs and BEVs. Let *i* index EV technologies (i.e., PHEV and BEV for each vehicle class), *j* index the model year (e.g., model year 2017 when $j = 2017$) and *t* index the age of each EV. The upfront credit value – C_{ij} (\$) by technology *i* for each model year *j* is calculated using the function in Equation (1).

$$C_{ij} = \sum_{t=1}^{15} PV(t, 7\%) \times \frac{\beta_{j+t-1} \times \alpha_t \times RIN^{price} \times FE_{ij} \times eVMT_i}{RIN^{equivalence\ value}} \quad (1)$$

The constants and variables used in Equation (1) are explained as follows:

- *$eVMT_i$ (miles) – first year eVMT by vehicle technology i:* Under the policy, the biogas generated electricity in the transportation sector can be used by both PHEVs and BEVs. The credit value depends on how much electricity is consumed, and is thus scaled based on the effective eVMT of each vehicle technology, with PHEVs getting a smaller credit than BEVs reflective of the lower electric miles driven (Carlson 2015). This data determines the first year eVMT.
- *FE_{ij} (kWh/mile) – electricity fuel efficiency by vehicle technology i in model year j:* Unadjusted combined electricity fuel efficiency is used to convert $eVMT_i$ to estimated electricity usage for each technology *i*.[2] The fuel efficiency values are based upon Autonomie model simulation (Moawad et al., 2016) for each vehicle class based on the EPA standard drive cycles using the same calculation method as in the CAFE rule (EPA, NHTSA and CARB, 2016). Therefore, the first electricity consumption for each technology *i* in model year *j* is determined as $FE_{ij} \times eVMT_i$.
- $RIN^{equivalence\ value}$ *(kWh/RIN) – equivalence value*: The equivalence value determines the number of kWhs required for each RIN. The number of RINs generated is inversely correlated to the equivalence value, with a higher equivalence value corresponding to fewer RINs for a given electricity use and therefore less value. The current equivalence value for electricity is 22.6 kWh/RIN (EPA, 2010). However due to the inverse relationship between equivalence value and eRIN credit, the majority of scenarios evaluated in this study use a 5.24 kWh/RIN equivalence value, as shown in Table 4. This lower equivalence value, proposed by the International Council on Clean Transportation (ICCT, 2015), serves as a bounding case to understand the extent of the impact of the equivalence value on eRIN generation and expand the analysis space to better observe the impact of other credit factors.
- RIN^{price} *(\$/RIN) – RIN price:* The conversion of eRIN credits to a dollar value requires an estimate of RIN prices. The biogas-to-electricity eRINs qualify as a cellulosic (D3)

[2] Using the unadjusted fuel economy reduces the eRIN generation in the early years relative to an adjusted fuel economy parameter, thus representing a conservative estimate of credit value. After 2025, the difference between adjusted and unadjusted fuel economy becomes negligible.

RIN that meets the highest greenhouse gas reduction target under the RFS (60% reduction relative to petroleum-derived fuels). Predicting future RIN prices is outside of the model and dependent upon future EPA rulemaking and other market forces. Therefore a constant cellulosic (D3) RIN price of $1.50/RIN in 2005 dollars was assumed for this analysis as a conservative estimate. This estimate is at the lower bound of today's D3 RIN prices, with 2015 D3 RINs currently trading at $1.75 and 2016 and 2017 RINs priced at $2.45 and $2.75 respectively (Progressive Fuels Limited, 2016).[3]

- α_t (%) – *annual driving distance by vehicle age t*: To account for the lifetime eVMT of each vehicle, we recognize the gradual decline in the eVMT as the vehicle ages. This concept is adopted from Table 8.10 in the Transportation Energy Data Book (Davis et al., 2015), beginning in year t. Note that, α_t is at its maximum of 100% for newly purchased vehicle (i.e., when $t = 1$), and decreases over time.
- β_{j+t-1} (%) – *eRIN biogas capacity reduction factor*: Biogas is currently being used to generate approximately 15.6 TWh/year (hereafter referred to as 15 TWh/year) of electricity generation (EIA, 2016; DOE, 2016), and an expanded biogas supply in the United States can support 41.2 TWh/year (hereafter referred to as 41 TWh/year) of electricity generation (USDA, EPA, DOE, 2014). The model shows that either biogas-to-electricity capacity level can eventually be surpassed by the load of the deployed EV fleet, limiting further eRIN generation. The model was updated to account for this limitation using the eRIN biogas capacity reduction factor. For example, if biogas electricity can only meet 75% of the EV demand in year 2030, then a BEV in model year 2017 ($j = 2017$) at its 14 years age ($t = 14$) will only receives 75% of the electricity credit value in that year (i.e., $\beta_{2017+14-1} = \beta_{2030} = 75\%$).
- $PV(t, 7\%)$ *(%) – discounted present value of future RIN generation value:* The accumulated generation of eRINs over time will depend on measured kWh use across the fleet and biogas availability. This uncertainty of future eRIN value is represented in the model by discounting the value of the credit in future years using a net present value calculation with a 7% discount rate, which is suggested by OMB (1992) in evaluating federal programs, such as the CAFE standards (EPA and NHTSA, 2012).
- *15 (years) – vehicle lifetime:* Based on (Davis et al., 2015) and (EPA, NHTSA and CARB, 2016), we adopted the average vehicle lifetime of 15 years as the time scope for calculating the upfront credit for each vehicle.

Ideally, the calculated C_{ij} by technology *i* and model year *j*, will be exogenous inputs of the MA^{3}T model as the upfront credit. Most of above parameters can be exogenously determined, except for the eRIN biogas capacity reduction factor β_{j+t-1} which depends on the actual electricity demand which is determined by the EV fleet market share. In other words, β_{j+t-1} depends on the output of the MA^{3}T model. This interdependency between inputs and outputs requires an iteration process using the MA^{3}T model to foresee the future EV deployment, which will be demonstrated in Section 2.3.

[3] Today's $1.75, $2.45 and $2.75/RIN corresponds to $1.42, $1.98 and $2.23/RIN in $2005, respectively, https://www.bls.gov/data/inflation_calculator.htm

2.3 SENSITIVITIES

Biogas capacity limitations: Biogas is currently being used to generate 15 TWh/year of electricity. An expanded generation potential of 41 TWh/year could be produced, as identified by USDA, EPA and DOE (2014).This biogas-electricity capacity will eventually limit eRIN generation, assuming continued growth in EV deployment. Modeling the impacts of the biogas-to-electricity pathway on biogas production is outside of this model, so a biogas capacity limit was built into the model to represent the current and a representative future biogas capacity. When EV deployment and the associated kWhs use reaches biogas capacity, the eRIN credit value is then reduced proportionally by the percentage of biogas-derived electricity serving the transportation sector in determining the upfront vehicle incentive. For example, if biogas electricity can only meet 75% of the LDV electric vehicle demand in a given year, each vehicle only receives 75% of the credit value for that year based on total electricity use.

Estimation of eRIN biogas capacity reduction factor: In order to implement the biogas capacity limitation described above, the upfront credit value may be reduced to account for the number of EVs projected in future years that can also generate eRIN credits. For simplicity, the eRIN biogas capacity reduction factor, β_{j+t-1}, can be denoted by β_k where $k = j + t - 1$. Note that k actually indexes years in the eRIN program. Although we are interested in the impacts of the eRIN program up to year 2030, β_k for later years ($k \geq 2030$) still needs to be determined, as they affect the upfront credit for vehicles sold before year 2030. Since the eRIN program is assumed to start in year 2017 and the MA^{3}T model can estimate vehicle demand up to year 2050, for consistency, we developed an iteration algorithm with the MA^{3}T to estimate β_k for each year k ($2017 \leq k \leq 2050$). The major concept of the algorithm is as follows. The β_k for each year k represents the reduction in the value of the eRIN credit. Prior to the iteration process, β_k lies between two initial bounds, namely, a lower bound value $\beta_k^L = 0\%$, and an upper bound value $\beta_k^U = 100\%$. The iteration process mainly updates the two bounds which will converge over time. The detailed iteration process is shown below.

- Step 0 – set $\beta_k^L = 0\%$ and $\beta_k^U = 100\%$ for each year k.
- Step 1 – set $\beta_k = \frac{\beta_k^L + \beta_k^U}{2}$ for each year k, and determine C_{ij} with formula (1).
- Step 2 – solve the MA^{3}T model and estimate electricity consumption EC_k(TWh) for each year k.
- Step 3 – Given the biogas electricity capacity *CAP* (TWh) for each year k, if $\beta_k \times \frac{EC_k}{CAP} \geq 1$, then update upper bound $\beta_k^U = \beta_k$; otherwise update lower bound $\beta_k^L = \beta_k$
- Step 4 – if β_k and β_k^U are sufficiently close for each year k, finalize $\beta_k = \frac{\beta_k^L + \beta_k^U}{2}$ and terminates the algorithm; otherwise, GO TO Step 1.

Allocation of credit along supply chain/value to consumer: The exact allocation of the credit along the biogas to electricity supply chain is unknown ahead of time and may be impacted by EPA decisions on a program structure as well as market forces. Because of this uncertainty and because any value that does not go towards reducing the vehicle purchase price is outside of the model, additional runs of the model were carried out to represent these uncertainty scenarios and to determine the impact on EV deployment if only a partial value of the credit was passed on to the consumer as a purchase price reduction. The 25, 50 and 75% credit value scenarios represent these cases, making no assumptions about where the remaining value goes outside the model. As shown in Figure 1, the flow of credit value will likely change over time depending on the factors that limit eRIN generation. In an efficient market, a greater fraction of the credit value will likely be used to increase the EV fleet when biogas-derived electricity exceeds electricity use by the transportation fleet and to increase production when demand for electricity by the EV fleet becomes constrained by biogas-derived electricity production. Testing the impact of credit value on incenting additional biogas-derived electricity production is outside the bounds of this model. Therefore the approach taken here is a coarse approximation used to understand the impact if credit value is used for purposes beyond reducing EV purchase prices.

2.4 EXAMPLE CALCULATION OF THE UPFRONT PURCHASE INCENTIVE

As described above, the policy is represented as an upfront vehicle price reduction in MA^3T. The magnitude of this purchase price reduction was calculated based on the assumed electricity over the vehicle lifetime, determined by eVMT for each vehicle class and the vehicle efficiency. Key assumptions in determining the credit value are shown in Table 1. The calculation for an MY2017 BEV 100 car is shown in Table 2.

Table 1. Key input assumptions to calculate credit value

Inputs	Value	Units
D3 RIN Value	1.5	$2005/RIN
Equivalence Value		
Current	22.6	kWh/RIN
ICCT Proposed	5.24	kWh/RIN
Efficiency	by vehicle class	eVMT/kWh
Electric Miles		
BEV	9500	eVMT/year
PHEV40	9000	eVMT/year
PHEV20	4000	eVMT/year
PHEV10	2500	eVMT/year
Discount	7	%
Vehicle Lifetime	15	years

Table 2. Sample eRIN credit value calculation for a MY2017 BEV100 car. Note that the fuel efficiency is fixed for a given vehicle over its lifetime, but the annual VMT (and therefore eVMT) decreases as a function of age.

Input Factor		
RIN value	1.50	$/RIN
RIN equivalence value	5.24	kWh/RIN
BEV_eVMT	9500	miles
Discount rate	7	%
Fuel consumption in MY2017 BEV100-Car	0.23	kWh/mile

Calculation/Input Factor	Age 1	Age 2	Age 3	Age 4	…	Age 15	Calculation Method
Annual driving distance vehicle age factor	1.00	0.96	0.92	0.89	…	0.57	given
Annual driving distance	9500.00	9127.50	8769.61	8425.74	…	5426.49	f*c
Electricity consumption	2217.87	2130.90	2047.35	1967.07	…	1266.86	g*e
Credit	634.89	609.99	586.07	563.09	…	362.65	h*a/b
Biogas capacity reduction factor	1.00	1.00	1.00	1.00	…	0.42	determined with iteration
Present value ratio (7% discount)	0.93	0.87	0.82	0.76	…	0.36	(1-d)^n
Present value of credit	593.35	532.79	478.41	429.58	…	55.28	i*j*k
Sum	**4297.10**						sum(k)

The credit value calculation shown above (Table 2) determines the credit value available for a BEV100 car in 2017.This calculation is computed separately for each vehicle class and model year under each scenario. The final value of the credit offered as an upfront incentive each year is listed in Table 3 for each vehicle class under the 15 TWh/year scenario where the full value is passed on to the consumer with the 5.24 kWh/RIN equivalence value.

Table 3. Credit value by vehicle class offered at purchase by year for the 15 TWh/year, 100% credit allocation, 5.24 kWh/RIN scenario. Credit value is calculated for each vehicle class at each model year. Declining value represents the limited credit availability as the capacity threshold is attained at higher levels of EV deployment as well as the improved vehicle efficiency in subsequent model year vehicles. (Numbers after vehicle type indicate all-electric range category. For example, PHEV10 means the category of 10-mile all-electric range, although the actual range can be 12 miles or evolve slightly over time due to technology progress).

Vehicle Type	2017	2018	2019	2020	…	2030
Car-PHEV10	$ 1,056.41	$ 1,020.22	$ 979.59	$ 934.37	…	$ 327.64
Car-PHEV20	$ 1,682.91	$ 1,625.63	$ 1,561.28	$ 1,489.56	…	$ 517.30
Car-PHEV40	$ 3,732.49	$ 3,602.03	$ 3,456.12	$ 3,294.14	…	$ 1,099.90
Car-BEV100	$ 4,297.10	$ 4,159.54	$ 4,003.32	$ 3,827.56	…	$ 1,253.40
Car-BEV200	$ 4,647.32	$ 4,491.05	$ 4,315.12	$ 4,118.68	…	$ 1,304.23
Car-BEV300	$ 4,997.53	$ 4,822.56	$ 4,626.92	$ 4,409.80	…	$ 1,355.07
Car-SUV-PHEV10	$ 1,205.97	$ 1,162.94	$ 1,114.98	$ 1,061.90	…	$ 377.71
Car-SUV-PHEV20	$ 1,970.33	$ 1,893.70	$ 1,809.44	$ 1,717.34	…	$ 592.00
Car-SUV-PHEV40	$ 4,527.77	$ 4,357.84	$ 4,169.96	$ 3,963.57	…	$ 1,376.65
Car-SUV-BEV100	$ 5,251.56	$ 5,069.52	$ 4,865.64	$ 4,639.03	…	$ 1,575.82
Car-SUV-BEV200	$ 5,692.62	$ 5,483.98	$ 5,252.44	$ 4,997.20	…	$ 1,637.35
Car-SUV-BEV300	$ 6,133.69	$ 5,898.45	$ 5,639.23	$ 5,355.36	…	$ 1,698.89
Pickup-PHEV10	$ 1,525.09	$ 1,467.08	$ 1,403.07	$ 1,332.89	…	$ 467.88
Pickup-PHEV20	$ 2,613.73	$ 2,510.49	$ 2,397.24	$ 2,273.73	…	$ 800.75
Pickup-PHEV40	$ 6,076.36	$ 5,838.18	$ 5,576.61	$ 5,291.03	…	$ 1,835.85
Pickup-BEV100	$ 7,049.33	$ 6,789.81	$ 6,502.00	$ 6,184.95	…	$ 2,091.18
Pickup-BEV200	$ 7,674.26	$ 7,373.83	$ 7,043.83	$ 6,683.48	…	$ 2,173.53
Pickup-BEV300	$ 8,299.18	$ 7,957.85	$ 7,585.65	$ 7,182.01	…	$ 2,255.88
Truck-SUV-PHEV10	$ 1,271.03	$ 1,228.02	$ 1,179.66	$ 1,125.70	…	$ 389.95
Truck-SUV-PHEV20	$ 2,122.11	$ 2,043.88	$ 1,957.14	$ 1,861.61	…	$ 655.17
Truck-SUV-PHEV40	$ 4,822.85	$ 4,642.60	$ 4,443.18	$ 4,223.97	…	$ 1,499.20
Truck-SUV-BEV100	$ 5,608.60	$ 5,418.46	$ 5,204.69	$ 4,966.29	…	$ 1,707.29
Truck-SUV-BEV200	$ 6,081.75	$ 5,862.63	$ 5,618.78	$ 5,349.30	…	$ 1,772.70
Truck-SUV-BEV300	$ 6,554.89	$ 6,306.80	$ 6,032.87	$ 5,732.31	…	$ 1,838.11

2.5 SCENARIOS

From the factors and sensitivities described above, a number of scenarios were constructed to evaluate the range of impacts that may be observed. The scenarios were constructed to show a range of point of purchase incentive values and test the impact of those incentives on EV deployment.

Given the range of uncertainty surrounding the program structure, the electricity equivalence value, future costs and the market forces that will determine the eventual impact of this program, this analysis is not intended to provide a definitive answer in terms of the impact of this program on EV deployment, but instead to show the possible outcome as a result of a range of credit values. Our analysis has sought to embody these factors both in the total credit value as well as how that credit is used to represent the policy in the model as discussed below. This analysis provides a reasonable estimate of the impact of the biogas-to-electricity program whereby the eRIN producer bundles the eRIN credit value and passes on that value to reduce the purchase price of EVs.

Table 4. Summary of scenario space evaluated

Scenarios Evaluated		
Biogas Availability	***Credit Allocation***	***Equivalence Value***
Baseline (no policy)	-	-
15 TWh/year	25%	5.24 kWh/RIN
15 TWh/year	50%	5.24 kWh/RIN
15 TWh/year	75%	5.24 kWh/RIN
15 TWh/year	100%	5.24 kWh/RIN
41 TWh/year	25%	5.24 kWh/RIN
41 TWh/year	50%	5.24 kWh/RIN
41 TWh/year	75%	5.24 kWh/RIN
41 TWh/year	100%	5.24 kWh/RIN
15 TWh/year	100%	22.6 kWh/RIN
41 TWh/year	100%	22.6 kWh/RIN

3. RESULTS

The results of the model show across all scenarios that a vehicle price discount generated from eRINS can accelerate the deployment of EVs, both BEVs and PHEVs, relative to a scenario without the eRIN policy. While BEVs receive a larger credit value based on greater use of electricity relative to PHEVs, both types of vehicles see an increase in sales as well as in the total share in the fleet mix over time. However, the extent of that impact will be determined by how much of the credit is passed on to the consumer in the form of a purchase incentive.

3.1 BIOGAS-TO-ELECTRICITY CAPACITY

As shown in Figure 4 below, under the baseline (no policy) case, the deployment of EVs does not exceed 9 million vehicles on the road in 2030. The baseline, which includes all existing federal and state incentives, results in 1.27 million PHEVs and 2.06 million BEVs in 2025 and 2.54 million and 6.09 million in 2030 PHEVs and BEVs respectively.[4]

Relative to this baseline, the biogas-to-electricity pathway adds 1.43 million PHEVs and 3.55 million BEVs in 2025 and 2.36 million PHEVs and 7.25 million BEVs in 2030 when utilizing only the existing biogas-to-electricity generation capacity if all of the credit value is passed on to the consumer. This results in a total of 4.90 million PHEVs and 13.34 million BEVs on the road in 2030.[5] Additional EV deployment is observed under the expanded 41 TWh/year biogas availability scenario where all of the credit value is used to reduce vehicle purchase price. In 2030, this 41 TWh/year scenario results in an additional 4.12 million PHEVs and 12.24 million BEVs in the fleet beyond the baseline for a total of 6.66 million PHEVs and 18.34 million BEVs.[6] The PHEV and BEV sales and fleet data for the baseline, the 15 TWh/year and 41 TWh/year, 100% scenarios are shown below using the 5.24 kWh/RIN equivalence value.

The peak in sales between 2017 and 2019 correspond to the federal tax credit phase-out as triggered when each manufacturer reaches 200,000 cumulative EV sales.

Fleet data (Figure 4) and annual sales data (Figure 5) are shown below for PHEVs and BEVs in the baseline and 15 TWh/year and 41 TWh/year biogas availability cap, 100% credit allocation scenarios using the 5.24 kWh/RIN equivalence value. The change in the fleet relative to the baseline for 15 TWh/year and 41 TWh/year full credit scenarios are shown in Figure 6. Full fleet data is shown in Figures S4-S7 in the Supplementary Information section.

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[4] This corresponds to 0.5% of the fleet being PHEVs and 0.8% BEVs in 2025 and 0.9% PHEVs and 2.1% BEVs in 2030.

[5] This corresponds to 1.0% of the fleet being PHEVs and 2.0% BEVs in 2025 and 1.7% PHEVs and 4.6% BEVs in 2030.

[6] This corresponds to 1.2% PHEVs and 2.6% BEVs in 2025 and 2.3% PHEVs and 6.3% BEVs in 2030.

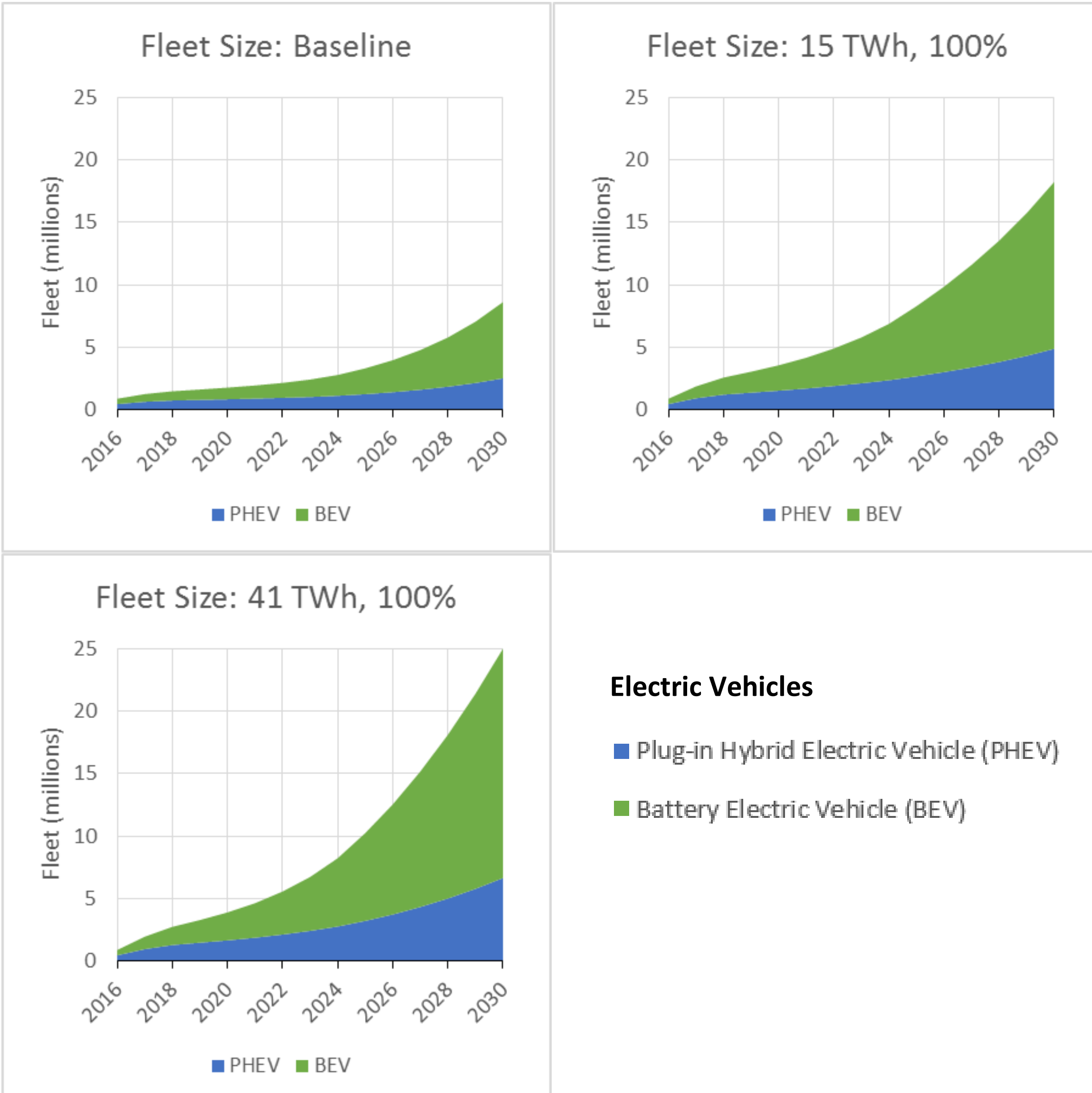

Figure 4. Fleet data for BEVs and PHEVs as a function of the biogas cap. Fleet data model output for the baseline, 15 TWh and 41 TWh annual biogas capacity scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

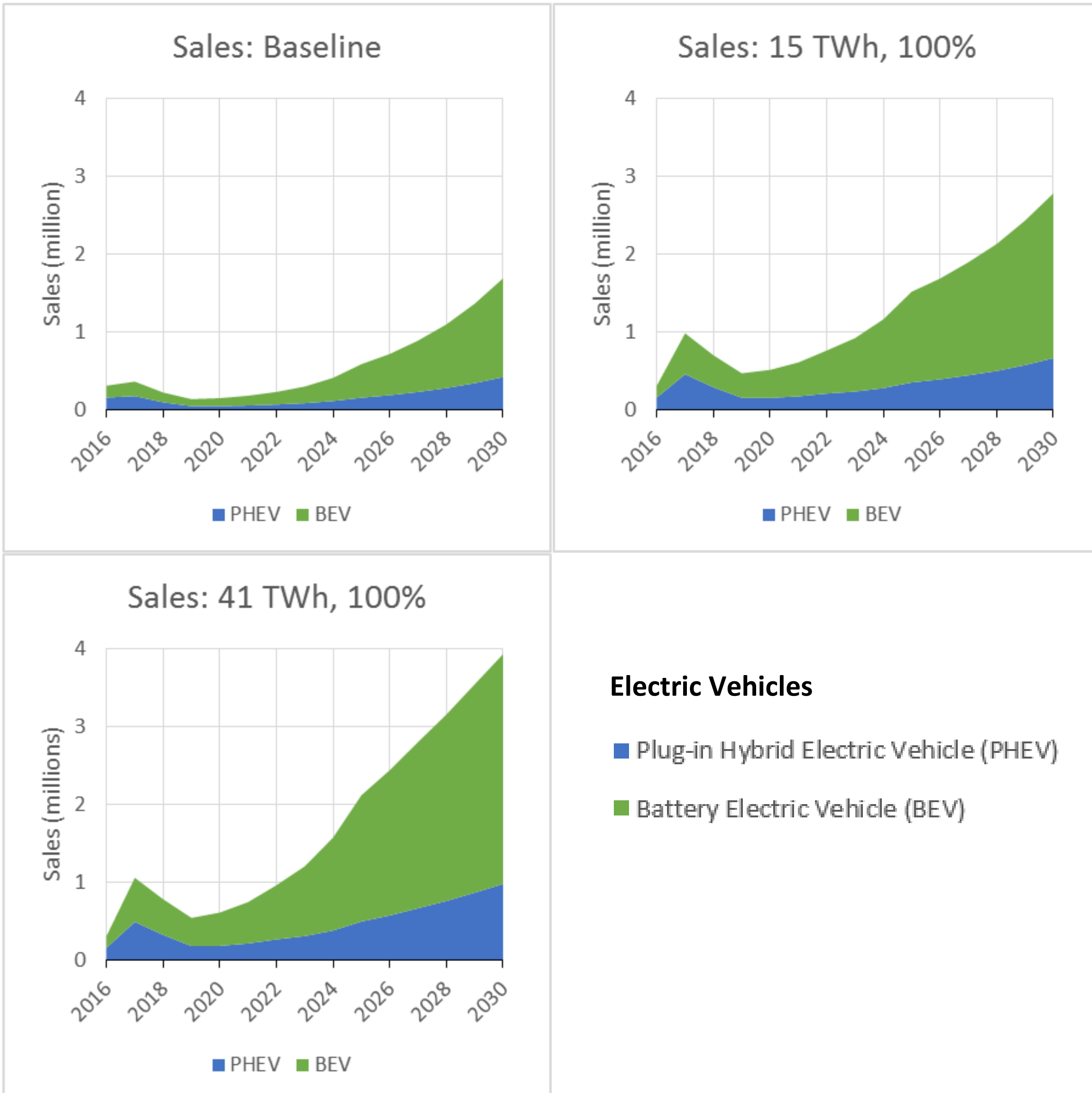

Figure 5. Annual sales data for BEVs and PHEVs as a function of the biogas cap. Annual sales data for the baseline, 15 TWh and 41 TWh annual biogas capacity scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

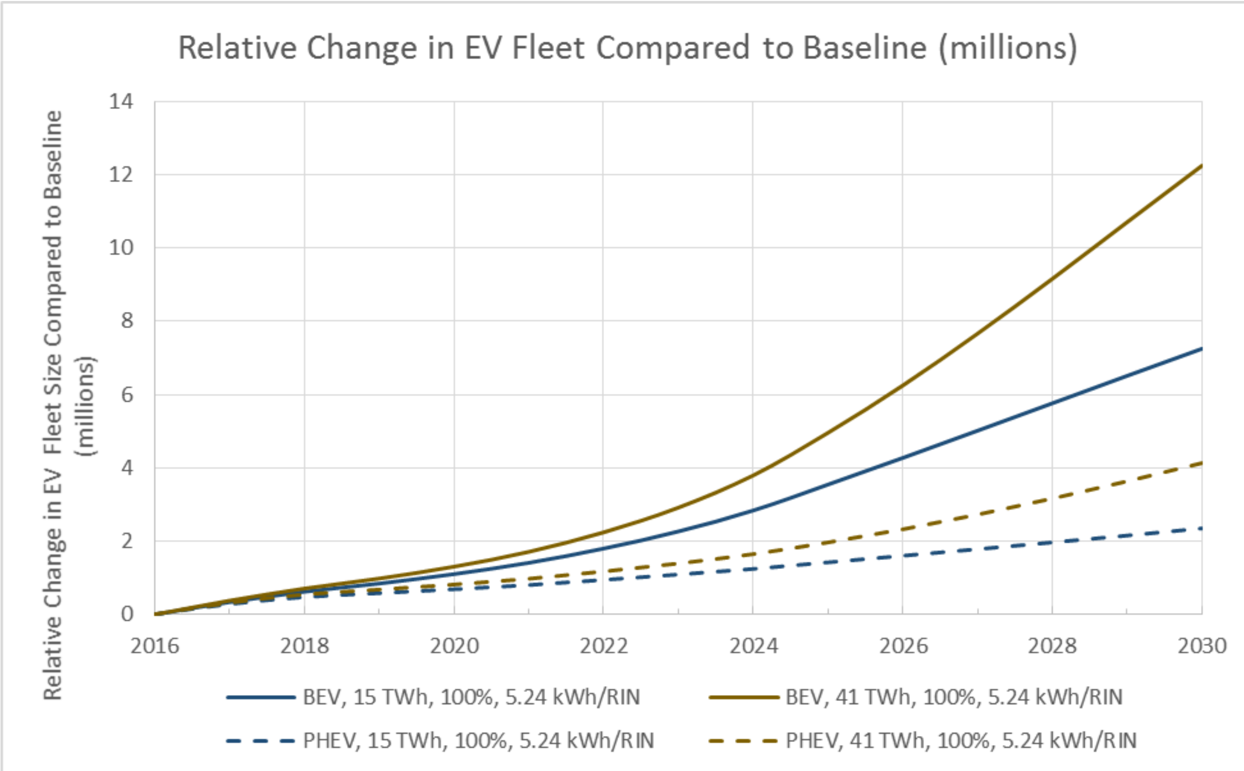

Figure 6. Relative change in EV fleet as a function of the biogas cap. The additional BEVs and PHEVs that are deployed as a function of the policy in the 15 TWh and 41 TWh annual biogas capacity scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

3.2 PERCENT OF VALUE PASSED ON TO CONSUMER

For the scenarios shown above, all of the credit value is passed on to the consumer to reduce the vehicle purchase price. To represent the situations where less than the full credit value is passed on to the consumer, a series of scenarios were run with 25, 50 and 75% of the credit value going towards the consumer with the remaining value assumed to go towards other purposes (offsetting production cost along the biogas-to-electricity pathways, offsetting EV production costs, administrative costs, etc.). In addition, since the credit value is bundled as an upfront price reduction, these scenarios also serve as an effective sensitivity analysis on the credit value parameters. Any factor that reduces the credit value 50% acts in the same way in the model as 50% of the credit going towards reducing the vehicle purchase price. Shown below (Figure 7) are the changes in PHEV and BEV deployment relative to the baseline for both the 15 TWh/year (blue) and 41 TWh/year (yellow) biogas capacity levels with 25, 50, 75 and 100% of the credit value passed on to the consumer to reduce the vehicle purchase price. As the fraction of the credit value that goes towards the consumer decreases, the impact on EV deployment is also reduced.

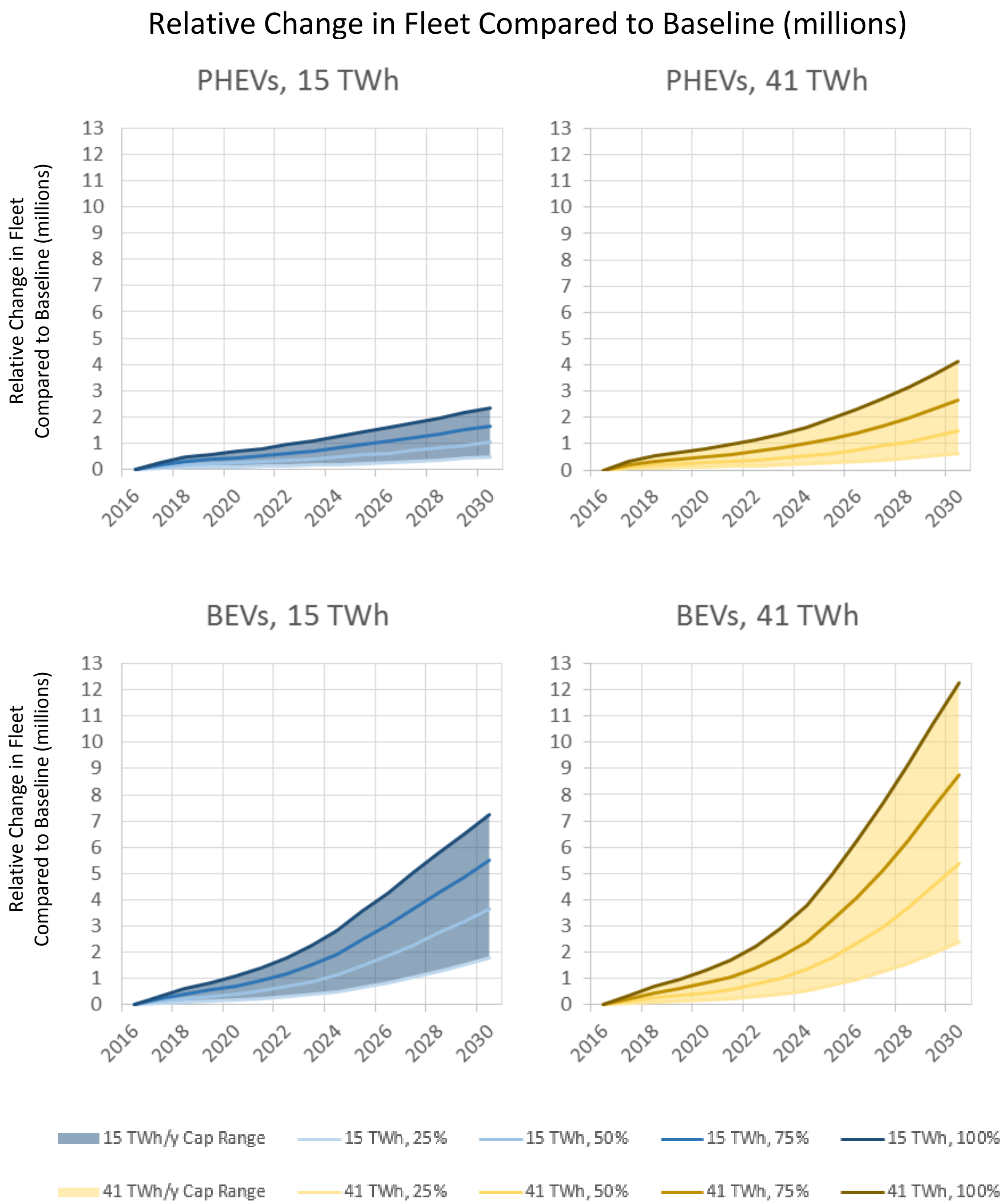

Figure 7. Relative change in PHEV and BEV fleet as a function credit allocation. The change in fleet for PHEVs and BHEVs relative to the baseline for the 15 TWh and 41 TWh annual biogas capacity limits in the 25, 50, 75 and 100% credit allocation scenarios. The 15 TWh/year range is shown in blue. The 41 TWh/year range is shown in yellow. All scenarios use the 5.24 kWh/RIN equivalence value.

3.3 IMPACT OF EQUIVALENCE VALUE

The results presented so far have used the ICCT proposed equivalence value of 5.24 kWh/RIN. The inverse relationship between the equivalence value and the total eRIN credit means that a higher equivalence value results in fewer eRINs generated for a given amount of electricity use. The ICCT value was used in the majority of cases to expand the analysis space and better understand the impacts of different credit value and policy parameters.

Relative to the results described above modeled with the 5.24 kWh/RIN equivalence value, under the current 22.6 kWh/RIN equivalence value, the impact of this policy is more limited as shown in Figure 8. However, even with the lower equivalence value, additional EV deployment is observed. With a 15 TWh/year biogas cap, an additional 236 thousand PHEVs and 657 thousand BEVs are in the fleet in 2025. In 2030, there would be 440 thousand additional PHEVs and 1.7 million additional BEVs on the road beyond the baseline EV fleet.

These equivalence value results demonstrate how the model responds equally to an equal change in eRIN credit value, regardless of the source. An equivalence value of 5.24 kWh/RIN where 25% of the credit goes towards reducing the EV purchase price has roughly the same impact on EV deployment as the 22.6 kWh/RIN equivalence value where 100% of the credit is used to reduce the EV price.

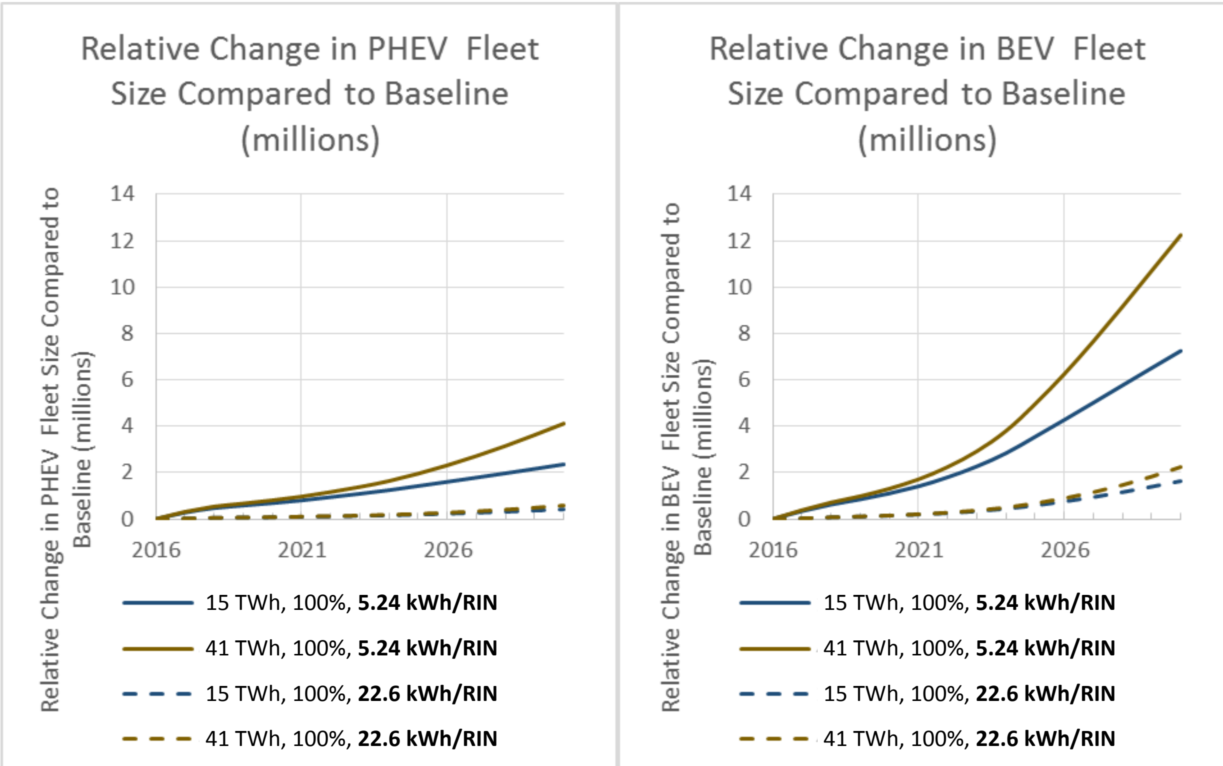

Figure 8. Relative change in PHEV and BEV fleet as a function of equivalence value. The change in fleet for PHEVs and BHEVs from the baseline, 15 TWh and 41 TWh annual biogas capacity scenarios for the 5.24 and 22.6 kWh/RIN equivalence values.

3.4 2025 AND 2030 EV FLEET AND ANNUAL SALES ACROSS SCENARIOS

The tables below summarize the results across all of the scenarios to show the range of impacts in terms of both fleet and annual sales in 2025 (Table 5) and 2030 (Table 6) for conventional vehicles (CVs) along with BEVs and PHEVs.

Table 5. Fleet and annual sales totals across scenarios in 2025

Total (Million), 2025								
Scenario			Fleet			Sales		
Biogas	%	Equivalence Value	CV	PHEV	BEV	CV	PHEV	BEV
Baseline	-	-	270.2	1.3	2.1	16.6	0.2	0.4
15	25	5.24	269.4	1.5	2.7	16.4	0.2	0.6
15	50	5.24	268.5	1.8	3.6	16.2	0.2	0.8
15	75	5.24	267.3	2.2	4.5	16.0	0.3	1.0
15	100	5.24	266.0	2.7	5.6	15.8	0.4	1.2
41	25	5.24	269.3	1.5	2.8	16.4	0.2	0.6
41	50	5.24	268.1	1.9	3.9	16.1	0.3	0.9
41	75	5.24	266.5	2.5	5.3	15.8	0.4	1.2
41	100	5.24	264.4	3.2	7.0	15.3	0.5	1.6
15	100	22.6	269.5	1.5	2.7	16.5	0.2	0.6
41	100	22.6	269.4	1.5	2.7	16.4	0.2	0.6

Table 6. Fleet and annual sales totals across scenarios in 2030

Total (Million), 2030								
Scenario			Fleet			Sales		
Biogas	%	Equivalence Value	CV	PHEV	BEV	CV	PHEV	BEV
Baseline	-	-	280.0	2.5	6.1	16.1	0.4	1.3
15	25	5.24	278.2	3.0	7.9	15.8	0.5	1.5
15	50	5.24	276.1	3.6	9.7	15.6	0.6	1.8
15	75	5.24	274.0	4.2	11.6	15.4	0.6	2.0
15	100	5.24	272.0	4.9	13.3	15.2	0.7	2.1
41	25	5.24	277.5	3.2	8.5	15.6	0.5	1.7
41	50	5.24	274.3	4.0	11.5	15.1	0.7	2.2
41	75	5.24	270.5	5.2	14.9	14.6	0.8	2.6
41	100	5.24	266.4	6.7	18.3	14.3	1.0	2.9
15	100	22.6	278.3	3.0	7.7	15.8	0.5	1.5
41	100	22.6	277.7	3.1	8.3	15.7	0.5	1.7

3.5 IMPACT ON FUEL USE

Beyond fleet mix and annual sales, the MA^3T model also tracks fuel use (e.g. gasoline, diesel and electricity) for the fleet over time. All policy scenarios result in an accelerated displacement of gasoline relative to the baseline scenario, with the potential to displace over 450 trillion Btus of gasoline in 2030 as well as smaller reduction in diesel (~10 trillion Btus, not shown). This travel demand is in turn met by an additional 132 trillion Btus of electricity. The exchange of 460 trillion Btus of petroleum derived fuels for 132 trillion Btus of electricity fuels reflects the substantially higher efficiency of EVs in converting energy into vehicle miles traveled. The relative petroleum and electricity consumption in the policy scenarios are shown in Figure 9.

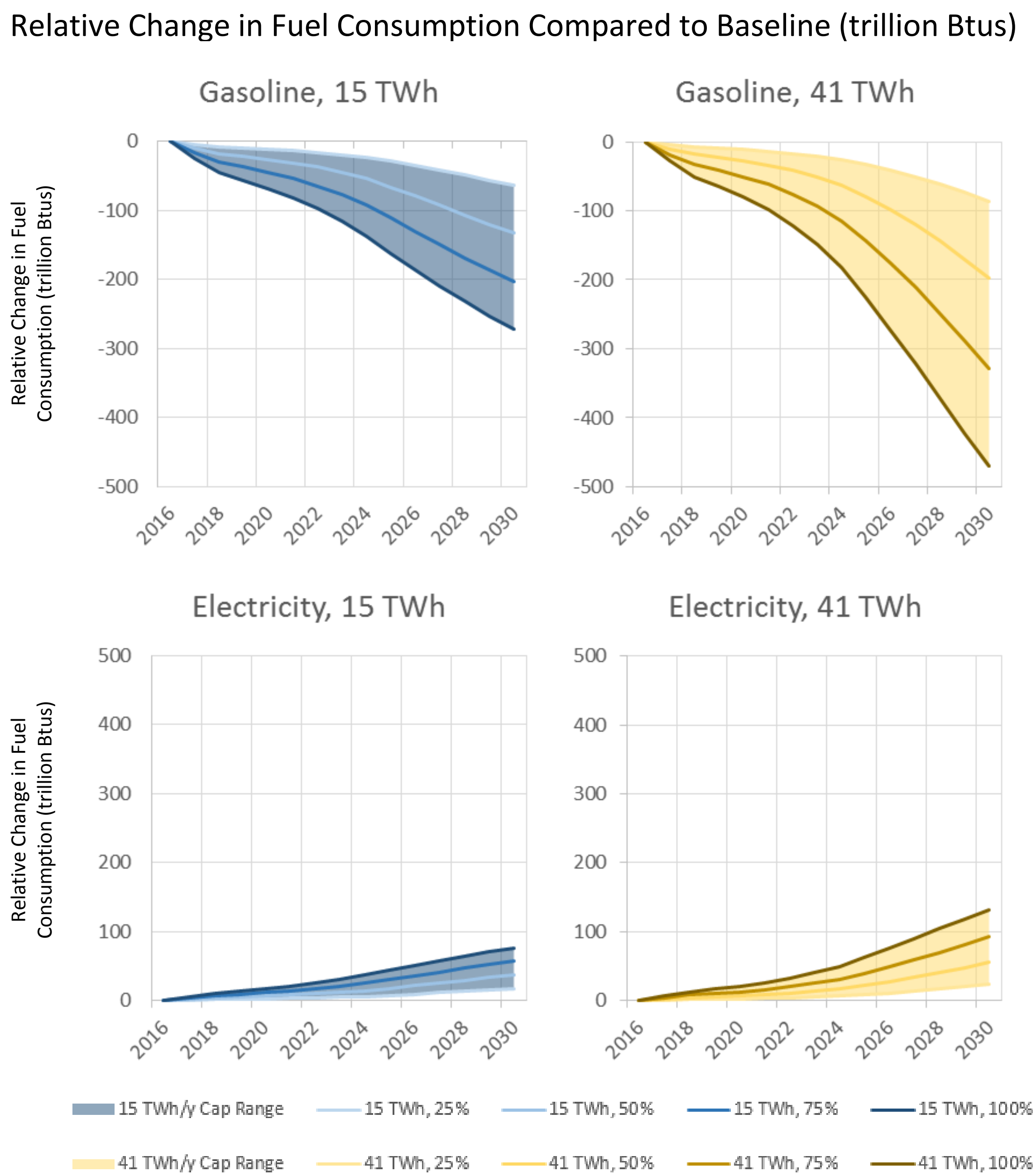

Figure 9. Relative change in gasoline and electricity consumption. The change in gasoline and electricity consumption relative to the baseline in the 15 TWh and 41 TWh annual biogas capacity limits for all credit allocation scenarios. The 15 TWh/year range is shown in blue. The 41 TWh/year range is shown in yellow. All scenarios use the 5.24 kWh/RIN equivalence value. (Note: 500 TBtus is roughly equivalent to 4.2% of 2016 fuel consumption)

3.6 IMPACT OF BIOGAS CAPACITY

The results described above incorporate the biogas-derived electricity generation limitation. Iterations of the model were run to provide effective foresight of future EV sales, which were used to determine final credit value used in the data presented here.

In order to implement this capacity limitations of the eRIN generating pathway, in this analysis electricity use was tracked over time and compared to the availability of biogas electricity generation. Once the solution converged, those credit values were used in the model runs presented herein. With the added EV deployment in the 15 TWh/year 100% scenario, electricity use in the transportation sector exceeds the capacity of biogas-derived electricity after 2025. In the model, after the cap is hit, the credit value in subsequent years is reduced using the eRIN biogas capacity reduction factor to account for this new constraint on the system. While not modeled here, this time point also reflects when a greater fraction of the credit value is likely to go towards biogas-derived electricity production to bring additional generation capacity online.

Since the expansion of biogas production would likely require some of the credit value to be shared with biogas producers, the biogas capacity analysis shown below for the 41 TWh/year biogas availability cap uses the 75% allocation case. In this scenario, the expanded biogas production is able to fully supply the EV fleet’s electricity demand out to 2030, made up of 5.2 million PHEVs and 14.9 million BEVs. The biogas capacity analysis results are shown in Figure 10, which shows the electricity use in the transportation sector, the amount of biogas-derived electricity and the percentage of electricity use that can be allocated to eRIN generation, which was used in the credit value calculation. For other scenarios where only a fraction of the value is passed on to the consumer, the slower deployment of EVs delays the year at which the biogas cap is hit. The full set of figures from the 15 TWh/y, 75% 5.24 kWh/RIN case is shown in Figures S1, S2 and S3 in the Supplementary Materials along with Tables 5 and 6.

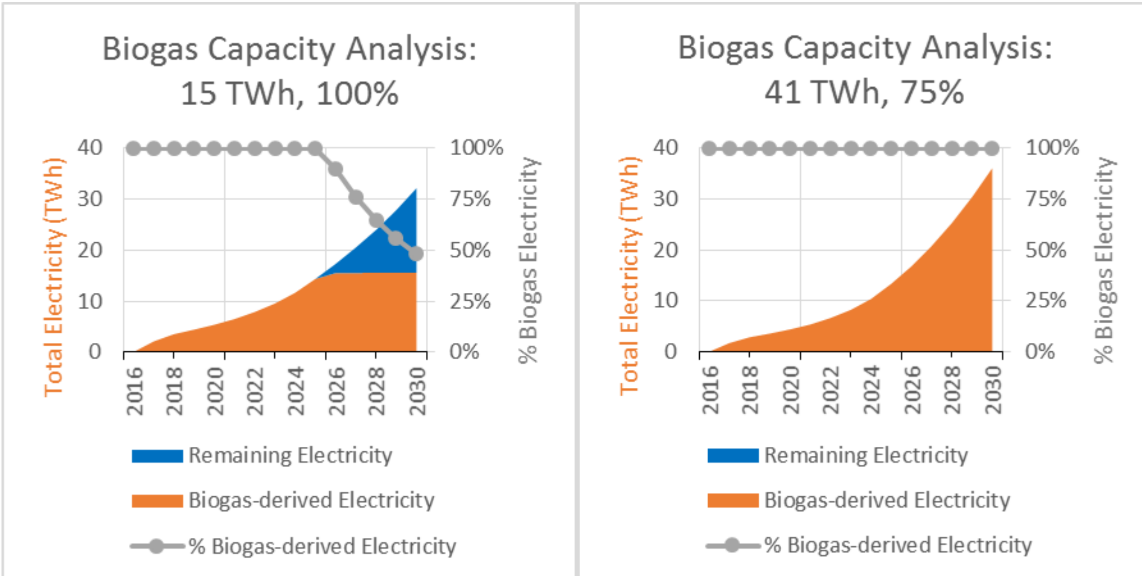

Figure 10. Biogas availability for eRIN generation. Biogas availability for the 15 TWh/year 100% credit allocation scenario and the 41 TWh/year 75% credit allocation scenario, both with the 5.24 kWh/RIN equivalence value. Electricity is shown on the left axis and percent biogas-derived electricity on the right axis.

4. DISCUSSION

Effective sensitivity analysis: As represented in the model, all of the factors that change between scenarios impact the credit value that is passed on to customers. However, each factor will impact that credit value to a different extent. The equivalence value has a large impact on credit value and therefore EV deployment as does the size of the biogas-to-electricity capacity limit. Increasing the number of kWhs required to generate each RIN by raising the equivalence value from 5.24 kWh/RIN to 22.6 kWh/RIN has a similar impact on the results as decreasing the extent of the credit value that goes to the customer from 100% to 25% since 5.24 is roughly one quarter of 22.6. As such the credit value allocation scenarios serve as an effective sensitivity analysis on the impact of credit value in the model.

RIN Prices: In order to determine the credit value, an assumed RIN price was used, as the dynamics that impact RIN prices are complex and outside of the model used here. A constant cellulosic (D3) RIN was assumed for this analysis. The model is run in constant 2005 dollars, making the $1.50/RIN value roughly equivalent to the current price of 2015 D3 RINs which are trading at $1.75 ($1.42 in $2005) and more conservative than 2016 and 2017 D3 RINs which are currently priced at $2.45 ($1.98 in $2005) and $2.75 ($2.23 in $2005) respectively (Progressive Fuels Limited, 2016).[7] Given the uncertainty of RIN markets and the volume targets that are set yearly by EPA, $1.50 seems to be a reasonable assumption. However the actual impact will depend on future RIN prices. The impact of the RIN price will scale similarly to the credit allocation scenarios, with a higher RIN price resulting in a greater credit value and thus a larger impact on EV deployment. The relative impact of alternative RIN prices can be estimated from other scenario runs.

Future value projections: In order to model this policy, the average eVMT and vehicle class efficiency was used to determine kWhs over the vehicle lifetime and thus eRIN credit value. Using this average annual eVMT is a practical assumption for the eRIN generator to make when offering the credit value upfront, before actual eVMT of a vehicle, and thus actual eRIN generation, is known. Since this value is provided upfront, to account for the time value of money the credit value is discounted using a net present value calculation with a discount rate of 7% to represent the ability of the eRIN producer to recover the price discount over the lifetime of the vehicle. If an eRIN producer assesses the situation and feels greater certainty in recovering cost or is looking to gain a competitive advantage, that discount factor could be lowered, resulting in a greater upfront price reduction for the consumer. Likewise, greater uncertainty would result in a higher discount rate and thereby a smaller credit value. This change would not be directly proportional to the credit allocation scenario runs, as a small change in the discount factor could have a relatively large impact on credit value and thereby EV deployment and would need to be assessed through separate scenario runs.

Impact of eRINs on RFS volume: The pathway modeled here has the potential to generate up to 7.9 billion eRINs yearly in an aggressive scenario (5.24 kWh/RIN, 41 TWh/year biogas cap, 100% scenario), but actual eRIN generation will depend on both the extent to which biogas generation increases over time and the equivalence value. The 41 TWh/year 75% scenario would

[7] https://www.bls.gov/data/inflation_calculator.htm

generate 1.3 billion D3 eRINs in 2022 and 6.9 billion eRINs in 2030, representing 8 and 43 percent, respectively, of the 2022 16 billion gallon RFS cellulosic biofuel target (EPA, 2010). If deployment occurred faster, eRIN generation would still be limited by biogas-electricity availability. In order to accommodate an increase in RIN generation without depressing cellulosic D3 RIN prices in a way that negatively affects the development of other cellulosic biofuels, EPA would need to account for these volumes in the annual rulemaking and adjust the volumes accordingly as has occurred with other fuels. The maximum yearly eRIN generation is shown in Table 7 as a function of biogas availability and equivalence value.

Table 7. Maximum yearly eRIN generation

Maximum Yearly eRINs (Billion)		Biogas-derived Electricity Generation Availability (TWh/year)	
		15.6	41.2
Equivalence Value (kWh/RIN)	5.24	3.0	7.9
	22.6	0.7	1.8

Competition between EVs and conventional vehicles: Underlying the MA^3T analysis is the relative cost and performance of vehicles. The vehicle costs are based on the DOE's Vehicle Technology Office's low technology progress case and are simulated by the Argonne National Laboratory (ANL)'s Autonomie Model to determine vehicle price. This is a relatively conservative case where EV costs are slower to decline than more optimistic cases. However, the cost of both EVs and conventional vehicles decreases overtime as performance increases, at differing rates by vehicle type. For each year in the model, the relative difference between these vehicles is assessed for each consumer segment. In the model, the value of the incentive is applied to the current model year vehicle price and factored into the consumer decision. If battery cost and EV performance improve faster than expected, EV deployment would be affected, both in the baseline as well as in the policy cases as the relative impact of the incentive could change. Likewise, the results depend on the cost and performance of conventional vehicles over time as well. The impact of the policy ultimately depends on the relative difference in price and performance between conventional vehicles and EVs and the extent to which the credit value can offset those price differences.

Impact on biogas production and credit allocation: The two biogas capacity limits were built into the model to represent the current biogas-derived electricity capacity and a future expanded capacity. The 15 TWh/year cap represents the currently available biogas-to-electricity production. The 41 TWh/year is an estimated future potential for biogas-to-electricity production.

Currently there is about 15 TWh/year of electricity production from biogas resources, including both landfills, which accounted for 12 TWh in 2014, and livestock which produced 3 TWh in 2015 (EIA, 2016; DOE, 2016). Additional resources are also available from wastewater treatment facilities, which are not readily reported. This biogas-derived electricity, available today, once verified and matched with electricity use in the transportation sector can be used immediately to generate eRINs. If no new biogas-derived electricity production comes online due to the policy, the policy still has the potential to increase the total number of PHEVs in the fleet in 2025 by 112% over the baseline and BEVs by 172% if all of the credit value is passed on to the consumer. That corresponds to 2.70 million PHEVs and 5.61 million BEVs on the road in 2025 (versus 1.27 and 2.06 million vehicles respectively in the baseline scenario). In 2030, the impact is even larger with 4.90 million PHEVs and 13.34 million BEVs on the road. If a smaller fraction of the credit is passed on to the consumer, EV deployment and thus petroleum displacement is still accelerated relative to the baseline, but to a lesser extent.

The impact of this policy will be even greater from a GHG reduction and petroleum displacement perspective if additional biogas-to-electricity production comes online as a result of the policy. Under the 41 TWh/year cap, this policy has the potential to increase PHEV's by 162% over the baseline scenario in 2030 and have an even bigger impact on BEV deployment where the larger credit value, proportional to the electricity used by the BEVs, could increase the deployment by 201% in 2030 if all of the credit value goes towards reducing EV purchase prices. The policy could have an even larger impact as this 41 TWh/year cap is likely a conservative estimate and other studies have identified even more biogas-to-electricity potential (Saur and Milbrandt, 2014).

The 25, 50, and 75% credit allocation scenarios represent a portion of the credit value flowing to other parts of the biogas-to-electricity supply chain that are outside of the model. If some of that value is shared with the biogas producer, it is possible to help bring additional biogas-derived electricity production online. To gauge the relative credit value in terms relevant to biogas electricity production, the credit value can be compared to the cost of developing new biogas electricity generation facilities. IRENA has reported the biogas electricity production costs in the range of 0.08-0.11 $2010/kWh (IRENA, 2012) and a Duke study has noted a range of 0.091 to 0.265 $/kWh (Cooley et al., 2013) for candidate landfills in North Carolina. In the NC study, wholesale electricity prices do not result in profitable projects. In NC, an estimated additional 0.03 $/kWh would be required to make the cheapest facility viable. At $1.50/RIN, an equivalence value of 5.24 kWh/RIN translates to 0.29 $/kWh which is more than enough to offset the higher production costs of biogas electricity production. Even if only 25% of that value goes to the biogas producer, at 0.07 $/kWh, some additional biogas production could be brought online. The same result can happen under the 22.6 kWh/RIN equivalence value, which also corresponds to 0.07 $/kWh. With a lower equivalence value a greater fraction of the credit would be necessary to make new biogas projects economical.

How the eRIN credit value is shared among the eRIN supply chain is not known at this time and could depend both on market conditions and EPA determinations for the pathway. However, assuming an efficient market for eRIN value, since EV deployment currently limits eRIN generation, until the cap is met a greater fraction of the credit value will likely go towards reducing vehicle price or other barriers that can increase EV deployment. That pattern would be expected to change when EV electricity demand exceeds biogas-derived electricity production, with the biogas producers likely receiving a greater fraction of the eRIN credit value under these conditions.

It is important to note that the biogas capacity analysis (Figure 10) is presented to provide context for the EV deployment data. The percent biogas electricity is used in determining the credit values for each scenario. After the demand for biogas-derived electricity exceeds supply, two changes occur could occur, only one of which is accounted for in the modeling. First the credit value is split among all EV vehicles and is represented in the model. In addition, though not modeled here, the credit value could shift away from EV purchase price reductions to enable greater biogas-derived electricity production, thus accelerating the decrease in credit value relative to the modeled scenarios. If credit value shifts and additional biogas-derived electricity is brought into production eRIN generation can further expand. This dynamic not is modeled here but could be explored through further model development. In addition, in both cases it is possible that local limitations may also restrict biogas-derived electricity generation. While not modeled here, this represents an additional factor that would need to be considered in assessing future eRIN generation potential and would likely affect the credit value allocation among eRIN supply chain participants.

Impact on petroleum displacement: While the data presented here focuses mostly on vehicle deployment, the outcome of a faster rate of EV deployment is an accelerated displacement of petroleum-derived fuels. Due to the higher fuel efficiency of EVs, the displaced petroleum-derived fuels are replaced with a smaller amount of energy from electricity. The yearly changes are small relative to fleet energy use, yet the cumulative impact quickly grows, displacing the equivalent of 3-25 billion gallons of petroleum over the baseline from 2016 to 2030 depending on the scenario.[8] These results show that the policy can be an effective driver in reducing petroleum-derived fuels. The actual greenhouse gas estimates have not yet been calculated but could be investigated in future studies. Since methane, which makes up a large fraction of the biogas, is a more potent greenhouse gas than carbon dioxide (IPCC, 1996), policies that incentivize the capture and use of methane can be an effective strategy to reduce greenhouse gas emissions.

[8] Based on conversion of 114,000 BTU/gal gasoline.

5. CONCLUSIONS

While there are many dynamics that will affect how this policy impacts petroleum displacement, the analysis shows that when the eRIN value is used to offset EV purchase prices, the deployment of EVs accelerates and thereby displaces greater amounts of petroleum-derived fuels. Though there are several simplifications that were made to represent the policy in the MA^3T model, the results across the scenarios show that a vehicle price reduction created by eRIN credit value can incent additional EV deployment and can generate substantial eRINs while leaving room for other cellulosic fuels. While the majority of the scenarios modeled here use a proposed equivalence value in order to better observe the impact of policy factors on EV deployment, even with the lower equivalence value that is in place today, additional EVs are brought to the market by the policy as modeled here. Given the multiple actors in the biogas supply chain, even if only a fraction of the credit value is passed on to the consumer, that value still has an incremental impact on the rate of EV deployment. Presumably, though not modeled here, as the current biogas availability becomes limiting, a greater fraction of the credit value will go towards developing additional biogas-to-electricity production facilities. Further analysis into the drivers of credit value across the biogas supply chain would provide a greater understanding of the overall impact of the biogas-to-electricity pathway and could inform additional MA^3T analysis wherein the cap changes over time reflective of the additional biogas availability.

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7. SUPPLEMENTARY INFORMATION

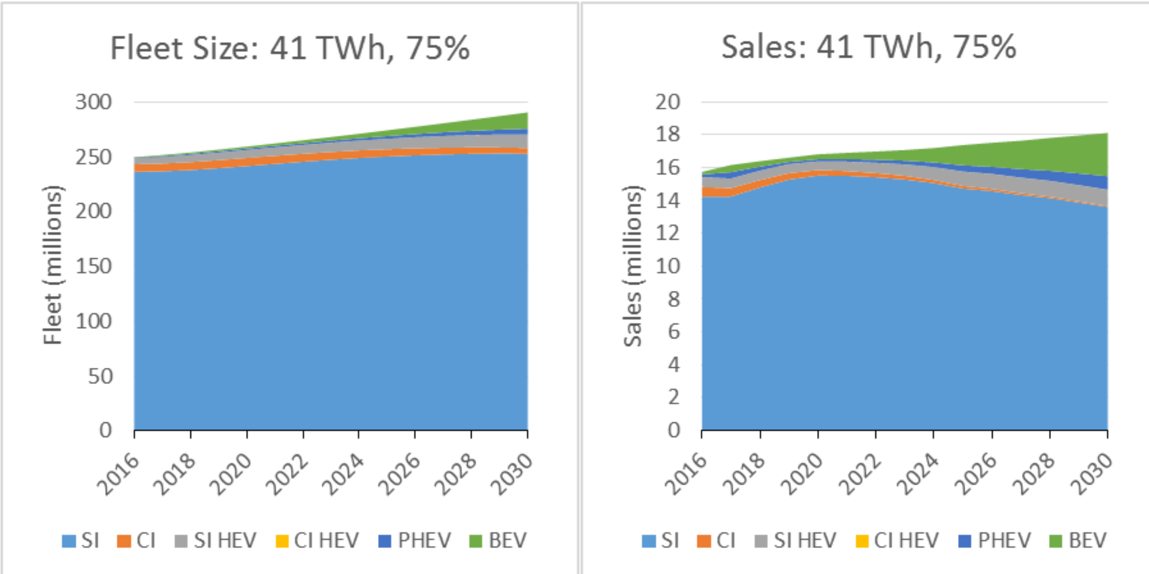

Figure S1. Fleet and annual sales data for the 41 TWh, 75% scenario. Fleet and annual sales data for all vehicle types in the 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 75% of the credit value goes to reducing consumer purchase price.

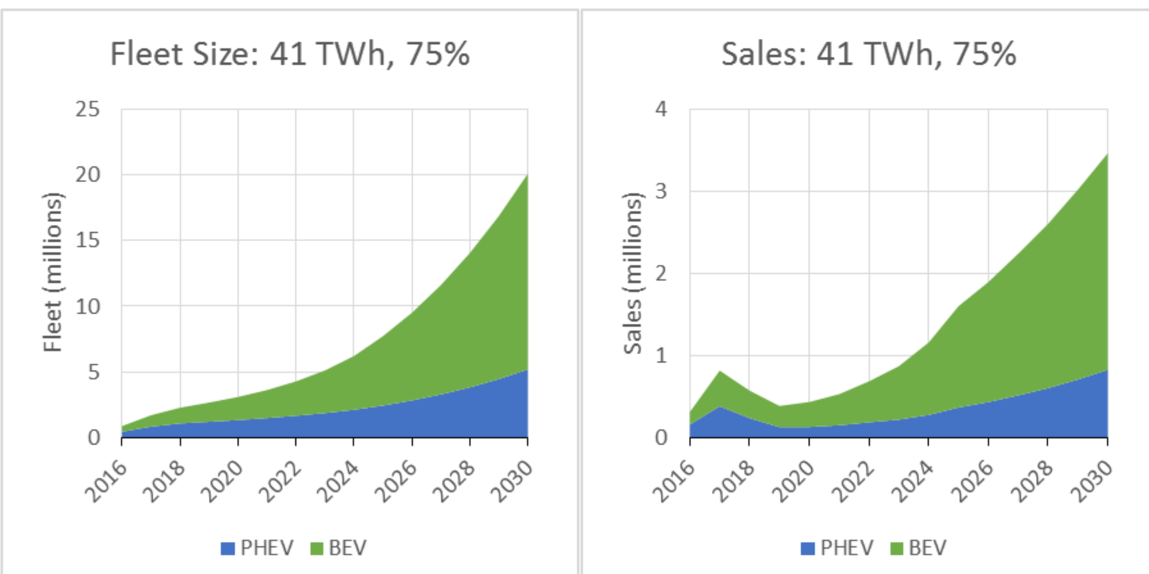

Figure S2. Electric fleet and annual sales data for the 41 TWh, 75% scenario. Electric fleet and annual sales data in the 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 75% of the credit value goes to reducing consumer purchase price.

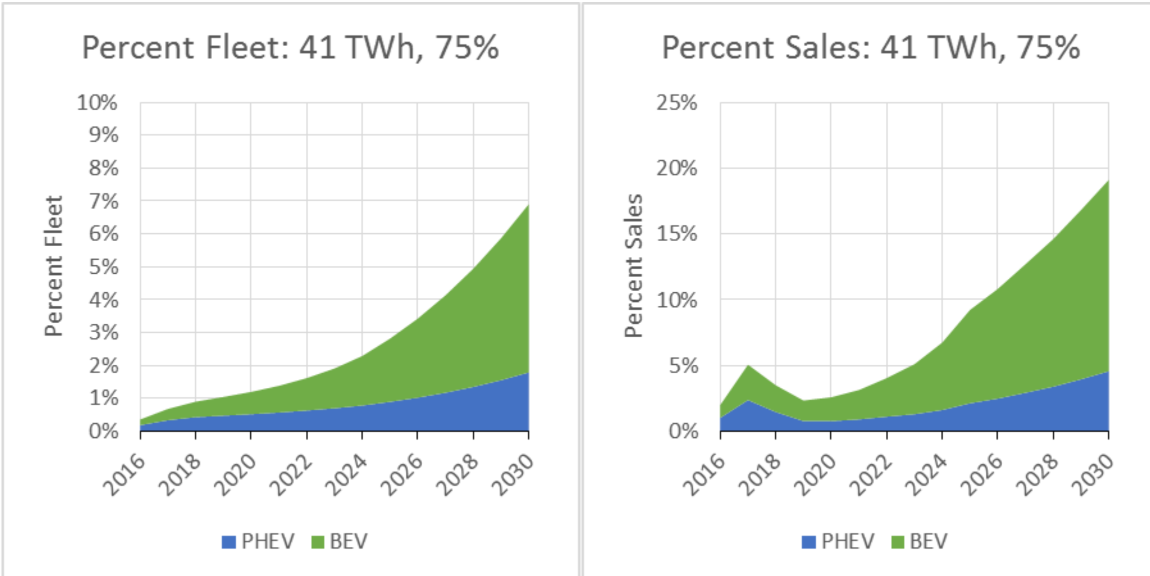

Figure S3. Percent electric fleet and percent annual sales data for the 41 TWh, 75% scenario. Percent electric fleet and annual sales data for the 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 75% of the credit value goes to reducing consumer purchase price.

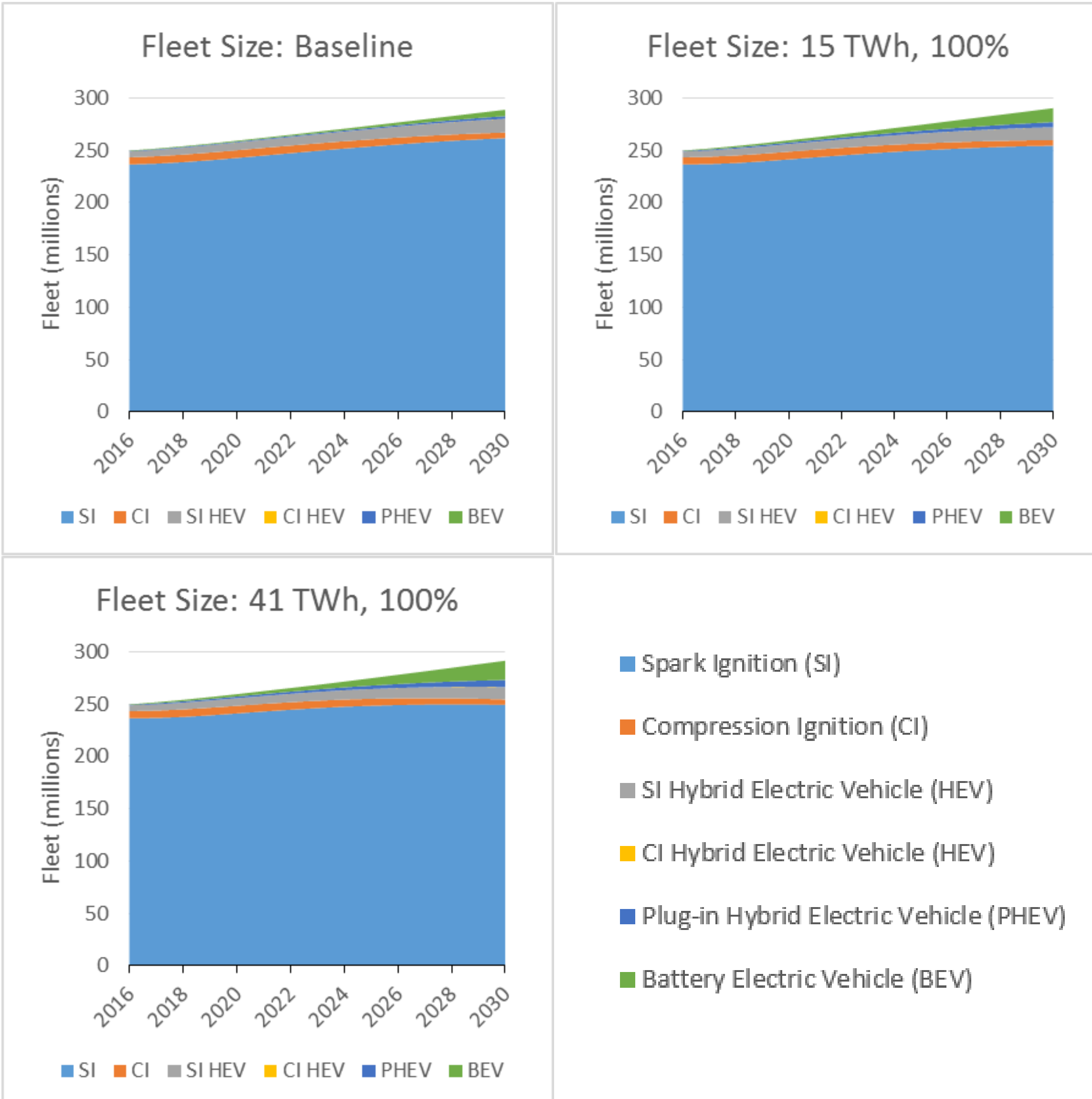

Figure S4. Fleet data as a function of the biogas cap. Fleet data for all vehicle types in the baseline, 15 TWh and 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

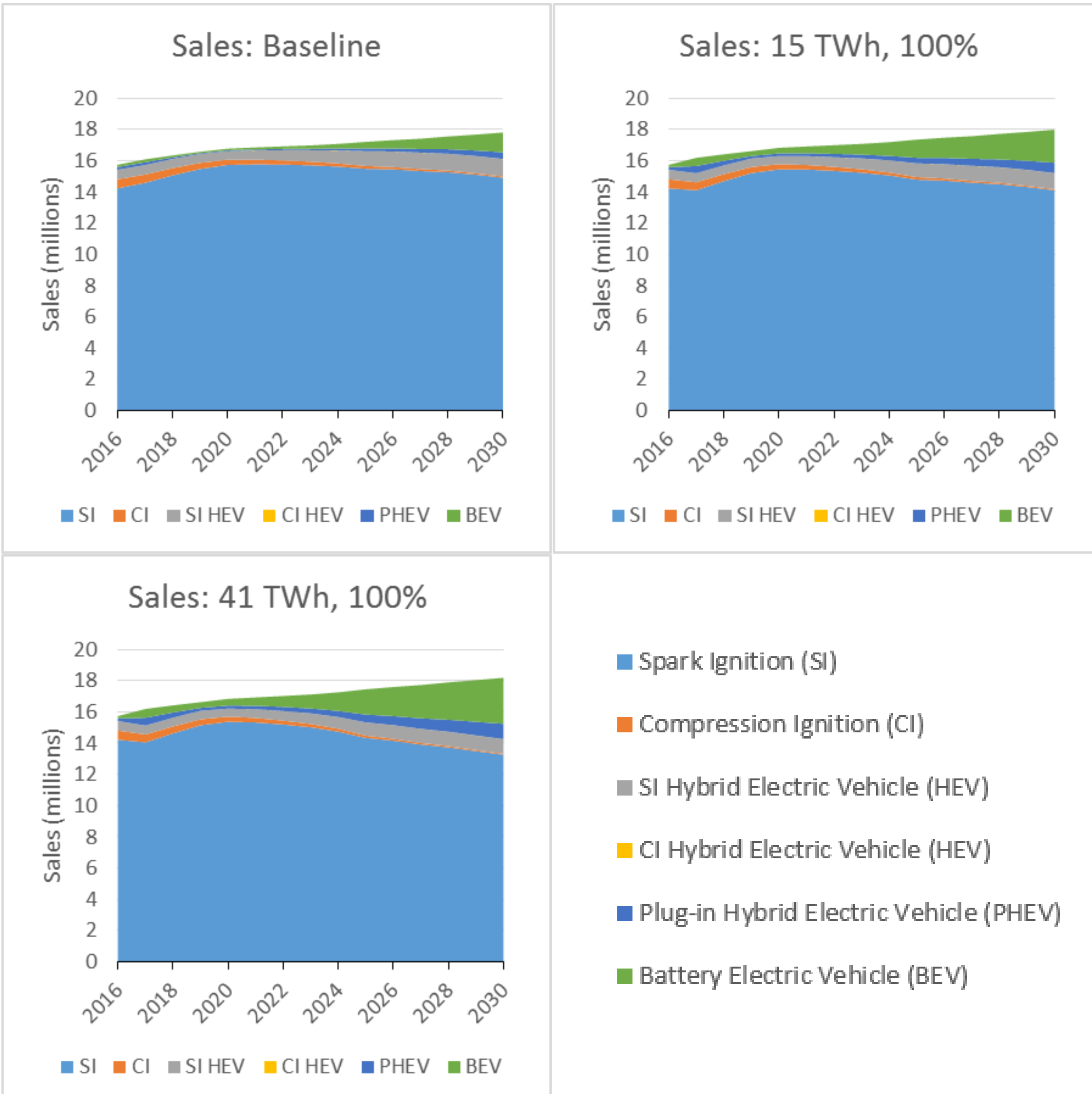

Figure S5. Annual sales data as a function of the biogas cap. Annual sales data for all vehicle types in the baseline, 15 TWh and 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

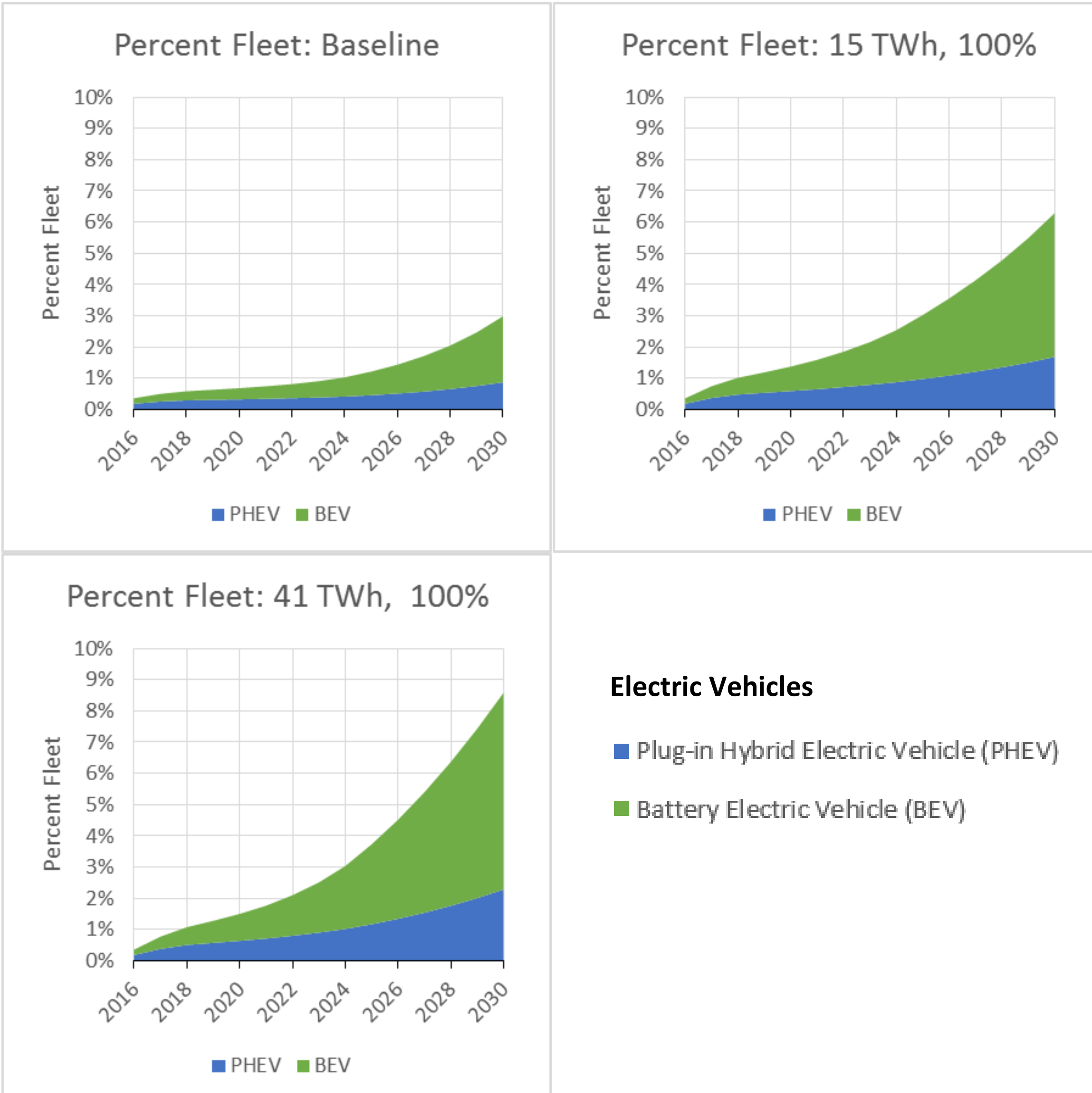

Figure S6. EV percent fleet as a function of the biogas cap. Percent fleet data for BEVs and PHEVs from the baseline, 15 TWh and 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.

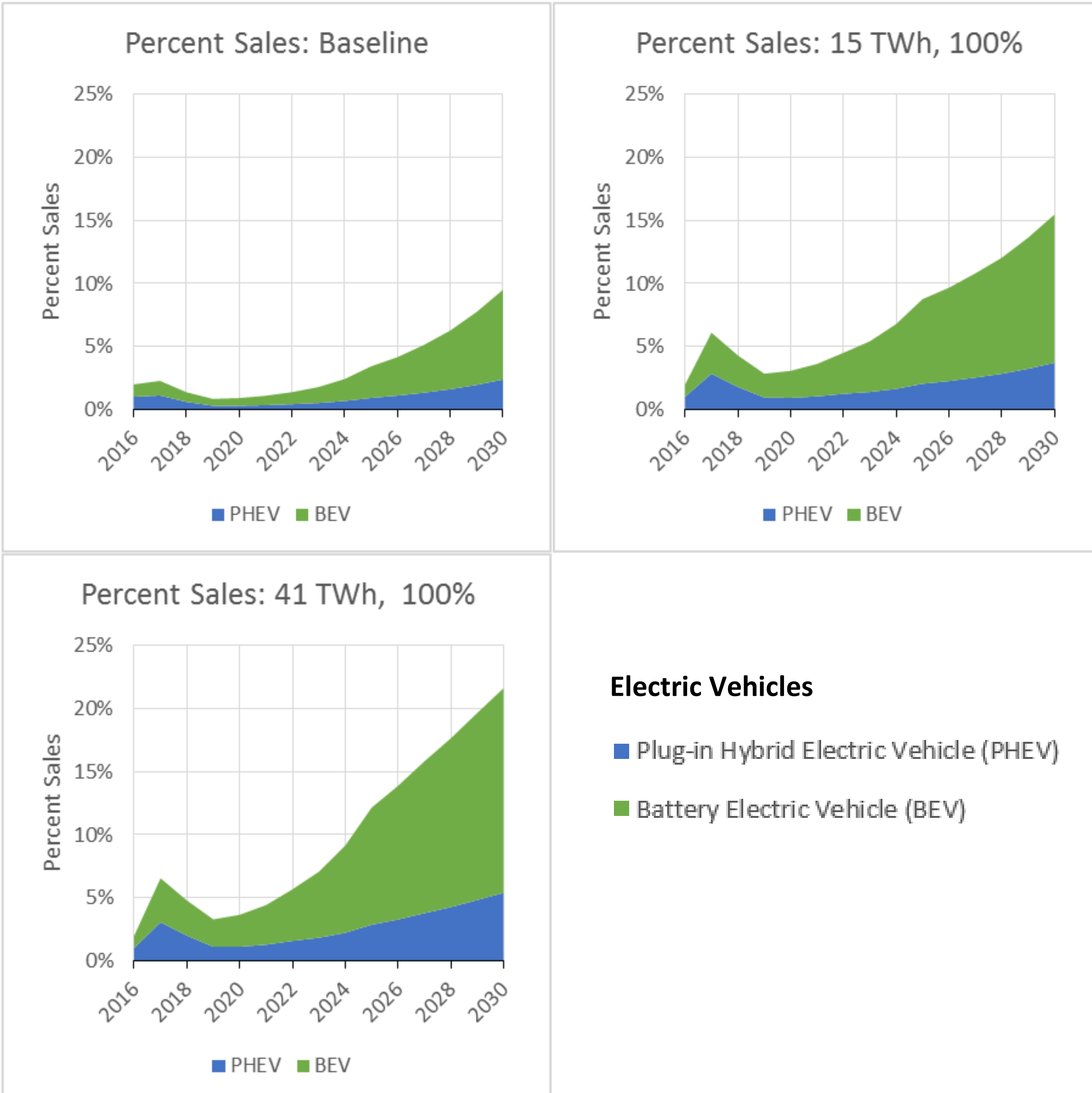

Figure S7. EV percent annual sales as a function of the biogas cap. Percent annual sales data for BEVs and PHEVs from the baseline, 15 TWh and 41 TWh annual cap scenarios (5.24 kWh/RIN equivalence value) where 100% of the credit value goes to reducing consumer purchase price.