Supporting Information for Energy, Economic, and Environmental Benefits Assessment of Co-Optimized On-Road Heavy-Duty Engines and Bio-Blendstocks

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ADOPT

Three triggers instigate the creation of new vehicle options. One trigger creates new variations of a vehicle when it sells exceptionally well for its price. Another creates additional options for several years when a new powertrain is introduced. A third creates new options for the best-selling powertrain. Poorly selling options are discontinued by ADOPT. New vehicle options are created by copying high-selling models and optimizing the component sizing based on future-year conditions to achieve the best-selling combination of vehicle attributes in new model options. The best-selling powertrains evolve the most over time.

Cost and performance specifications of new vehicles include assumptions about the evolution of battery, fuel cell, hydrogen storage, motor, and compression ignition engine technology. Figures A1-A3. show key technology cost and performance assumptions used in ADOPT for this analysis.

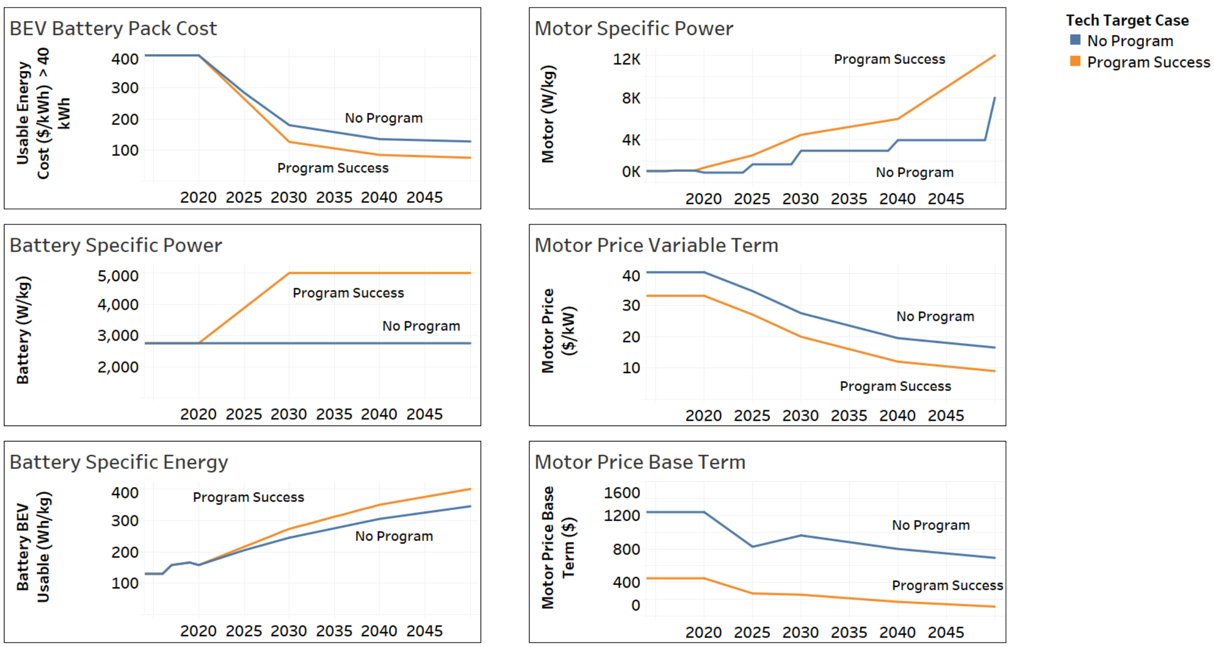

Figure A1. Battery and Motor Technology Cost and Performance Assumptions for the No Program and Program Success Cases

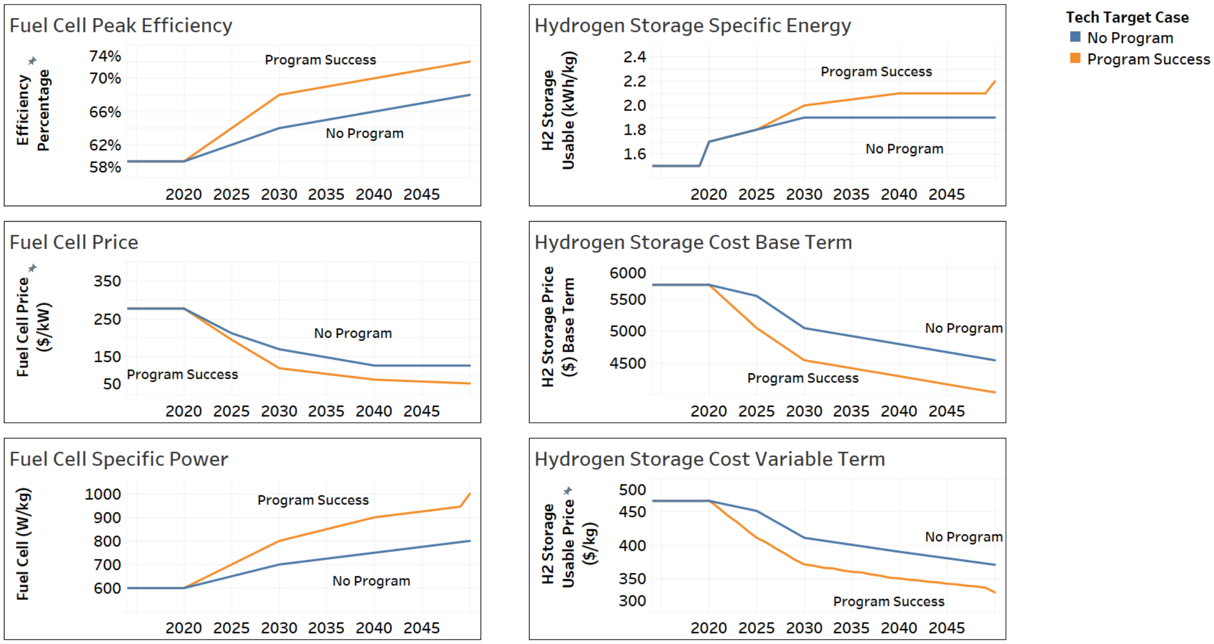

Figure A2. Fuel Cell and Hydrogen Storage Technology Cost and Performance Assumptions for the No Program and Program Success Cases

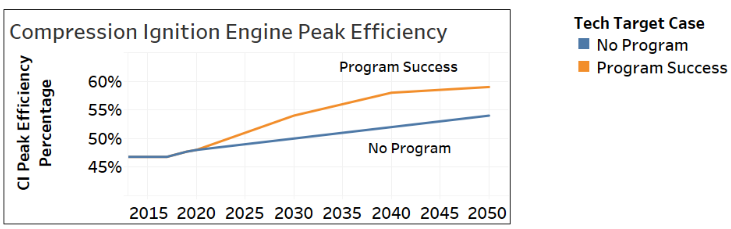

Figure A3. Compression Ignition Engine Peak Efficiency Assumptions for the No Program and Program Success Cases

Fuel prices used in this analysis are shown in Figure A4 for diesel, electricity, and hydrogen. Diesel and electricity price inputs were the same for all cases and were based on prices from the EIA Annual Energy Outlook (AEO) 2021 Reference Case.[1] Hydrogen prices differed between the No Program and Program Success cases and were set by the Hydrogen Fuel Cell Technology Office. Co-optimized fuel prices were set equal to diesel prices on a per gallon basis.

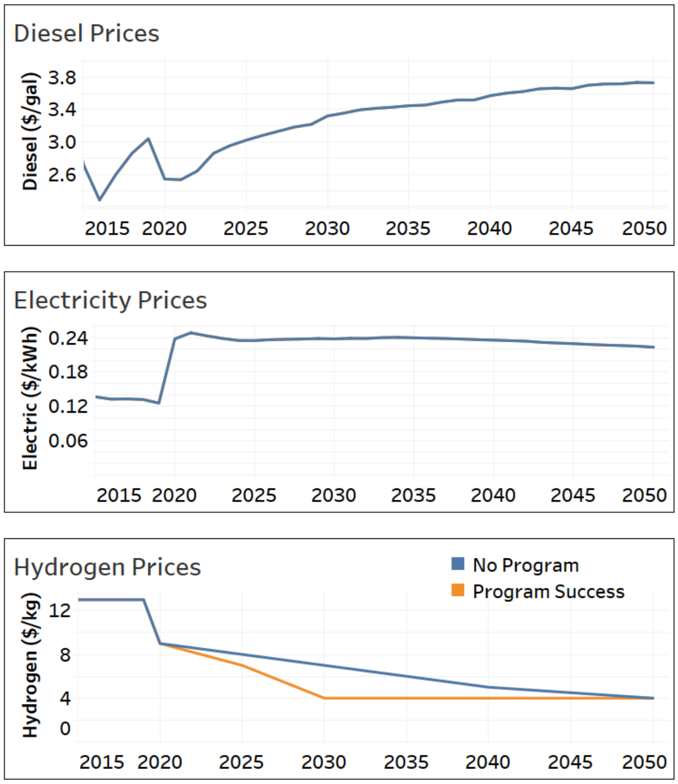

Figure A4. Diesel, Electricity, and Hydrogen Prices used in ADOPT scenarios for the No Program and Program Success Cases

Job Analysis Methodology

Economic impact analysis is often used to calculate changes in employment, income, and tax revenues that could result from new or existing economic activities.[2-3] The fundamental rationale behind economic impact analysis is that changes in economic activity are multiplied through the entire economy because of inter-sectorial linkages, i.e., flows of commodities and services between sectors. In other words, a change in inputs required for production in one sector results in a cascading change in demand throughout its upstream supply chain that involves all the supply-chains of each input supplier, ultimately affecting all sectors of the economy (with various degrees of intensity). Input-output analysis is one of the most commonly used approaches to tracking the ripple effects of changes in economic activity throughout an economy.[3]

Input-output analysis has been widely used to assess the contribution of existing energy sectors in the U.S. economy.[4-7] In modeling the what-if scenarios, where a new industry is assumed to be introduced to the existing economy in the future, input-output analysis has also been widely applied. For instance, a study from IHS Markit[2] evaluated the expansion of unconventional oil and natural gas from 2012-2025 in terms of GDP, employment, and tax revenue contributions to the U.S. economy. In that work, expected capital investments (expenditures in equipment and buildings) and changes to production linked to the sector were used as shocks in the economy to determine annual impacts. Similarly, Lamers et al. estimated the economic and environmental impacts of a future 5 billion gallon cellulosic ethanol industry from two pathways (biochemical and thermochemical), using the same model employed in this paper (BEIOM).[8] Net impacts were estimated by displacing gasoline on an energy basis. The approach used in Lamers et al.[8] is similar to the one used in this paper to evaluate net direct and indirect effects. Jackson et al. estimated the impact of introducing three different pathways using woody biomass as their main feedstocks in a rural area in central Appalachia.[9] A meta-analysis of studies looking at the impact of different advanced biofuels pathways is also available from bio-era.[10]

To estimate the employment impacts resulting from the adoption of new MCCI bio-blendstocks, we expanded the original Bio-based circular carbon economy Environmentally-extended Input-Output Model, or BEIOM with new pathway-specific sectors.[11] We did this by leveraging the most up-to-date cost data (e.g., from techno-economic analysis) along with feedstock production and logistics data from BSM outputs to model the supply chain and relevant expenditures associated with each bio-blendstock pathway examined in this analysis.

BEIOM is a demand-driven input-output model (a commonly used method in economic impact analysis) that estimates the economic effects, including new jobs created, from the expenditures made by biorefineries during their construction and operation phases. Input-output analysis requires a detailed accounting of expenditures and proper allocation of each expenditure to the impacted sectors within an economy. The economic sectors affected by each expenditure are identified by matching the description of the expenditure (e.g., type of equipment purchased and installed) with the North American Industry Classification System (NAICS). NAICS is a standard used by federal agencies (e.g., U.S. Bureau of Economic Analysis) to classify business establishments for the purpose of collecting and analyzing statistical data related to the U.S. economy. BSM/ADOPT simulation results such as changes in demand for MCCI bio-blendstocks are used to inform the model inputs to BEIOM for estimating the jobs impacts.

In addition to quantifying the new jobs that would be created by growth in demand for MCCI bio-blendstocks, the employment change in the mature petroleum industry resulting from the change in petroleum consumption (estimated by ADOPT/BSM) is also considered in the model. To estimate the potential employment change in the petroleum industry due to the introduction of new bio-blendstocks, we modified the underlying input-output table used in BEIOM to account for the new production levels of diesel and substitution between diesel and the new biofuel blendstock. Fuel substitution in each sector is performed on an energy basis and then converted into dollar values, similar to the approach employed in Lamers et al.[8]

The BEIOM model used in this study is based on the national 2012 input-output benchmark table from the U.S. Bureau of Economic Analysis, which includes 405 commodities and 405 sectors.[12] The model is in constant 2012 prices. Employment data are based on the National Income and Products Accounts for 2017 and comprise two metrics: full-time equivalent jobs and full-time plus part-time jobs.[13] The former provides a lower bound for our estimates, while the latter, an upper bound. For this analysis, we focus on direct and indirect (ripple effects throughout different supply-chains) job effects.

To better capture fuel substitution effects, the outputs from the petroleum refining sector were further disaggregated into diesel, gasoline, jet fuel, kerosene, and other petroleum refineries' products.[8] BEIOM also has disaggregated sectors for corn ethanol and soybean biodiesel supply chains.[11] Following the same approach described in Lamers et al.[8], additional biofuel pathways were introduced into BEIOM based on techno-economic analysis (TEA) for each pathway as shown in Table A1. All MCCI pathways were created using n^{th}-plant assumptions. Operation and construction expenses were derived from the TEAs and encompass equipment, buildings, raw and intermediate materials, and direct labor requirements (for plant operation). These itemized expenses were then matched to the commodity- level aggregation in BEIOM.

Table A1. Additional MCCI bio-blendstock pathways introduced in BEIOM

MCCI Bioblendstock	***Feedstock***	***n^{th} Plant Size (MMgal/yr)****	***Data Source***
POME	*Forestry Residue*	*35.0*	*Dutta et al.*[14]
AAEE	*Corn Stover*	*53.7*	
HEFA Swine HTL	*Swine Manure*	*28.0*	*Snowden-Swan et al.*[15]
Sludge HTL	*Sludge*	*28.0*	*Snowden-Swan et al.*[15]
FOG via HEFA	*Used Cooking Oil*	*34.2*	*Tao et al.*[16]

**Bio-blendstock actual production per year.*

As illustrated in Figure 2 in the main manuscript, BEIOM uses external information generated from BSM/ADOPT to simulate technology change, fuel substitution, and production levels in each year. Construction impacts are based on the number of new biorefineries projected (by BSM) to be built to produce bio-blendstocks to meet demand. We assume a typical 3-year construction spending schedule (Year 1, 8%; Year 2, 60%; Year 3, 32%), with the plant fully operational by Year 4. Construction costs and itemization are technology-specific (Table A2) and are scaled from an n^{th} size plant according to the actual size provided by BSM. The average yield of the biorefineries' portfolio in each year is used to scale the variable costs of biorefineries in BEIOM. Total fuel production informs the required production levels for each year. Demand is then allocated between final demand and sectors according to the consumption structure of 2012 for diesel and any substitution effect is done on an energy basis. The BEIOM model accounts for changes in fuel yield for each bio-blendstock pathway over time according to outputs from the BSM model, modifying the production function of the industry, which produces the biofuel.

Table A2. Construction, annual O&M costs, and jobs per plant by pathway

MCCI Bioblendstock	***Construction (million 2012$)***	***Annual O&M (million 2012$)***	***Direct Jobs***
POME	*$ 372*	*$ 179*	*62*
AAEE	*$ 437*	*$ 164*	*60*
HEFA Swine HTL	*$ 592*	*$ 153*	*46*
Sludge HTL	*$ 474*	*$ 139*	*46*
FOG via HEFA	*$ 184*	*$ 205*	*60*

We estimate net employment impacts, defined as the difference in the number of annual full-time equivalent jobs under each scenario compared to the BAU, considering the employment effect in the relevant biofuel and petroleum sectors. Job effects account for both construction and operation in each year and are estimated at the national level. Net effects reflect reduced employment from conventional diesel production and the positive effect from the deployment and expansion of MCCI bio-blendstocks. Production volumes for each type of fuel and construction schedules are provided by BSM.
It is worth noting that an Input-output model such as BEIOM can only estimate change in number of jobs due to a change in demand for a product. Therefore, the estimated change in jobs reflects the demand side rather than job supply or availability of labor force, which meets the desired skills. The occupational dataset we are currently adding to our model will allow us to breakdown total job numbers by occupations

and their respective wages, skill levels, education, and training requirements, but these will represent demand for workers. The availability of skilled workers will depend on locations and other factors and is not addressed in the paper as it is beyond the scope of our model.

Additional Information on the Biomass Scenario Model (BSM)

Techno-economic characteristics change over time in the BSM, as the industry matures with more biorefineries being built. The BSM takes nth-plant conversion costs and uses a learning curve calculation, along with current technology maturity, to determine the modeled annual cost for constructing and operating the biorefineries. Costs and yields for the specific conversion technologies improve over time as more biorefineries are built.[17] More information on BSM logic, including learning curves, can be found in Peterson et al.[18]

Also, in addition to MCCI fuel pathways, the BSM model includes currently available biofuel pathways (biodiesel from transesterification and starch ethanol) and other feedstocks (dairy manure, food waste, algae) and conversion technologies (e.g., indirect liquefaction, catalytic fast pyrolysis, fermentation) that could be available in the future. These technologies can produce fuels other than diesel (i.e., gasoline, jet fuel, bio-oil).

Carbon Tax Additional Information

The level of tax required to offset the energy density difference is different for each bio-blendstock. Among the MCCI fuels, only POME has the potential for an engine efficiency gain, but it is estimated at a modest 1%. With an energy density of only about 62% that of diesel fuel, POME fuel as a replacement for diesel will lead to the largest fuel economy decline, despite the small engine efficiency gain. Renewable diesel via Sludge HTL, HEFA, and swine manure HTL have energy densities that are comparatively closer to that of diesel. Renewable diesel via Sludge HTL has about 3% fewer BTUs per gallon, FOG has about 6% fewer BTUs per gallon, and swine manure has only about a 3% difference in BTUs per gallon. The implication is that RD—via Sludge HTL, FOG, and swine manure—could be cost competitive with diesel under smaller price differentials than the other fuels would require.

We considered several tax structures (Figure A5) and compared adoption results. Tax structure 1 had an initial cost penalty of $15/metric ton of CO_2 emissions, which increased at a linear rate of $10 per year. Tax structure 2 had an initial cost penalty of $35/metric ton of CO2 emissions and increased at a rate of 5% year over year, resulting in a steeper rise each consecutive year. Tax structure 3 had an initial cost penalty of $52/metric ton of CO2 emissions and increased at a linear rate of $1.06 per year. Tax structure 3 resulted in a smooth adoption curve for co-optimized vehicles, and was applied to the carbon tax ADOPT scenarios.

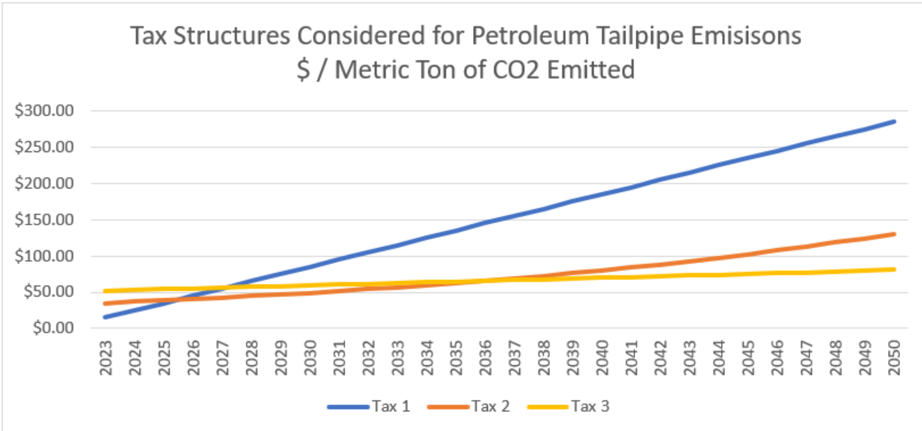

Figure A5. Tax structure considered for petroleum tailpipe emissions.

We performed trial runs in the ADOPT model to examine the effects of each tax structure on vehicle sales and to determine under which structure co-optimized fuels would be price competitive, not only with diesel fuel but also with fuel cell and battery electric vehicles. Fuels at the lower range of energy density (such as POME) were not price competitive under any tax structure. If too little tax was applied, POME was not price competitive with diesel. However, if too great a tax was applied, fuel cells and battery electric vehicles saw more sales benefits than co-optimized vehicles. In this analysis, co-optimized fuel was blended with diesel fuel, and so a tax on diesel fuel still increased the operating costs of co-optimized powertrains in relation to powertrains that do not rely on diesel fuel at all (fuel cells and battery electric vehicles). For the higher energy density fuels, imposing a sales tax on diesel fuel CO_2 emissions could offset the slightly higher price per BTU of the co-optimized bio-blendstock without increasing the diesel fraction's price so significantly that the fuel cell and BEVs become more affordable than the co-optimized vehicles. The ADOPT sales results are shown for Scenario 1.3 Renewable Diesel via Sludge HTL (Figure A6).

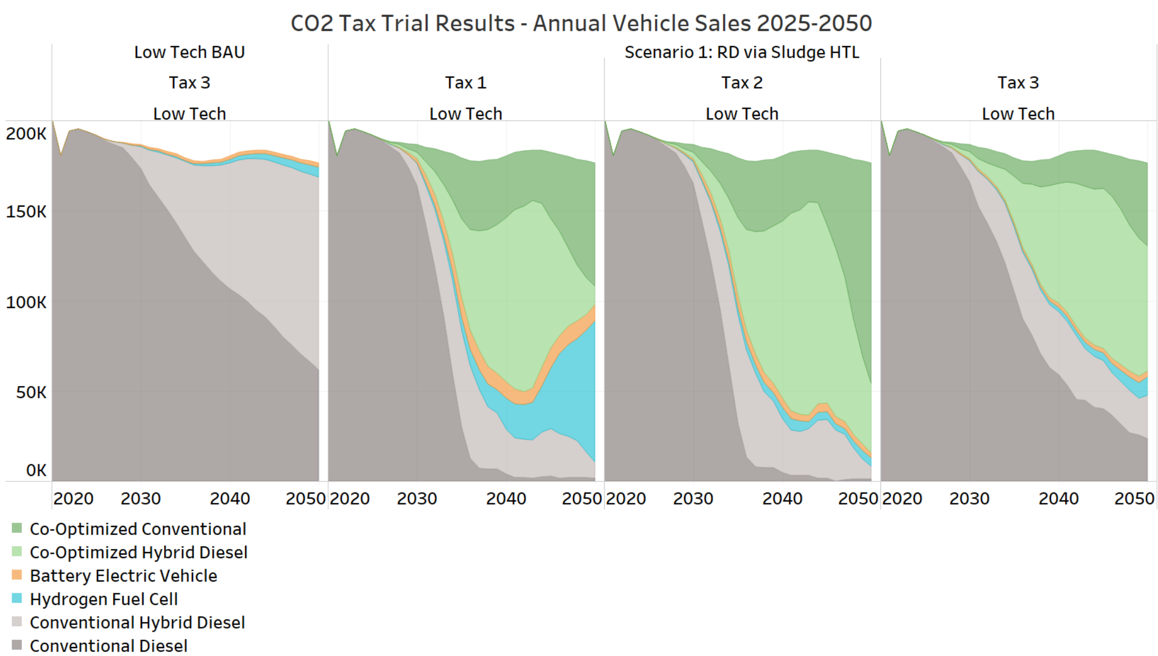

Figure A6. CO_2 tax scenario results

In the scenario with no carbon tax, we see very limited adoption of co-optimized vehicles (maximum of 16% of total annual vehicle sales). In the "Tax 1" scenario (which had the highest tax on diesel CO_2 emissions) we see rapid increases in the sales of co-optimized vehicles until about 2040, at which point fuel cells begin to displace co-optimized sales. In the "Tax 2" case, we again see a rapid increase in the sales of co-optimized vehicles, which continues mostly through 2050 except for during the period in the early to mid-2040s. In the "Tax 3" case, we see a smoother and more gradual increase in the sales of co-optimized vehicles per year, and this tax was selected for the ADOPT carbon tax scenarios.

Vehicle Analysis Additional Results

The carbon tax helps co-optimized vehicles to compete with diesel powertrains only. Electric vehicles and fuel cell vehicles (powertrains that consume no diesel fuel) are not affected by this carbon tax. Under the price and blend fraction assumptions in this analysis, for some of the lower energy density fuels there is no tax level at which co-optimized vehicles can outcompete both diesel and other alternative powertrains. If the tax level is set high enough to price-advantage co-optimized vehicles over 100% diesel vehicles, then it is also set too high for co-optimized vehicles to compete with BEVs and fuel cells. In order to drive sales of vehicles powered by POME and AAEE, the prices of these fuels would need to be reduced to compensate for the energy density differences, or the blend fraction would need to be increased and a carbon tax at a high enough level would need to be imposed.

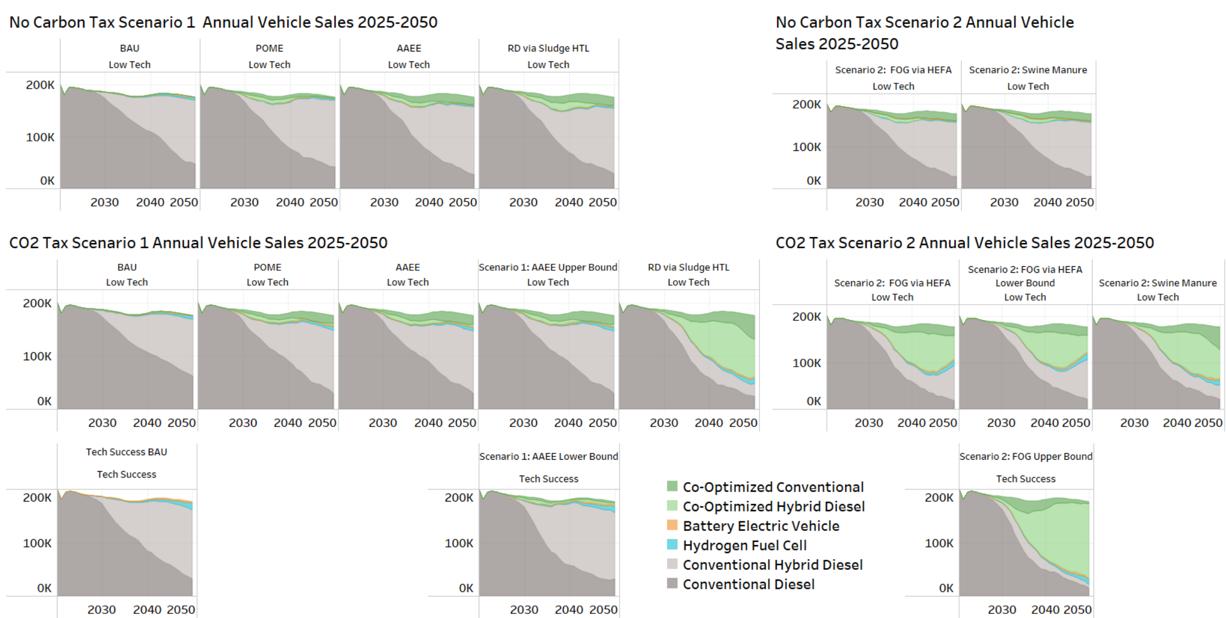

Figure A7. Annual vehicle sales 2020-2050 for different carbon tax scenarios

Job Analysis Additional Results

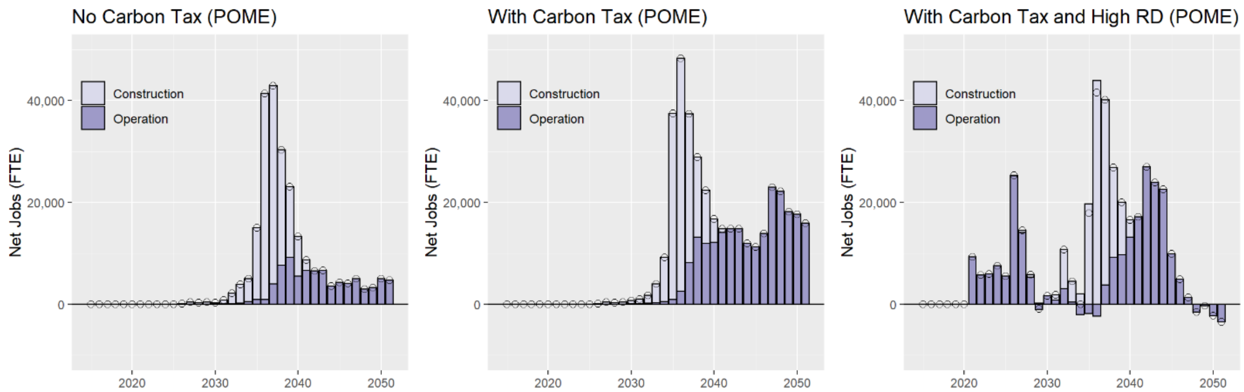

Figure A8. Net jobs (FTE) by MCCI bio-blendstock, diesel market, breakdown, POME

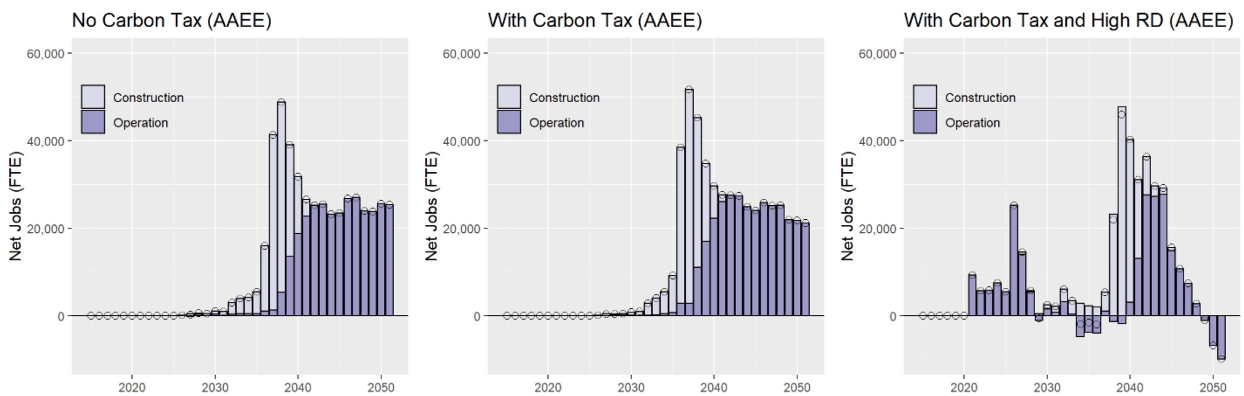

Figure A9. Net jobs (FTE) by MCCI bio-blendstock, diesel market, breakdown, AAEE

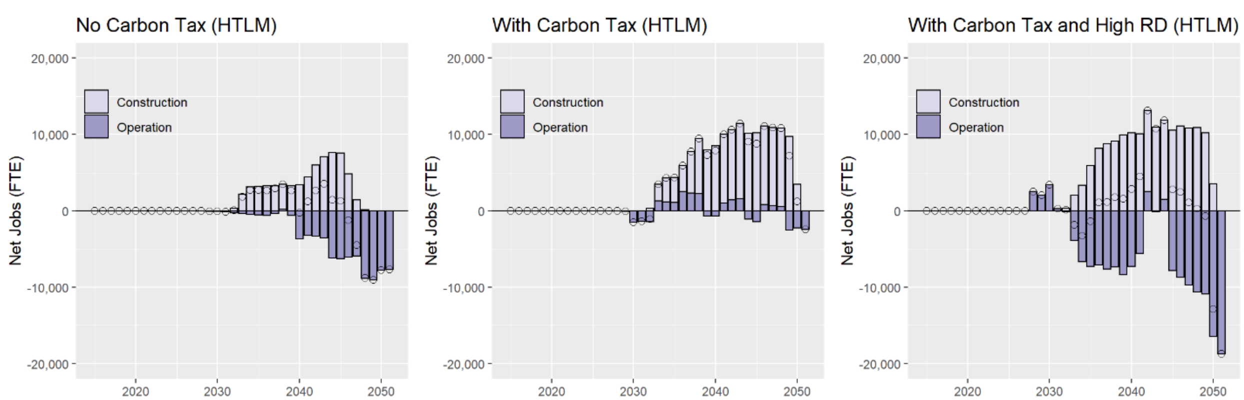

Figure A10. Net jobs (FTE) by MCCI bio-blendstock, diesel market, breakdown, HEFA swine HTL

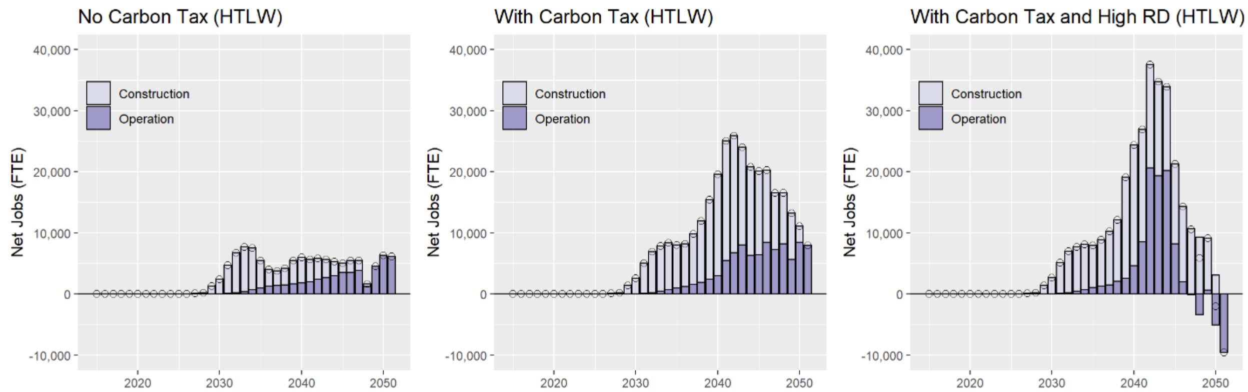

Figure A11**.** Net jobs (FTE) by MCCI bio-blendstock, diesel market, breakdown, sludge HTL

Sensitivity Analysis

Table A3. Key modeling assumptions for the optimistic and pessimistic bounding cases of each scenario

		Scenario 1		Scenario 2		Scenario 3	
		Optimistic, Upper Bound	Pessimistic, Lower Bound	Optimistic, Upper Bound	Pessimistic, Lower Bound	Optimistic, Upper Bound	Pessimistic, Lower Bound
MCCI Bio-blendstocks		AAEE	AAEE	FOG via HEFA and Swine manure HTL	FOG via HEFA and Swine manure HTL	AAEE	AAEE
ADOPT Key Variables	Blend fraction	30%	10%	30%	10%	30%	10%
	Co-optimized engine efficiency improvement	0%	0%	0%	0%	0%	0%
	Incremental cost	$100	$1,000	$100	$1,000	$100	$1,000
	Aftertreatment cost reduction	($4,932)	($4,563)	($4,932)	($4,563)	($4,932)	($4,563)
	Tech targets	Baseline Tech Goals	Tech Success	Aggressive Goals	Baseline Goals	Aggressive Goals	Baseline Goals
	Price of Co-optimized fuel assumption	Diesel		Diesel		Diesel	
	Prices of conventional fuels	2021 TDA		2021 TDA		2021 TDA	

BSM Key Variables	Policy effects	RFS RINs & LCFS credits: Base - Included	RFS RINs & LCFS credits: Sensitivity - Excluded	RFS RINs & LCFS credits: Base - Included	RFS RINs & LCFS credits: Sensitivity - Excluded	RFS RINs & LCFS credits: Included for more/all regions	
	Biorefineries are Built to Meet Demand	Yes	No	Yes	No	Yes	No
	Consumer price sensitivity	High	Expected	High	Expected	High	Expected
	Capital cost of refineries	Low	High	Low	High	Low	High
	Maximum number of biorefineries built per year	Unlimited	25	Unlimited	25	Unlimited	25
	Rate of return required from biorefinery investors	Low	High	Low	High	Low	High
Bioeconomy AGE Key Variables	Feedstock type	Corn stover	Corn stover	FOG	Swine manure	Corn stover	Corn stover
	Life-cycle GHG Emissions (g CO_2e/MJ)	32.5	32.5	11.2	-31.5	32.5	32.5

We perform sensitivity analysis with AAEE and HEFA swine HTL RD as the bio-blendstocks considering a pessimistic case and an optimistic case (Table A3) with carbon tax and with carbon tax and high RD.

With carbon *tax case*

The GHG emissions for the BAU and sensitivity cases is given in Figure A12. In the pessimistic case, although the blending level of AAEE bio-blendstock is lowered to 10%, the excess supply of AAEE above the demand by the co-optimized vehicles coupled with greater success and progress in conventional vehicle technologies relative to the MCCI vehicles results in ~23% reduction in GHG emissions relative to the BAU with carbon tax. This reduction is primarily driven by the decrease in fuel use in the AAEE 10% scenario due to higher vehicle fuel economy driven by technology success, with about 10% of the benefit associated with the bio-blendstock. Compared to AAEE scenario, emissions reduction in the HEFA swine HTL with a 10% blending level reach ~7% in 2050 relative to BAU, with the primary driver being the bio-blendstock.

In the optimistic case, GHG emissions decrease by ~12% (given a 15% market share of AEE in 2050 at a 30% blending level combined with excess production consumed by the conventional vehicles) in the AAEE scenario and a 34.4% reduction in the HEFA swine HTL scenario. The emissions reduction in the HEFA swine HTL scenario is primarily driven by the combined effect of co-optimized technologies and fuel reduction due to improved fuel economy because of progress in conventional vehicle technologies. The benefit also can be partly linked to the increase in BD/RD consumption to make up for the inability of HEFA swine HTL RD to meet the demand in the case with carbon tax only (Table A4).

With carbon tax and high renewable diesel case

With carbon tax and high penetration of RD in the BAU and the sensitivity cases, emissions decreased by ~24% and 5% in the AAEE and HEFA swine HTL scenarios, respectively, relative to the BAU with carbon tax and high RD in the pessimistic case. In the optimistic case, the HEFA swine HTL scenario offers GHG emissions benefit in 2050 representing 66 million metric tons or ~45% reduction driven by high penetration of co-optimized fuel/vehicle technologies and improved fuel economy in conventional vehicle technologies. GHG emissions also decrease by 15 million metric tons, or ~10%, in the AAEE scenario, driven by the reduction in the petroleum diesel consumption in 2050 (Table A4).

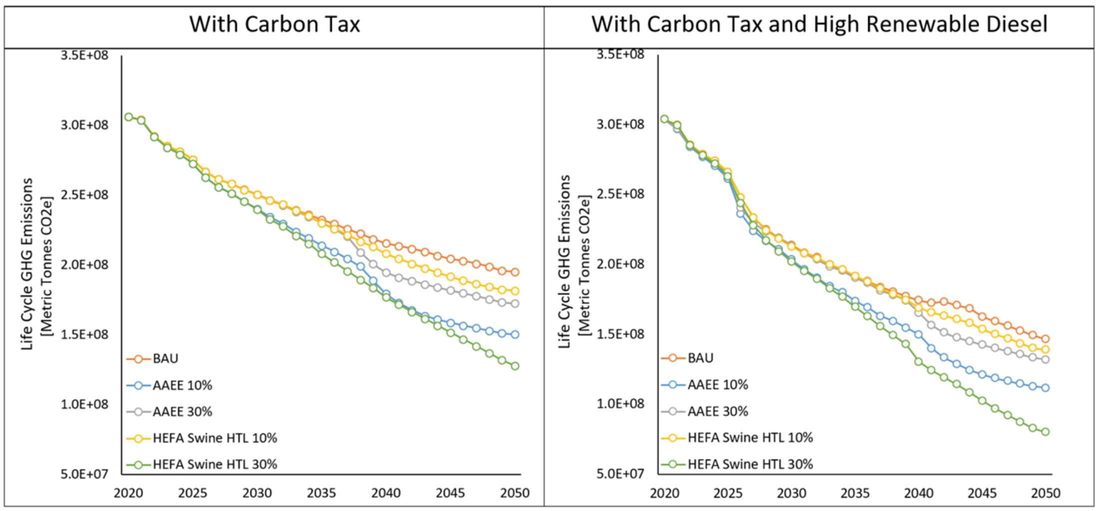

Figure A12**.** GHG emissions of BAU and sensitivity cases

Table A4. Fuel share by fuel type (energy basis) in 2050

	With carbon tax					**With carbon tax and high RD**				
	BAU with C tax (%)	AAEE 10% (%)	AAEE 30% (%)	HEFA swine HTL 10% (%)	HEFA swine HTL 30% (%)	BAU with C tax and high RD (%)	AAEE 10% (%)	AAEE 30% (%)	HEFA swine HTL 10% (%)	HEFA swine HTL 30% (%)
Diesel blendstock	80.9	64.3	66.9	77.3	57.6	55.9	41.4	45.6	55.6	38.8
Biodiesel	11.8	13.3	11.9	12.5	24.3	16.7	18.3	16.5	15.4	17.0
RD	6.5	6.5	5.3	6.1	12.9	26.7	24.1	21.7	24.4	27.0
Electricity	0.5	0.7	0.5	0.7	0.7	0.5	0.7	0.5	0.8	0.7
Hydrogen	0.3	0.5	0.3	0.5	0.4	0.3	0.5	0.3	0.5	0.4
AAEE		14.8	15				15	15.4		
Swine manure HTL				2.9	4.0				3.3	16.1

Tech Success and Sensitivity Cases

The tech success represents a scenario with greater success and progress in conventional vehicle technologies relative to the co-optimized vehicles. Figure A13 illustrates the GHG emissions between the tech success and selected sensitivity scenarios (scenarios with tech success and co-optimized technologies) with carbon tax and with carbon tax and high RD, respectively. In all cases, the AAEE scenarios (pessimistic case) show lower GHG emissions than the tech success because of a reduction in diesel consumption due to the increased production of MCCI fuel (Table A5). The HEFA swine HTL scenario (optimistic case) also shows lower emissions in all cases than the tech success: 24% and 33% lower emissions than the tech success in the case with carbon tax and with carbon tax and high RD, respectively.

Table A5. Fuel share by fuel type (energy basis) in 2050

	With carbon tax			**With carbon tax and high RD**		
	Tech success (%)	AAEE 10% (%)	HEFA swine HTL 30% (%)	Tech success (%)	AAEE 10% (%)	HEFA swine HTL 30% (%)
Diesel blendstock	78.2	64.3	57.6	49.8	41.4	38.8
Biodiesel	13.3	13.3	24.3	18.8	18.3	17.0
RD	7.4	6.5	12.9	30.2	24.1	27.0
Electricity	0.7	0.7	0.7	0.7	0.7	0.7
Hydrogen	0.5	0.5	0.4	0.5	0.5	0.4
AAEE		14.8			15	
Swine manure HTL			4.0			16.1

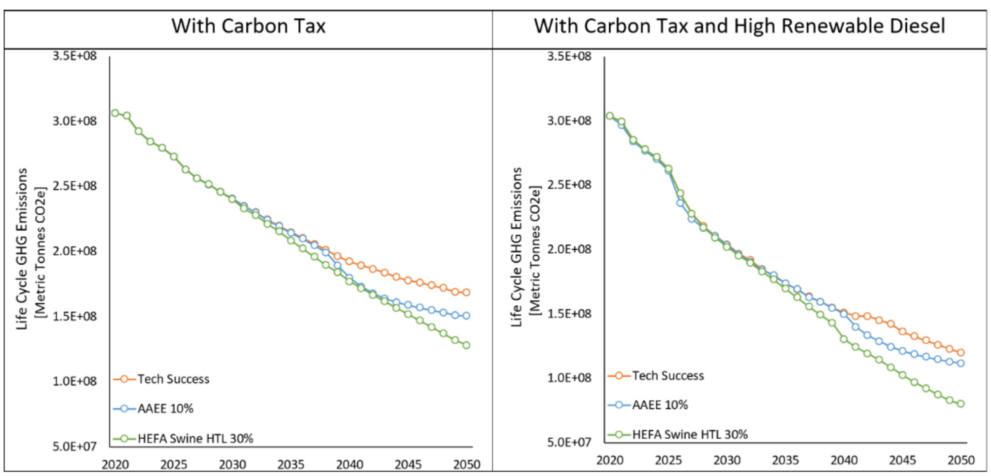

Figure A13. GHG emissions of tech success and sensitivity cases

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