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Insights from Adding Transportation Sector Detail into an Economy-Wide Model: The Case of the ADAGE CGE Model

Yongxia Cai, Jared Woollacott, Robert H. Beach, Lauren E. Rafelski, Christopher Ramig, Michael Shelby

Abstract

The transportation sector is expected to undergo major structural changes in the coming decades, particularly with the emergence of new vehicle technologies. There is a need to understand the economy-wide impacts of evolving conditions in the transportation sector, and computable general equilibrium (CGE) models can provide valuable insights in this area. However, to date, few CGE models have established detailed representations of the transportation sector. In this study, we develop an enhanced version of the Applied Dynamic Analysis of the Global Economy (ADAGE) CGE model that incorporates disaggregated representation of transportation modes and multiple advanced vehicle technologies (e.g., battery electric vehicles [BEVs]) for on-road passenger and freight transportation. We assess the impacts of these inclusions on U.S. vehicle efficiency trends, overall transportation patterns, and economy-wide energy consumption and greenhouse gas (GHG) emissions. We also simulate illustrative global oil price cases to assess potential differences in transportation sector and economy-wide responses in ADAGE to shifting oil prices with and without transportation sector technology detail. We find that adding technologies and disaggregating sub-sector modes in a CGE model significantly alters the simulated impact of oil prices on global trade and freight patterns, energy consumption, and GHG emissions. Specifically, we find that (1) representation of alternative-fuel vehicle technologies is possible in a CGE, and is essential for capturing changes in the transportation sector, (2) on-road vehicle electrification can significantly reduce emissions with concomitant electricity sector decarbonization, and (3) higher (or lower) oil prices can hasten (or slow) the transition to electric vehicles (EVs) with hybrid vehicles moderating the transition. Economy-wide simulations that can interact rich technology detail with a range of potential energy market outcomes can provide essential insight from future

analyses of technological developments in transportation, changes in energy and other markets, and energy and environmental policies.

Keywords: alternative fuel vehicles, economic modeling, oil price, transportation policy

1. Introduction

Transportation is an important sector for global economic modeling of energy systems, accounting for 29 percent of global final energy consumption in 2018 (International Energy Agency (IEA) 2020). However, this sector has generally received less attention in economy-wide models than some other major parts of the energy system, particularly the electricity sector (Babatunde, Begum, and Said 2017). Key challenges in modeling transportation include sectoral heterogeneity, technical complexity, representation of consumer travel behavior, and data availability (Tavasszy, Thissen, and Oosterhaven 2011, Yeh, Mishra, Fulton et al. 2017, Zhang, Caron, and Winchester 2018). In addition, previous literature has suggested the transportation sector offers relatively less potential for substantial changes in technology than other components of the energy system, citing limited cost-competitive fuels (Mathiesen, Lund, Connolly et al. 2015). However, recent advancements in vehicle technology, especially electric vehicles (EVs), provides motivation to update assessments of the transportation sector's potential for substantial shifts in emissions and energy consumption.

Passenger and freight transportation services typically rely on long-lived vehicles with a variety of important physical attributes, including, but not limited to, energy type, energy efficiency, range, capacity, and lifetimes. Each of these vehicle attributes requires some level of definition in transportation modeling to accurately simulate energy, emissions, and economic outcomes. The consumer value of vehicles is determined by their age and their energy requirements, performance characteristics (e.g., power/torque), and other amenities (e.g., comfort/safety) (Greene, Hossain, Hofmann et al. 2018). Cost and consumer utility trade-offs associated with vehicle attributes (e.g., between capital cost and vehicle range) can be challenging to analyze when modeling vehicle consumer choices.

Taken together, transportation system complexities can quickly outstrip data availability and model computational capabilities and therefore generally require a significant amount of simplification. Modelers looking to represent additional transportation sectoral, technological, and spatial detail as part of a larger modelled economic system face tradeoffs under constraints from numerical solution algorithms and computing power limitations. Computable general equilibrium (CGE) models typically use standard economic data from national income accounts and offer a rich set of endogenous economy-wide feedback, but they generally do so at the expense of sub-sectoral detail and specific individual technology characteristics, and most CGE models are constrained in the amount of technological detail they can incorporate. Thus, balancing the trade-offs of adding in the technological and spatial details of transportation sector-only models while gaining the insights from an economy-wide CGE perspective requires some degree of modelers' judgement.

Despite these challenges, enhancing representation of the transportation sector within CGE models may improve understanding of potential economy-wide impacts of future shifts in energy and transportation service consumption. Prior work (e.g., Wade et al., 2019; Zhang, Caron, and Winchester (2018); Britz and van der Mensbrugghe (2016)) has shown that aggregation of technological and spatial detail in economic models can mask important sources of heterogeneity, potentially leading to substantially different predicted outcomes between models employing different levels of aggregation. In CGE models, this is sometimes labeled "aggregation bias." For example, Cai and Arora (2015) explore the importance of disaggregating electricity generation in a CGE model when assessing the impacts of environmental policy, finding that incorporation of heterogeneous generation technologies has important effects on the estimated cost of mitigation.

Within the transportation sector, there are opportunities for passenger and freight mobility demands to substitute among modes (e.g., between freight services provided by truck, rail, and marine shipping) and energy technologies (e.g., petroleum, battery electric, hydrogen fuel cell electric). Aggregating these modes and representing only conventional technologies, as many CGE models do, prevents substitution, either by fixing market shares for modes and/or technologies or by allowing only for exogenous changes in market shares. This reduced flexibility limits options for modeling how the economy adjusts to economic and policy shocks or long-term developments in the transportation sector. Even if technologies' cost structures are expected to remain constant over time, modeled shifts in resource costs or other exogenous macroeconomic shocks can still affect technologies' competitiveness. Models with single technology and aggregated mode representations that do not allow for endogenous substitution among alternative technologies and modes of transport are likely to find different economic outcomes than models that allow such competition through more-detailed representation.

To study the potential significance of more-detailed transportation technology and sectoral representation in economy-wide modeling, we disaggregate transportation sector modes in the Applied Dynamic Analysis of the Global Economy (ADAGE) global CGE model and incorporate technologies representing multiple types of alternative-fuel vehicles (AFVs). We then compare results between two versions of the model that incorporate disaggregated transportation modes, both with and without the addition of AFVs. Incorporating AFV technologies (version 1) has a substantially larger impact on energy and emissions results than disaggregating transportation modes alone (version 2); therefore, we focus on comparing model results with and without AFV technologies in the results and discussion sections.

The scenarios presented in this study are based on illustrative oil price trajectories, a key driver of transportation service costs for traditional vehicles with internal combustion engines. We find including new vehicle technology options for on-road transportation modes in ADAGE leads to differences in the modeled mix of transportation energy demand, energy intensity of transportation services, and total greenhouse gas (GHG) emissions. Specifically, we find that (1) on-road vehicle electrification can significantly reduce emissions with concomitant electricity sector decarbonization, (2) higher (or lower) oil prices can hasten (or slow) the transition to EVs with hybrid vehicles moderating the transition, and (3) representation of AFV technologies is essential for capturing these changes. These differences illustrate the economic and environmental significance of sectoral technology representation in economy-wide models. These findings may inform future studies of modeled technology competition and environmental impact assessment of the transportation sector.

2. Methodology

2.1. ADAGE Model Overview

The Applied Dynamic Analysis of the Global Economy (ADAGE) model is a multi-region, multi-sector, recursive dynamic CGE model. ADAGE follows the classical Arrow-Debreu general equilibrium framework (Arrow and Debreu 1954) covering all aspects of the economy, including factor endowments, production, private and public consumption, trade, and investment. ADAGE includes eight regions (Africa, Brazil, China, European Union 27, United States, Rest of Asia, Rest of South America, and Rest of World) and simulates regional and global economic activity from 2010 to 2050 in five-year increments. Intertemporal dynamics in ADAGE are represented by (1) growth in the available effective labor supply from population growth and changes in labor productivity; (2) capital accumulation through savings and investment; (3) changes in stocks of natural resources; and (4) technological change from improvements in energy efficiency, productivity, and advanced technologies (e.g., AFVs) that become cost competitive in later time periods.

Within each period, representative firms in each sector maximize profits subject to technology constraints also specified by a constant elasticity of substitution (CES) functional form. This production structure guides the transformation of factors of production and intermediate inputs into commodities. The model includes more than 60 sectors with distinct representations of fossil fuels, electricity generation technologies, and transportation modes. One representative household per region allocates its earnings to consumption of these commodities and investment. The composition of consumption of goods and services is responsive to relative prices and is guided by a nested CES function. Households allocate their time to earning income in labor markets and enjoying leisure, with the relative prices of consumption and labor hours (i.e., wages) guiding their allocation. ADAGE represents bilateral trade flows among regions, with households and firms exhibiting preferences between consumption goods by origin (i.e., domestic versus foreign) via Armington aggregation (Armington 1969).

ADAGE tracks environmentally important inputs and outputs (e.g., land, fuels, emissions) in physical and monetary units. The representation of the economy with rich sectoral detail makes ADAGE suitable for analyzing a wide range of economic and environmental policies and estimating how all parts of an economy respond to those policies (Clarke, McFarland, Octaviano et al. 2016, Calvin, Beach, Gurgel et al. 2016, Lucena, Hejazi, Vasquez-Arroyo et al. 2018, Kober, Summerton, Pollitt et al. 2016, van Ruijven, Daenzer, Fisher-Vanden et al. 2016). The core database underlying ADAGE is GTAP version 7.1 (Narayanan and Walmsley 2008), complemented by numerous other data sources to extend the physical and technological detail in ADAGE. This study is the first application of a new version of ADAGE with an enhanced version of the transportation sector. Thus, we focus on describing the modifications introduced to the transportation and energy sectors within this paper. See Cai et al. (2021) for full documentation of the ADAGE model, including detailed discussion of our additions and modifications to the data available from the GTAP database.

2.1.1. Production in the Transportation Sector

The transportation sector in ADAGE includes (1) eight modes of transportation that use conventional technologies (light-duty passenger, passenger buses, heavy-duty freight, rail freight, rail passenger, airline, water transportation, and other transportation) and (2) four types of AFV technologies (battery electric vehicles [BEVs], hybrid vehicles, compressed natural gas vehicles, hydrogen fuel cell EVs) for all on-road transportation. On-road vehicles are assumed to have a maximum useful lifetime of 30 years in the model, with the average survival rate lower for LDVs than for passenger buses and heavy-duty freight. The production of transportation service for each on-road mode and technology in ADAGE is vintaged, with *new vehicles* defined as those from age zero through the end of age four, and *used vehicles* being vehicles aged five or above.

Production of new vehicles using conventional and AFV technologies is structured with a series of nested CES functions using energy, capital, labor, and materials as inputs (see Figure 1). Energy used in transportation varies by mode and technology, as shown in Figure 2. Currently, most finished gasoline in the United States contains up to 10% ethanol by volume (E10), whereas a smaller amount of biodiesel is blended into petroleum diesel. Overall, biofuels accounted for about 5% of total U.S. energy consumption in the transportation sector in 2020, with ethanol supplying about 4% and biodiesel and renewable diesel combined supplying about 1% (EIA, 2021). For this study, first- and second-generation biofuels can be blended with refined oil and replace refined oil used in all on-road transportation modes. The fuel blending ratio differs for LDVs, freight trucks, and passenger buses with relatively more ethanol than biodiesel in LDVs and more biodiesel in heavy-duty vehicles. Refined oil-biofuel blends and electricity are used in hybrid vehicles at a fixed ratio to represent the average hybrid vehicle in each global region. Because hydrogen is not presently modeled as a commodity in ADAGE, we collapse the production of hydrogen, which uses electricity and natural gas as inputs, and the production of transportation service, which uses hydrogen and other inputs, into one composite production function for fuel cell technology. Natural gas vehicles represent the combination of natural gas–only vehicles and bi-fuel vehicles (gasoline and natural gas), where natural gas and refined oil cannot substitute with each other in ADAGE. Battery vehicles use electricity and do not differentiate the electricity source (fossil fuel or renewables). In general, battery vehicles have the highest energy efficiency, followed by fuel cell vehicles, hybrid, and conventional. Natural gas vehicles have the lowest fuel efficiency.

For each new vehicle technology, the energy mix bundle can substitute with capital to improve energy efficiency. The resulting energy/capital composite is then combined with materials and labor within a Leontief production function (i.e., assuming no substitution between these inputs). A fixed factor is included for new vehicle production with an elasticity of substitution of 0.1 (fuel cell vehicles and natural gas) or 0.2 (battery and hybrid electric) at the top level of the production function (see Figure 1 for new vehicle production structure). The fixed factor is assumed to be 0.1% of service production value with an equivalent endowment in 2010. As the model solves for later periods, the endowment is updated to larger or smaller values based on the solution from the previous period. The approach for defining the fixed factor reflects the fact that retirement of conventional technology and adoption of AFVs are both determined by more than cost per mile travelled. The fixed factor acts as a proxy for the cost and availability of supportive infrastructure, consumer preferences regarding vehicle technologies, and other non-priced factors that might slow AFV adoption beyond what an input cost-per-service basis would imply.

Vehicle technologies in the U.S. region are subject to national fuel efficiency standards. More specifically, we assume that the U.S. region transportation sector must meet the Phase 2 fuel efficiency and GHG emissions standards for both light-duty and heavy-duty vehicles (40 CFR 85, 86, 600, 40 CFR 9, 22, 85, 86, 600, 1033, 1036, 1037, 1039, 1042, 1043, 1065, 1066, 1068, 75 FR 25323-25728). For our representation of the real-world fuel economy levels required to meet these standards, we rely on average fuel economy projections for LDVs, freight trucks, and buses from the AEO 2018 Reference Oil Price case, which assumes full compliance with these standards (U.S. Department of Energy 2018). These assumed average fuel economy levels must be met on average across all new vehicles sold, so no one vehicle technology need satisfy the standard unless there is only one technology. To model the fuel efficiency standards, technologies purchase credits for their fuel use and produce credits at the rate implied by the efficiency standard. Thus, technologies more efficient than the standard are subsidized at the expense of less efficient technologies, the latter of which must purchase more credits than they produce. The model structure and elasticity of substitution are described in the ADAGE documentation (Cai et al., 2021).

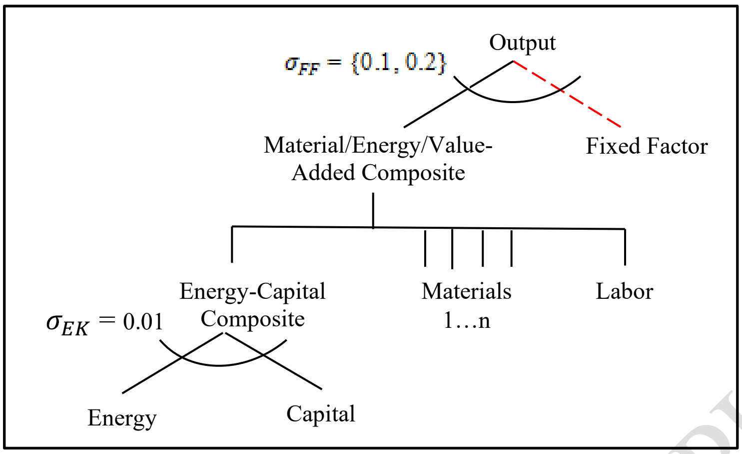

Figure 1. New On-road Transportation Production Structure by Mode and Technology

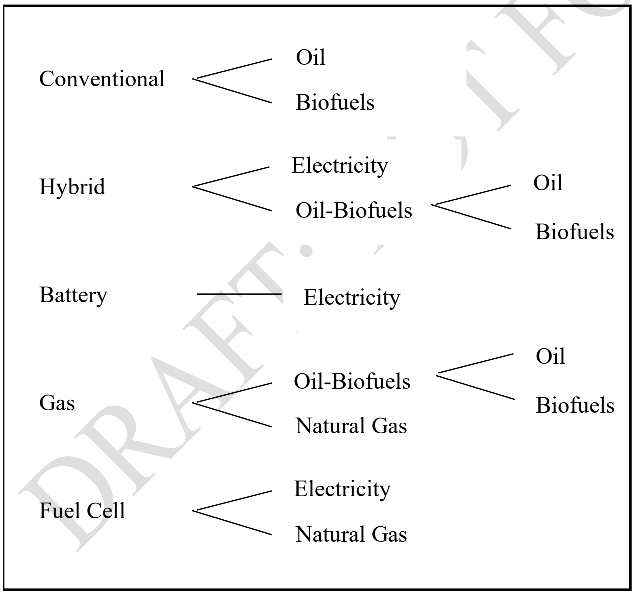

Figure 2. Energy Used in On-Road Transportation by Technology

To characterize AFVs in each mode where they are available (e.g., LDVs, heavy-duty vehicles, buses), we use a bottom-up approach to obtain vehicle purchase costs, expenses for charging stations and other infrastructure, vehicle insurance, maintenance costs and fuel economy over time and see how they change relative to each vehicle's conventional counterpart. The parameter values used in this work were informed by external data including DOE battery pack and fuel cell stack technology, interim and ultimate target fuel intensity and costs (Nyquist et al 2015, DOE 2015), and Annual Energy Outlook 2019 data (EIA, 2019). However, these illustrative forward-looking estimates are ultimately based on this paper's authors' combined expert judgment. The authors have developed plausible values of future vehicle efficiency and cost for use in scenarios demonstrating the novel transportation sector methods employed in ADAGE and reported in this paper. However, these estimates do not constitute a projection of future vehicle costs or efficiencies and should not be interpreted in such a manner.

AFV purchasing costs are aggregated to capital, labor, and materials inputs in ADAGE. Purchase and infrastructure costs are amortized into annual capital costs using an assumed 30-year maximum lifetime for all on-road vehicles. Energy input cost is derived from energy price in the ADAGE base year and fuel economy. The sum of labor, capital, materials, and energy input costs form the transportation service production cost and vary by region of the world. Figure 3 provides a comparison of production cost per mile traveled for all new on-road vehicles in the United States. For conventional vehicles, the cost reduction is induced by fuel efficiency improvements only, whereas for AFVs, cost declines also stem from technology improvements that reduce capital, labor, and material costs. We assume battery, hybrid, and fuel cell vehicle costs decline over time. One or more of these AFVs become cost-competitive with conventional vehicles by 2030, although the trajectories vary by mode. The current pace of change for AFV costs in these sectors is rapid and any cost estimates will likely change in the future. Still, these figures show the types of inputs required to operationalize and demonstrate the validity of these methods.

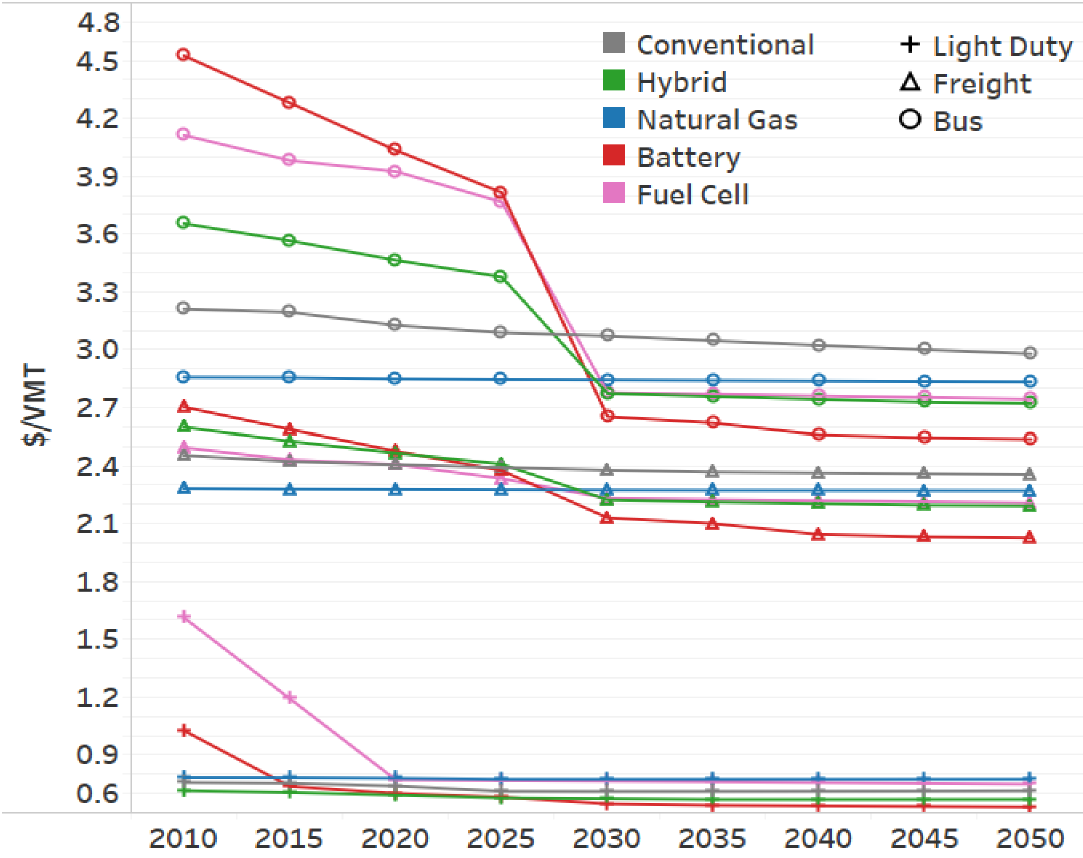

Figure 3: Transportation Service Cost for All On-Road New Vehicles in the United States During 2010-2050 ($/VMT)[1]

The transportation service production cost (e.g., energy, capital, insurance, maintenance, and infrastructure costs) for new vehicles is updated in each period in the model using data in Figure 3. The new vehicle's fixed-factor endowment in each current period is assumed to be proportional to its service production in the previous time period. The service production cost for used vehicles is guided by the age structure of vehicles added in prior periods. A vintaged capital

[1] In this paper, costs and prices are presented in 2010$.

stock serves a comparable role to the fixed factor in new vehicles, which is not present for used vehicles. Transportation service production for used vehicles (aged 5–29 years) for both conventional and alternative fuel technologies use the same set of energy, capital, labor, and materials inputs as when a given vintage of used vehicle was new with no substitution possibilities (i.e., the input mix is determined when new vehicles are produced, but can no longer be changed once they have been made). Therefore, the used fleet efficiency can only be improved by the retirement of old vehicles and the adoption of new, more efficient vehicles. The relative proportions of vehicle miles travelled (VMT) being provided by vehicles in each vintage are determined by the number of new vehicles added in each prior period adjusted for the average VMT driven by vehicle age. A vehicle survival rate combined with a VMT schedule for surviving vehicles by age (in annual time steps) informs the weighting of surviving vehicle attributes (e.g., fuel efficiency, non-fuel costs) in the vintage stock, with data coming from the MOVES 2014a model, developed by the U.S. Environmental Protection Agency. Vehicle survival rates and annual VMT decline as vehicles age, reducing the relative influence of older vehicles on the vintage fleet efficiency. Conventional vehicles and AFVs are assumed to have the same average VMT schedule.

2.1.2. Demand for Transportation Services

Transportation services are demanded by producers, governments, and households. For producers and governments in ADAGE, transportation services enter a Leontief structure, meaning, for example, that there is no substitution between on-road freight and rail freight transportation (taken as a simplifying assumption). The ADAGE model uses a nested CES structure to represent household consumption preferences. In each period, households generate utility from consumption of leisure and composite goods (see Figure 4). A *composite good*, aggregated from housing, food, manufacturing, transportation, and others, can be traded against leisure time to obtain a specific utility for each household in each period. The elasticity of substitution between the composite good and leisure (σ_{cl}) represents how willing households are to trade off leisure time for consumption (i.e., sacrifice leisure time to earn a wage and purchase more consumption goods and services). Within the composite good, transportation is substitutable with an *other goods* aggregate consisting of a combination of all other goods, including housing and an aggregate of food, other goods, and services with an elasticity of substitution, σ_{ch}, equal to 1.0. The food, goods, and services aggregates have an elasticity of substitution, σ_c, of 0.5. Housing includes an energy bundle (coal, gas, electricity, and oil) with an elasticity of substitution, σ_{he}, of 0.5. Within housing, energy and capital have an elasticity of substitution, σ_{hk}, of 1.0. The demand structure and elasticity of substitution above are discussed in the ADAGE documentation (Cai et al., 2021) and shown in Figure 4.

Transportation aggregates, composed from passenger transportation and non-passenger transportation, substitute with an aggregate of all other goods and services at an elasticity of 0.5 (σ_{ct}). Households cannot substitute between freight and passenger transportation ($\sigma_{tr} = 0$) nor among modes of freight (e.g., water, train, truck, and other; $\sigma_{tf} = 0$). Household substitution among passenger modes (e.g., airline, bus, train, and auto) is possible with a substitution of $\sigma_{tp} = 0.5$. Within transportation modes, transportation vintages and technologies produce undifferentiated goods that compete freely with one another (implied elasticity $\sigma_{tpf} = \infty$) constrained only by their fixed factor and capital stocks.

Transportation service demand in each region is a function of GDP per capita, population, and region-specific preferences among travel modes. Based on Dargay, Gately, and Sommerdue (2007), we used the S-shaped Gompertz function to project the relationship between vehicle ownership growth rate and per-capita income, urbanization, and population for all ADAGE regions over the model horizon. The calculated trend in vehicle ownership is then used to calibrate

ADAGE's trend in household demand for light-duty and passenger bus transportation service as a fraction of income over time. Household passenger service demand is mainly driven by population growth in the United States with modest per-capita VMT growth, whereas in China and Africa, both GDP and population growth drive VMT growth rates. The passenger vehicle ownership growth trend is presented in the ADAGE documentation (Cai et al., 2021).

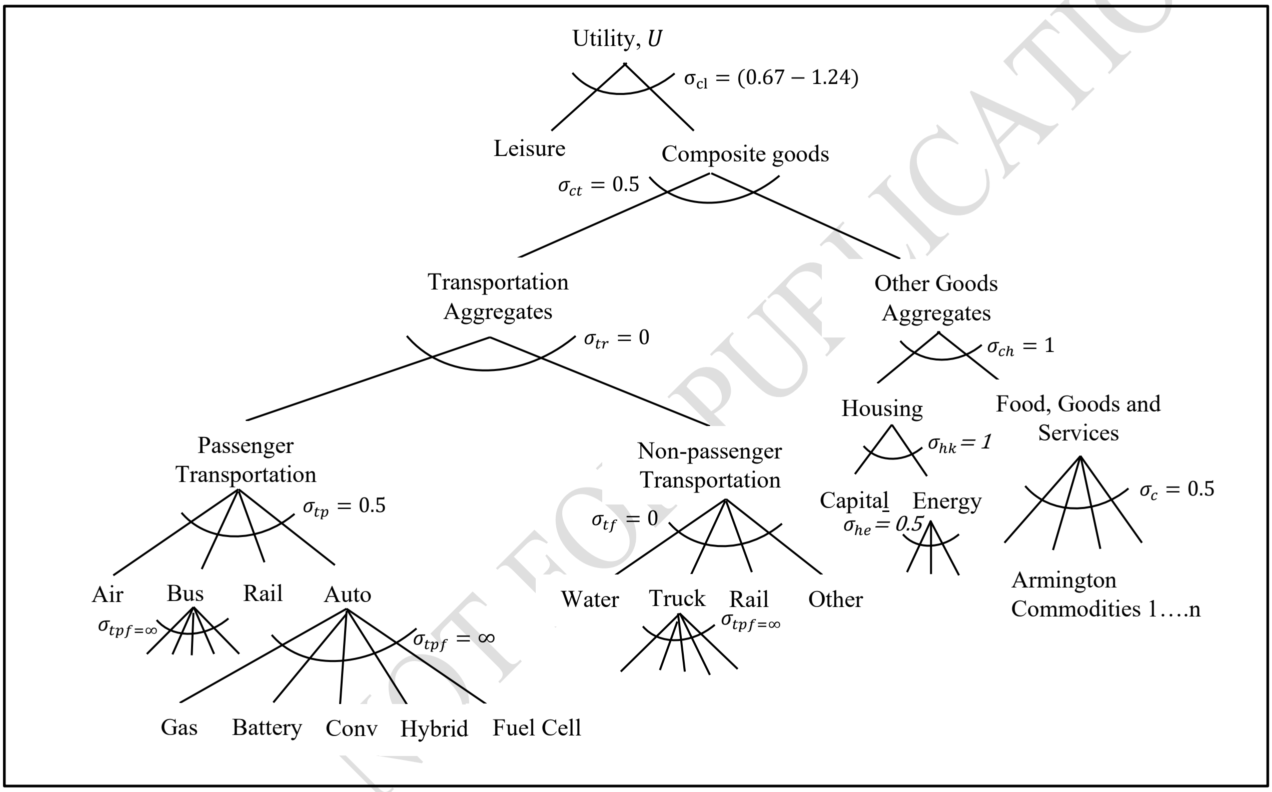

Figure 4. Model Structure for Household Demand

2.1.3. Electricity Production and the Energy Sector

The rapid cost reduction of AFVs in recent years and assumed in the future (Figure 3) indicate that AFVs may take an increasingly significant role in the transportation sector in the future. The substitution of other energy sources, especially electricity for liquid fuels, means that representation of future energy production plays a vital role in analyses of changing technologies in the transportation sector and in determining implications for net GHG emissions. Ten electricity generation technologies (conventional coal, natural gas, refined oil, combined cycle natural gas, and renewable electricity from solar, wind, nuclear, hydro, geothermal, and biomass) are included in ADAGE. Each technology has an independent CES production function. ADAGE includes fixed factors of production in the top nest of the electricity production function for renewable and combined cycle natural gas generation. Price competition across different electricity generation technologies is limited by an aggregation elasticity. Consumers purchase one undifferentiated electricity good. The electricity generation cost for these technologies is taken from 2020 Annual Technology Baseline from U.S. National Renewable Energy Laboratory (National Renewable Energy Laboratory (NREL) 2020).

In the energy sector of ADAGE, fixed factors are incorporated into the production functions for coal, natural gas, and crude oil used to represent natural resource constraints. Crude oil is assumed to be a homogeneous product trading at a single world price, with adjustments for tariffs, export taxes, and transport margins. Armington aggregation differentiates coal, gas, refined oil, and electricity from domestic production versus imports from other regions of the world.

2.2. Scenario Implementation

For this study, we present two versions of ADAGE: the *NoAFV* version, which includes eight modes of transportation (auto, freight truck, bus, air, rail freight, rail passenger, water, and all other transportation) with only conventional technologies available for all modes, and the *YesAFV* version, which includes the same eight modes of transportation as *NoAFV* and incorporates AFV technologies in all modes of on-road transportation (auto, bus, freight trucks) in all regions. Technology costs in the *NoAFV* version are representative of conventional technologies. In the base year of the *YesAFV* version, only conventional technologies are calibrated to be operating, but new vehicles are chosen endogenously based on cost, meaning AFVs could be produced immediately if economical.

We then present illustrative oil price scenarios under the hypothesis that different assumptions about long-term future oil prices will significantly affect the modelled energy and transportation system results for each ADAGE version. The crude oil price paths in these sensitivity scenarios are taken from the U.S. Energy Information Administration (EIA) 2018 Annual Energy Outlook (AEO), specifically the Reference Oil Price case (referred to hereafter as *REF),* High Oil Price case (hereafter *HOP*) and Low Oil Price case (hereafter *LOP*) (see Figure 5).[2] Those oil price cases assume a range of exogenous global crude oil price paths for each model version. The *REF* represents an increasing trend projection for both global oil supply and demand, with crude oil prices rising steadily across the projection period from $62/barrel in 2020 to $101/barrel in 2050. The *HOP* and *LOP* encompass a wide and asymmetric range of crude oil prices to demonstrate ADAGE behavior under an array of plausible fuel price paths. Prices diverge after 2015, bounding the *REF* price path and illustrating variations in modelled global demand for and supply of, among other things, petroleum and other liquid fuels, energy as a whole, and transportation service.

[2] The crude oil price in the *LOP* case starts at $28/barrel in 2020 and rises slowly to $46/barrel in 2050. The crude oil prices in the *HOP* case starts at $109/barrel in 2020 and rise to $205/barrel by 2050. As noted under the previous footnote on the *REF* case, we continued using the 2018 AEO projections for the *LOP* and *HOP* scenarios as well with the same rationale. Neither the AEO projections nor the ADAGE model include the impact of countries' commitments under the Paris Agreement that are not already enacted in law.

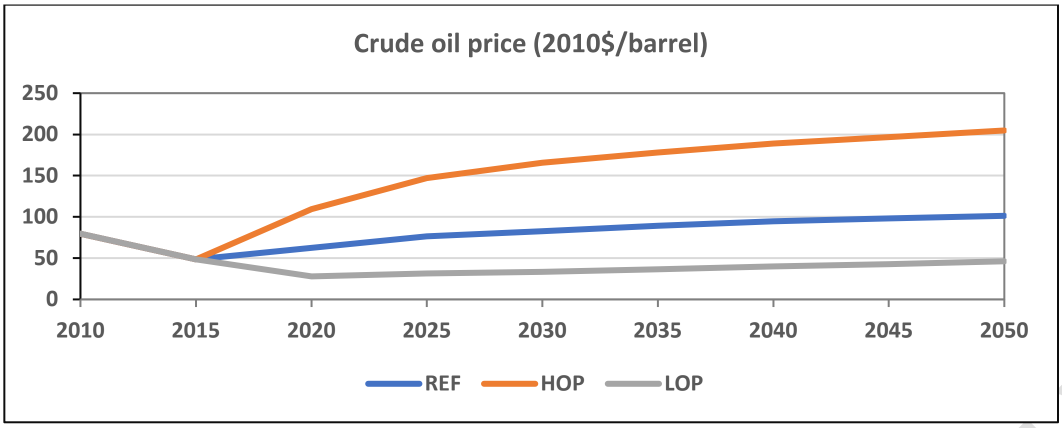

Figure 5: Crude Oil Price Cases from AEO2018 (2010$/Barrel)

3. Results

In this Results section, we examine how adding alternative fuel technologies alters the ADAGE *REF* case results for VMT, vehicle stock fuel efficiency, energy markets, and GHG emissions. Although ADAGE is a global model, we focus on results for the United States. We then examine technology trends across transportation modes under AEO 2018 *REF*, *LOP*, and *HOP* to understand how changes in oil prices can alter U.S. economic and environmental outcomes such as changes in VMT, AFV adoption, and GHG emissions.

3.1. Reference Oil Price Scenario

3.1.1. U.S. VMT

In both versions of our *REF* case, the *NoAFV* version and the *YesAFV* version, VMT grows for each vehicle type over time (Figure 6). In the *NoAFV* version, U.S. light-duty VMT demand comes mostly from households, and the growth rate of 0.7% per year (from 2,612 billion miles in 2020 to 3,180 billion miles in 2050) reflects ADAGE's calibrated decline in households' transportation demand per unit of consumption over time. Freight truck demand is proportional to

U.S. economic output, and its growth rate is the highest of the three on-road modes (1.8% per year, resulting in an increase from 300 to 509.4 billion miles between 2020 and 2050). Passenger bus demand grows by 1.3% per year (from 9.9 billion miles in 2020 to 14.4 billion miles in 2050).

Including additional technologies in the model in the *YesAFV* version results in faster growth in LDV (0.9% per year) and passenger bus demand (1.1% per year) and a decline in the growth of freight demand (1.7% versus 1.8% per year in the *NoAFV* version). The *YesAFV* version also results in 100% replacement of conventional vehicles by hybrids and BEVs by 2050 across auto, freight truck, and passenger bus modes (Figure 6). As described in Figure 3 above, based on our assumptions about improvements in their efficiency and declining capital costs, total transportation service cost for BEVs and hybrids becomes lower than conventional vehicles over the 2020–2030 period and continues to decline through 2050. Higher projected capital costs for fuel cell vehicles and the assumed lower fuel efficiency of natural gas vehicles leads to higher cost per mile for these two technologies. This results in minimal penetration across all three modes in these results, although fuel cell vehicles do play some role in freight trucking.

Replacement of conventional vehicles is also driven by the retirement of older vehicles, either at the end of their useful life or earlier via economic retirement. Economic retirement occurs in the ADAGE model if the cost to operate an existing vehicle is higher than the cost to operate and cover capital payments on a new vehicle. Economic retirements occur for some conventional and hybrid vehicles in the 2030–2050 timeframe. Economic retirement of conventional passenger bus and freight trucks in the *YesAFV* version is evident after 2040 from conventional vehicle VMT declines that are larger than would occur from end-of-life retirements alone.

The roles of hybrids and BEVs in the transition to AFVs vary by mode. For light-duty vehicles, the *YesAFV* results show hybrid vehicles serving as a "transition" technology from 2020 to 2040. These results show BEVs gaining greater adoption after 2030 and becoming the dominant technology by 2050. Hybrid vehicles play a smaller role in freight truck and passenger bus segments of the U.S. transportation sector. Instead, these modes transition more directly from conventional technology to battery electric technology. Our assumptions about technology costs and the flexibility of consumer preferences influence the timing of the transition to AFVs, and highlight areas of uncertainty in this transition. As we will discuss below, additional research should further explore the issue of the transition to AFVs.

The availability of lower-cost LDVs in later modeled periods leads to increases in passenger VMT but decreases in freight truck VMT in the *YesAFV* version relative to the *NoAFV* version. The ADAGE structure allows for all global regions to have the same ability to purchase AFV technologies. The availability of efficient AFVs causes non-U.S. regions to rely more on domestic freight transportation production instead of imports from the United States. Increased freight truck VMT over time is met by a growing share of EVs rather than by hybrid vehicles.

Figure 6: Vehicle Miles Travelled in the United States, Reference Oil Price Projections (Billion VMT)

3.1.2. U.S. Fuel Efficiency

Absent alternative fuel technologies, the vehicle fleet within each mode can only improve efficiency by investing in improvements for new conventional vehicles and then retiring older, less-efficient vehicles. In addition to exogenous efficiency improvements for new vehicles over time, ADAGE allows for endogenous efficiency improvements for new conventional vehicles in response to the relative prices of capital and fuel, and the *NoAFV* version uses this ability to increase vehicle efficiencies in the *REF* case to some extent. With AFVs, the model outcomes for fleet fuel efficiency improvements parallel hybrid and BEV technology adoption across modes, leading to larger fuel efficiency improvements by 2050 for LDVs, freight trucks, and buses (see Figure 7). More-rapid EV adoption around 2040 produces visible inflection points in aggregate fuel efficiency increases in the *YesAFV* version. Concurrently, the introduction of light-duty AFVs reduces pressure on the transportation sector to invest in conventional vehicle efficiency after 2020. Under the assumptions used in the *YesAFV* version, the ADAGE model simulates that the least-cost solution is to concentrate investment capital in the relatively more efficient BEVs and hybrids. As a result, conventional vehicle fuel economy does not grow as rapidly after 2020 as it does in the *NoAFV* version.

For freight trucks and passenger buses, assumed differences in conventional and AFV costs are such that conventional vehicles remain the least cost solution for most of the modeled period. Like LDVs, freight trucks and buses are subject to U.S. federal vehicle fuel efficiency standards (discussed in Section 3.1.1). The assumed efficiency standard targets for trucks and buses are much closer to the modeled future conventional technology efficiencies in these results. Endogenous changes in conventional freight truck and bus efficiency are therefore smaller than those for LDVs.

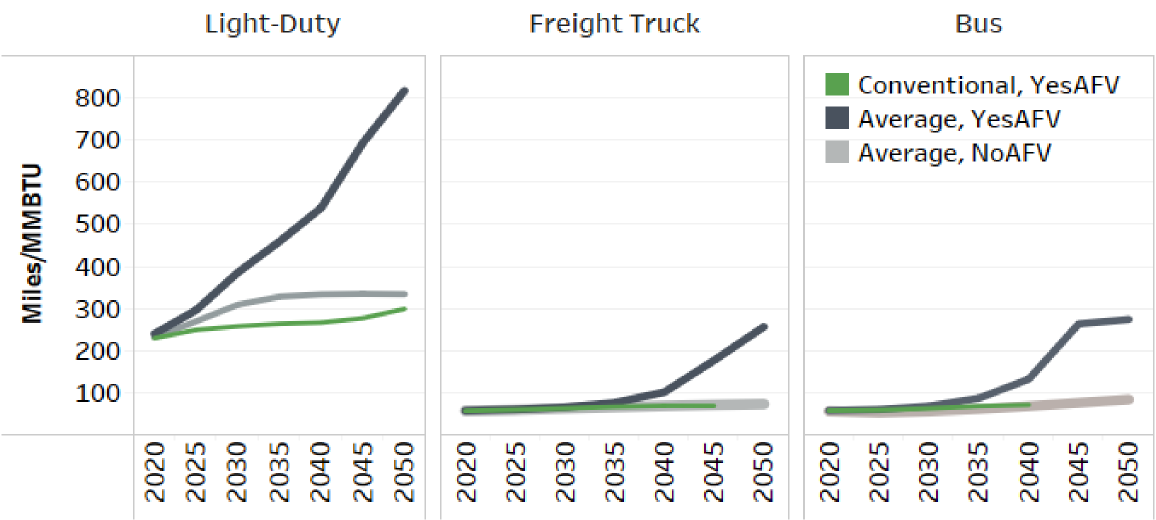

Figure 7: U.S. Fleet-Wide Fuel Economy for On-Road Transportation in the United States (Miles/MMBTU)

3.1.3. U.S. Energy Markets and GHG Emissions

In the *NoAFV* version, energy consumption in the U.S. transportation sector grows at a gradual rate of 0.5% per year, from 25.5 quads in 2020 to 30 quads in 2050. Even without AFVs, LDV energy consumption declines as efficiency improvements more than offset the slight rise in light-duty VMT (see Figure 8-a). The introduction of AFVs in the *YesAFV* version leads to a net increase in VMT across modes but a significant decrease in total energy consumption (see Figure 8-a and 8-d). This result is driven by the marked rise in energy efficiency for all on-road modes over the 2020–2050 period. The rest of the U.S. transportation sector (air, water, rail, and other modes), where AFVs are not assumed to be an option in these scenarios, accounts for a growing fraction of total U.S. transportation energy demand and most U.S. transportation energy demand by 2050. Most of the energy demand from other U.S. transportation modes is served by fossil fuels. Including AFVs for these modes in the model could produce results with reduced energy use for these subsectors, as occurs for on-road vehicles in the results presented here, depending on the projected assumptions made about those AFVs.

The expansion of EV technology also has a marked impact on U.S. electricity generation by 2050; in the *YesAFV* version, electricity generation in 2050 is estimated to be 28% higher than in the *NoAFV* version (see Figure 8-b and 8-e). ADAGE's cost projections for the U.S. electricity sector show electric generation capacity expansion that proportionally favors more efficient, lower GHG emitting combined cycle natural gas plants, solar and wind power over coal-fired electricity generation. However, whereas coal is a proportionally smaller share of the 2050 energy mix than the 2020 energy mix in the *YesAFV* version, electricity generation from coal is slightly higher in these results than in the *NoAFV* version. In ADAGE, this can be interpreted as delayed retirement of pre-existing coal generation capacity rather than construction of new capacity. As electricity demand rises in the *YesAFV* version, so do electricity prices.

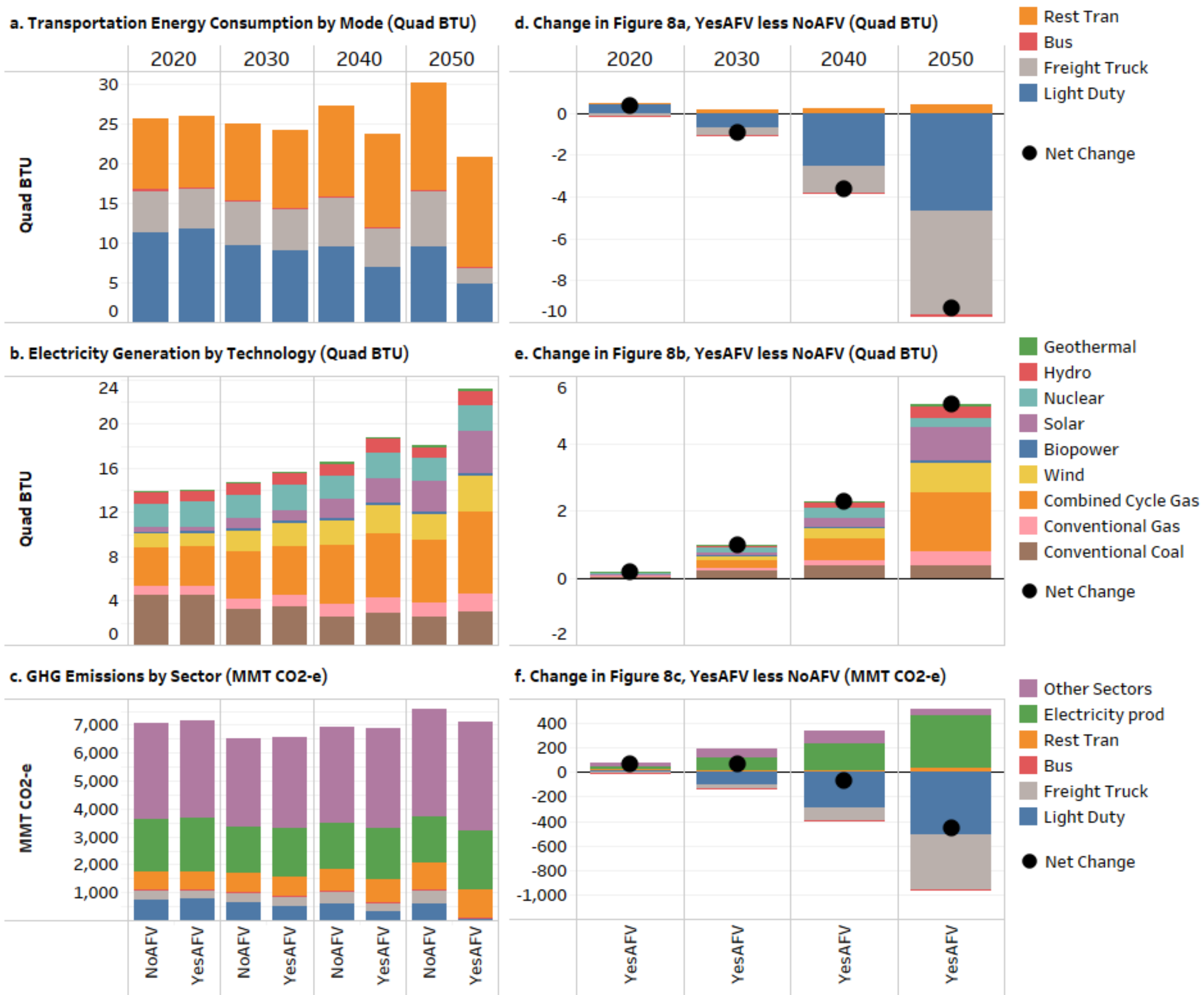

Figure 8: Level and Change in Transportation Energy Consumption (a, d), Electricity Generation by Technology (b, e), and GHG Emissions by Sector (c, f)

Total U.S. GHG emissions in the *NoAFV* version rise by 6.7% (7,089 to 7,561 MMT CO_2 equivalence [CO_2-e]) from 2020 to 2050, with most of the increase coming from outside the on-road transportation and electricity sectors. The introduction of AFVs brings down the total U.S. GHG emissions by 0.7 percentage points (from 7,153.9 to 7,101 MMT CO_2-e) during 2020 to 2050, where the largest reduction comes from light-duty, freight truck, and passenger bus transportation (1,106.91 to 99.5 MMT CO_2-e by 2050; see Figure 8-c and 8-f). The net effect on total annual U.S.

GHG emissions in 2050 is a 6.4% decrease from the *NoAFV* to the *YesAFV* version. U.S. electricity GHG emissions in 2050 are higher in the *YesAFV* version than in the *NoAFV* version (2,113 MMT CO_2-e in the *YesAFV* version versus 1,679 MMT in the *NoAFV* version) owing to increases in transportation sector demand and moderated by relative declines in coal that reduce electricity-sector emissions intensity. The higher energy efficiency of AFV technologies and declining electricity generation GHG emissions intensity over the time period modeled mitigate additional emissions associated with the increase in transportation electricity demand in the *YesAFV* results (see Figure 8-c). In both versions, other transportation (especially air transportation) and other sectors (especially manufacturing and household demand for energy) contribute to rising emissions.

3.2. Alternative Oil Price Cases

In this section, we examine the impacts of different oil price paths on U.S. transportation and energy sector outcomes and net GHG emissions in the two ADAGE versions. As shown in Figure 5, the *HOP* path from EIA has crude oil prices that are approximately double the prices in the *REF* case by 2050, and the *LOP* case has crude oil prices that are roughly half the *REF* by 2050.

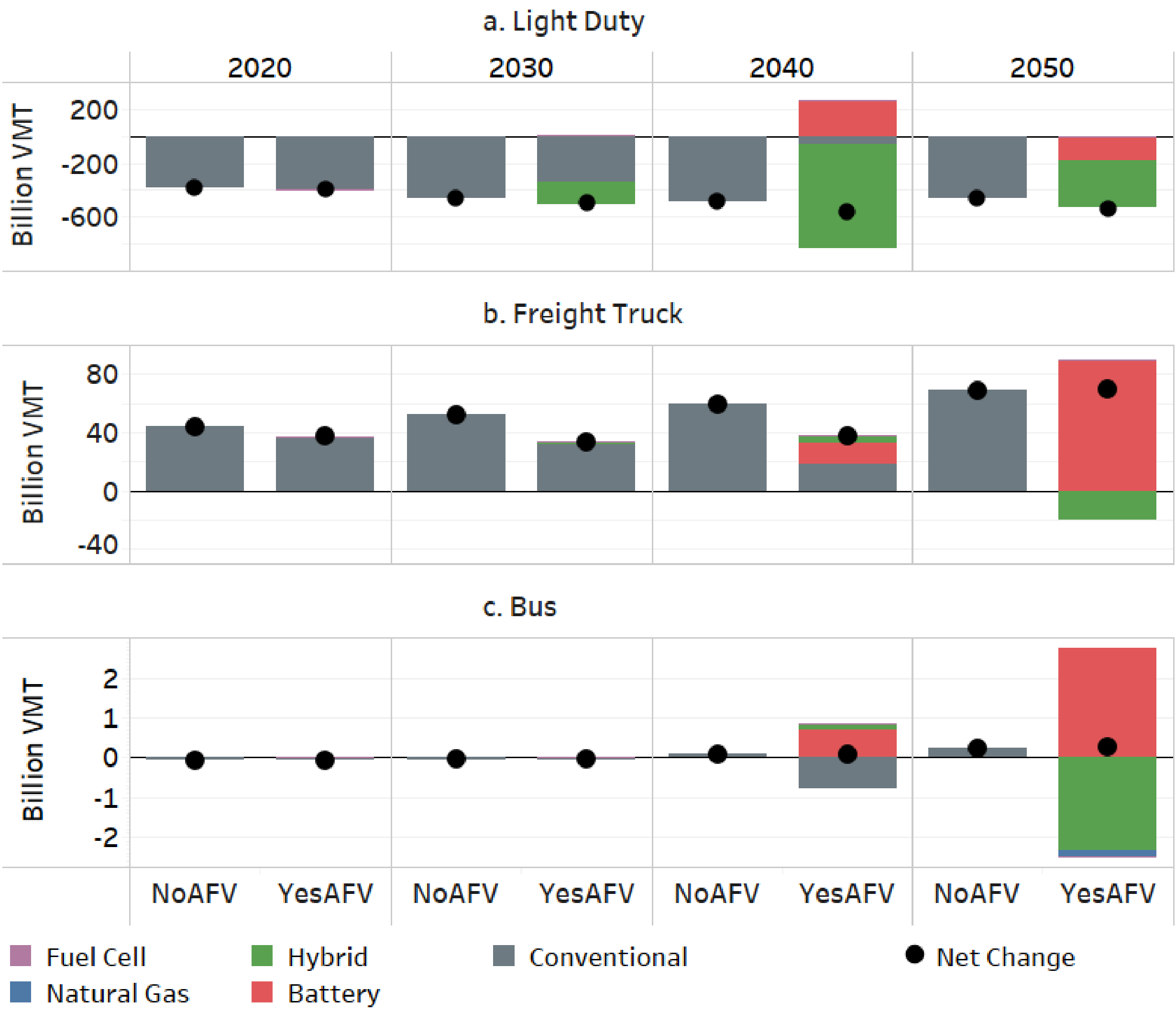

Figure 9: Change in U.S. Vehicle-Miles-Traveled in *HOP* Case Relative to *REF* Case (Billion VMT)

The *HOP* case results in a 15% reduction in light-duty VMT in 2050 relative to the *REF* case in both the *NoAFV* and *YesAFV* versions of the model (Figure 9). The comparable percentage reduction in VMT across different assumptions about the availability of AFVs suggests that lower light-duty VMT stems more from income effects on U.S. households under high oil prices than from substitution effects associated with higher VMT costs. Conventional LDVs and buses also phase-out sooner in the *HOP* case than in the *REF* case. Hybrid AFVs play less of a transition technology role for LDVs with higher oil prices, as BEVs gain a comparative cost advantage over hybrids sooner with higher oil prices. Low oil prices induce proportionally opposite behavior, with LDV hybrids serving longer as a transition technology.

Freight truck VMT increases by around 14% with higher oil prices. The historical data on which ADAGE is built reveal that the United States has a relatively more energy-efficient manufacturing sector than most global competitors, such as China and Brazil (World Bank 2012). Rising oil prices therefore tend to benefit the United States, improving competitiveness for the United States relative to foreign manufacturers and increasing U.S. manufacturing output (Figure 10) and manufacturing demand for freight (as well as increasing GDP). Freight VMT is proportionally lower in the *LOP* case with lower U.S. manufacturing demand. Consistent with light-duty and bus technology composition, in the *YesAFV* version, the increased VMT for freight trucks is met by a larger share of EVs than by hybrid technology.

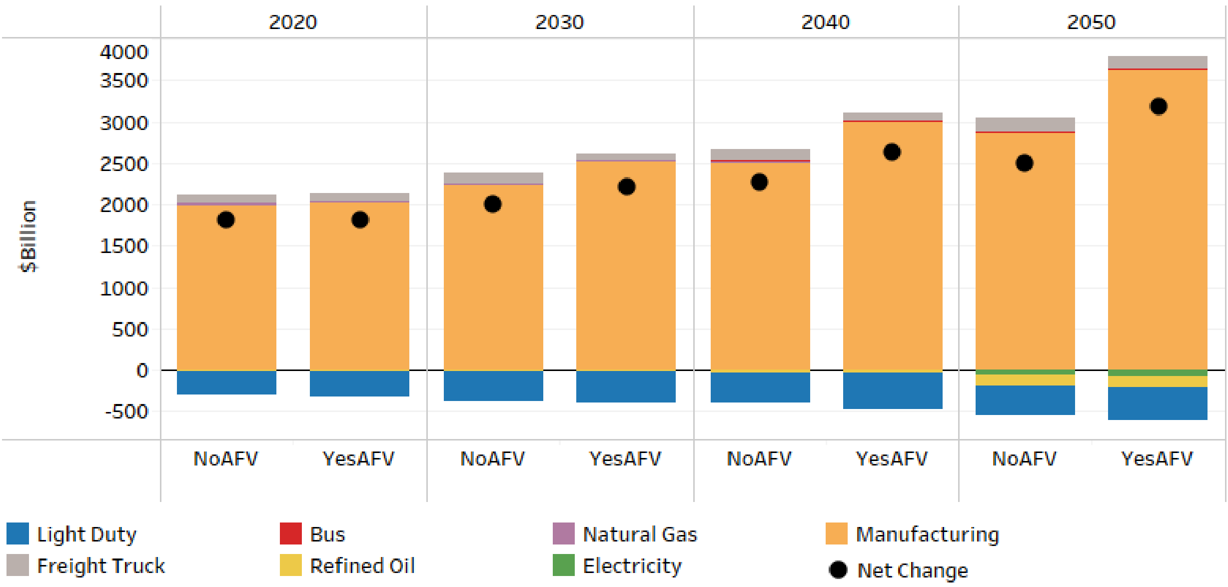

Figure 10: Change in U.S. Economic Output by Sector in *HOP* Case Relative to *REF* Case ($Billion)

In the early periods of the *HOP* case in the *YesAFV* version, most of the VMT reduction comes from conventional vehicles, which are not offset by AFVs. Minimal AFV adoption in early periods means fleet fuel efficiency improvements are limited to the endogenous efficiency response of new conventional vehicles, which are also being added at a slower rate as a result of lower VMT growth. In later periods in the *HOP* case, increased adoption of EVs improves fleet efficiency further relative to the *REF* case, but as this is primarily at the expense of hybrid vehicles, the fleetwide efficiency improvements are modest. Conversely, relatively small decreases in U.S. fuel efficiency occur in the *LOP* case, with less endogenous efficiency improvements and slower AFV adoption, particularly for LDVs.

Freight truck vehicles, whose VMT is increasing in the *HOP* case in the *NoAFV* and *YesAFV* versions and where EV adoption does not begin until the 2040s, show little efficiency gains with higher oil prices, until a slight increase in the early 2040s. Freight truck EV adoption is rapid in 2040–2050, leaving relatively little room for large compositional changes that would significantly change efficiency in either the *LOP* or *HOP* cases.

In both the *NoAFV* and *YesAFV* versions, U.S. transportation energy consumption declines by approximately five quads by 2050 in the *HOP* relative to the *REF* case, with about one-fifth of that decline due to LDVs and the rest from the rest-of-transportation sector (Figure 11). AFVs allow for slightly larger reductions in LDV energy consumption in 2020–2040 in the *HOP* case from earlier conventional vehicle retirement and EV adoption in *REF*. Reductions in U.S. transportation energy demand come from refined oil over the entire period, but this is slightly offset by small increases in biofuels, which can be blended with oil for use in conventional and other vehicles.

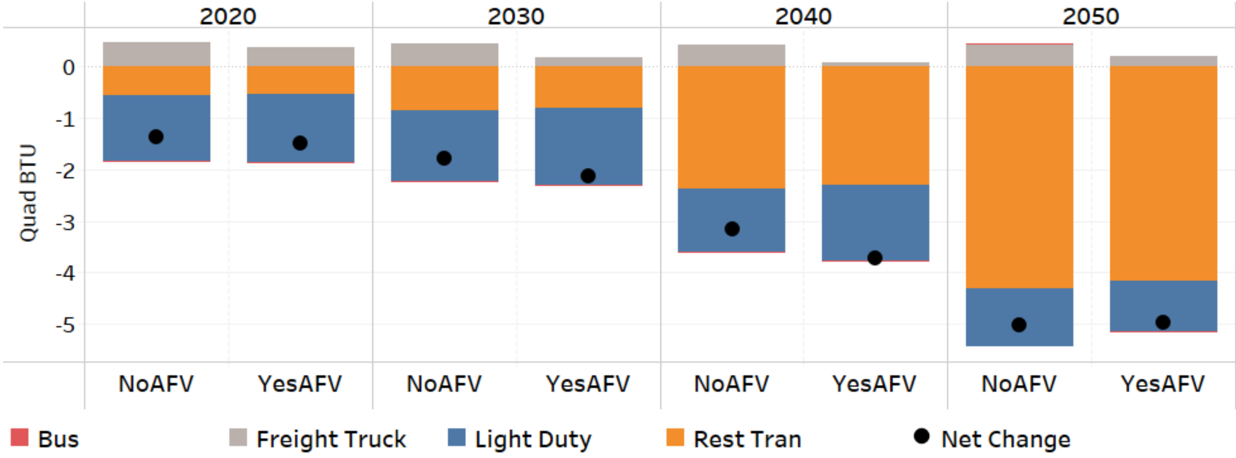

Figure 11: Change in U.S. Transportation Energy Consumption, *HOP* Case Relative to *REF* Case (Quad BTU)

Net U.S. GHG emissions decrease under higher oil prices both with and without AFVs (Figure 12), although the reduction relative to *REF* from LDVs is smaller in later years than earlier years with AFVs because most of the on-road vehicle inventory has already been electrified by 2050 (Figure 6). Total U.S. GHG mitigation of approximately 850 MMT CO_2-e in 2050 represents a decline of approximately 12% of total GHG emissions relative to *REF* for the United States from roughly doubling oil prices. Conversely, low oil prices lead to a 290-350 MMT CO_2-e increase in emissions by mid-century relative to *REF* (). ADAGE assumptions and structure project that roughly doubling oil prices in *HOP* relative to *REF* by 2050 leads to a percentage reduction in U.S. transportation sector GHG emissions of 32% in *YesAFV* and 18% in *NoAFV*. Roughly halving oil prices in *LOP* relative to *REF* leads to an increase in U.S. transportation sector GHG emissions of 27% in *YesAFV* case and 14% in *NoAFV* case.

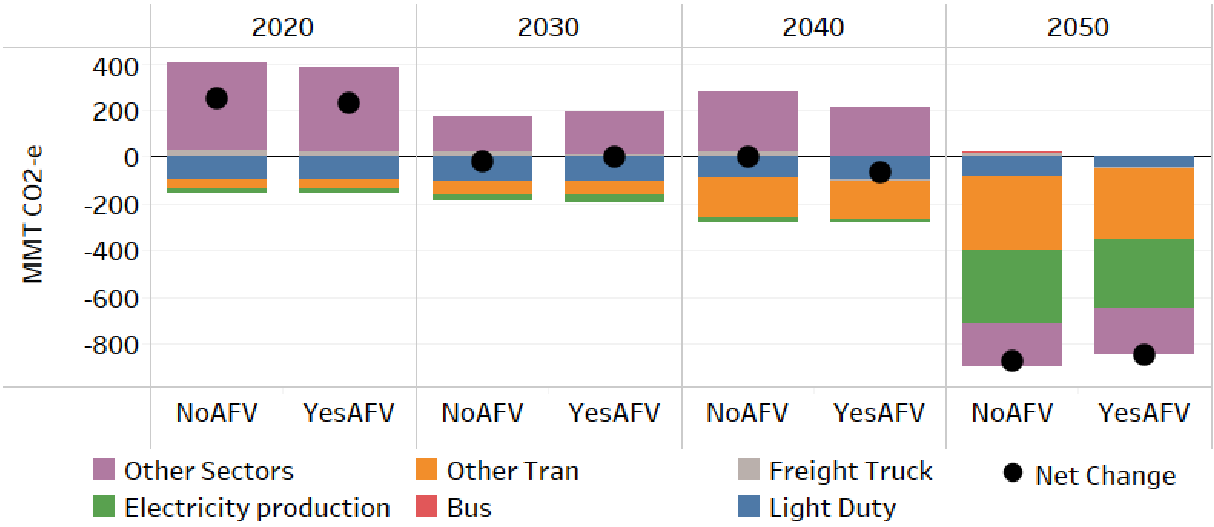

Figure 12: Change in U.S. GHG Emissions by Sector, *HOP* Case Relative to the *REF* Case (MMT CO_2-e)

4. Discussion

Inclusion of AFV technologies in the transportation sector in economic models is of increasing importance given their growing presence in global markets and the potential impacts they may have on energy consumption and GHG emissions. Our results suggest that including AFV technologies in a CGE model may alter the modeled energy and emissions outcomes; for example, adoption of BEVs may increase economywide electricity usage. Given the cost and performance characteristics of AFVs assumed in this analysis, including AFVs in ADAGE's on-road passenger and freight sectors produces significant changes in the projected level of U.S. transportation service demand, sector fuel efficiency, energy consumption, and GHG emissions.

Cost and performance estimates for both battery packs and fuel cell stacks are changing frequently and analysis seeking to characterize the current or likely future state of these markets should endeavor to use the most up-to-date estimates available. The ADAGE model methodology presented in this paper provides a framework within which up-to-date vehicle cost and performance estimates can be used and continually updated for current analyses. However, even the most up-to-date projections of cost and performance carry uncertainty (regarding the pace of technological learning, the potential for technological breakthroughs, etc.). Modeled outcomes are likely to be sensitive to these uncertain assumptions, which suggests that uncertainty analysis and model sensitivity analysis are essential components of future work in this area. Future work could seek to characterize model parameter and scenario sensitivity using the ADAGE model or other CGE models.

The impacts described in our results also vary depending on assumed future oil market conditions. Under our assumptions, the model results suggest that BEVs could capture a substantial and growing market share in the coming decades, and that hybrid technologies have the potential to play an important role in the next 10–15 years, particularly in model scenarios with lower oil prices. ADAGE estimates show higher oil prices speeding up the transition to EVs and shortening the intermediate transition role hybrid vehicles play. However, vehicles have complex and capital-intensive supply chains with high fixed costs, and these supply chain capital dynamics are not fully represented in ADAGE and thus the results presented here should be viewed with caution from that perspective.

While the future cost and performance characteristics of AFV technologies remain uncertain, it is clear from our results that exploration of potential future scenarios concerning energy consumption, GHG emissions, and economic output in CGE modeling frameworks would benefit from greater transportation sectoral detail and technological specificity. AFV technologies introduce new factors and dynamics to the transportation sector, such as new linkages with the electricity sector, which more aggregated representations of the sector cannot capture well. Leaving out AFV technologies limits the possibilities for changes in transportation sector and economy-wide energy consumption, emissions, and economic output; frameworks which do so may miss potential shifts in all of these outcomes in their scenario analyses. Our results demonstrate that these dynamics can and should be considered in CGE modeling frameworks, regardless of the specific cost, performance, or energy market or macroeconomic assumptions used to conduct a specific scenario analysis.

5. Conclusions

The U.S. transportation sector is anticipated to undergo vast structural changes over the next several decades because of emerging market forces and evolving responses to the issue of climate change. CGE models, which examine the impacts of market forces on the whole economy, can be particularly useful in assessing emerging economic trends. To date, CGE models addressing GHG emissions have carried the most technological and subsector detail in the electricity sector portion of their models. Only a few CGE models have developed detailed representations of the transportation sector that can address structural changes likely to occur in this segment of the economy over the next several decades.

Calibrating the ADAGE model to AEO 2018 oil price paths, we examine a case based upon one assessment of projected future efficiencies and costs of AFVs. This allows for a demonstration of the novel transportation sector methods employed in this enhanced version of ADAGE. Different assumptions about vehicle efficiencies and costs lead to different model results for U.S. transportation sector outcomes and economy-wide outcomes. As a result, the major contribution of this paper is to demonstrate, and provide insight into, how transportation subsector and technological detail influences modelled economic and environmental outcomes in this framework. The results presented in this paper indicate modelled outcomes based on cost assumptions and model structure, not predictions of specific future outcomes. They provide a useful diagnostic tool for gaining insight on likely directions and relative magnitude of market and environmental outcomes under different technology and cost assumptions.

The ADAGE model represents the whole economy, and the transportation and electricity sector are integrated with one another. This feature makes the model well-suited to estimate sectoral and economywide GHG impacts, as well as the GDP impacts, which might result from a modelled shift in on-road vehicle fleet composition given a set of assumptions about technological options. Based on the assumptions used in this study, increased penetration of EVs results in significant reductions in U.S. transportation sector GHG emissions, increases in U.S. electricity sector GHG emissions, and reductions in economy-wide U.S. GHG emissions relative to results where ADAGE did not include AFVs as an option. As expected, simulations with higher oil prices lead to more rapid penetration of AFVs, and lower oil prices lead to slower penetration of AFVs.

This work shows the significance of including transportation technology representation in an economy-wide model, and provides an example of how this detail was applied to a particular CGE, ADAGE. However, there are limitations to the approach described here that could be improved in ADAGE or other CGEs. Extending subsector and technological detail introduced for on-road vehicles, as undertaken in this effort, throughout the whole transportation sector is a valuable next step in identifying future market and environmental outcomes for the transportation sector overall. Transportation modes in which technological detail could be added include air, rail, and marine. Each of these transportation modes will have a different set of technologies with different performance and cost characteristics that would need to be considered in developing detailed, technological assessments. In addition, developing explicit representation of hydrogen in a CGE model could allow for more detailed understanding of potential impacts of fuel cell vehicles.

Finally, analyzing criteria air pollutants in a CGE model would allow key assessments of multi-pollutant effects of air quality and climate change simultaneously from alternative scenarios. The transportation sector technological detail presented in this paper, as well as these areas for potential future research, could help make CGE models more useful in understanding impacts of future shifts in the transportation sector.

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