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Driving emissions down: Whole-supply-chain mitigation of greenhouse gases from passenger vehicles

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Abstract

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Greenhouse–gas emitting human activities have caused the warming of the earth surface temperature by 0.97°C relative to pre–industrial levels. In order to prevent the most catastrophic consequences of climate change, most countries are committed to pursue action to limit global warming to well below 2°C under the Paris Agreement. Global transportation is the single largest user of energy as well as the largest carbon–dioxide emitting end–use sector, chiefly driven by passenger vehicles. Emissions caused by vehicles do not only occur at the vehicle tailpipe though. Pollutants are released along the entire vehicle supply chain, ranging from electric power plant discharges for electric vehicle charging, to industrial emissions from vehicle manufacturing and fuel processing. Detailed process models are used in this work in order to quantify the environmental burden of vehicle emissions along the entire supply chain. It is further investigated how these emissions can be mitigated, focusing on material efficiency and fueling behavior. These and other polluting processes are usually insufficiently considered in aggregate models of climate change mitigation. Therefore, it is also explored how the representation of vehicle supply chain emissions can be improved in these models. Finally, an integration of supply chain emissions with a climate change mitigation model of the US economy is achieved and several insights are gained from that exercise. It is shown that these emissions can significantly affect the composition of the US vehicle fleet and thus, the optimal climate change mitigation pathway of the US vehicle sector. In summary, this work contributes to a better understanding of future emissions of low–carbon vehicle systems. The results can guide future transport policy and investment decisions regarding low–carbon vehicle technology portfolios and their supporting infrastructure.

Driving Emissions Down: Whole–Supply–Chain Mitigation of Greenhouse Gases from Passenger Vehicles

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1 Introduction

1.1 Whole–supply–chain mitigation of greenhouse gases from passenger vehicles

Greenhouse–gas emitting human activities have caused the warming of the earth surface temperature by 0.97°C (based on 2006–2015 mean compared to 1850–1900).[1] This man–made climate change has severe and irreversible impacts on the environment such as the melting of the Greenland ice sheet, loss of the arctic sea–ice and change in El Niño-Southern Oscillation amplitude and frequency. Key consequences that are already apparent today include ecosystem changes, sea level rise, droughts, biodiversity loss, and in turn, forced human migration, social conflicts, and economic losses.[2,3] In order to avoid the most catastrophic consequences, most nations have made commitments to substantially reduce emissions from vehicles and other sectors, in order to keep global warming to well below 2°C.[1]

Globally, passenger vehicles are responsible for more than one tenth of energy–related carbon dioxide emissions, released directly through tailpipes,[4–6] therefore significantly contributing to climate change. But emissions can also occur off–site, along the entire vehicle supply chain, for example due to manufacturing vehicles and batteries, generating electricity to charge electric vehicles, and producing liquid and gaseous fuels.[7–9] In order to curb growing tailpipe emissions from vehicle fleets, national governments increasingly promote alternative fuel vehicles. However, there is concern that it can come at the cost of increased supply chain emissions,[10–12] which are insufficiently if at all regulated by current transport policies. Therefore, it remains unclear to date to what extent potential growth in supply chain emissions might counteract gains in tailpipe emission reductions and therefore jeopardize effective mitigation.

In addition, the transition to a low–carbon economy, including electrified vehicles and renewable electricity generators, could be hampered by the long lifetime of the current stock of mostly fossil–fuelled vehicles and power plants, which is typically around 10+ and 40+ years.[13–15] Therefore, additional measures may be needed in the short and medium term in order to accelerate effective emission reduction. One promising measure could be material efficiency.[16–18] While emission reductions due to fuel economy improvements or alternative powertrains have been studied extensively, material efficiency in vehicles has received relatively little attention to date. Therefore, it is still unclear to what extent different individual and bundled material efficiency measures could reduce pollution. Another question is how these measures compare to, and interact with, above mentioned measures, such as fuel economy improvements, alternative powertrain deployment, or low–carbon energy supply.

Large–scale deployment of battery electric vehicles is further challenged by high battery costs, and in some regions, a lack of charging infrastructure, high electricity prices and load shedding.[11] Therefore, plug–in hybrid vehicles, that can be driven on both electricity and fuel, are a popular alternative. The smaller batteries of plug–in hybrids also incur considerably lower upfront costs. However, in order to maximize emissions abatement, it is important that plug–in hybrids are primarily charged by low–carbon electricity, while fuel–powered driving is minimized. Convenience of charging and electric range are important determinants for environmentally favorable fueling behavior. However, it is unknown so far how the fueling behavior of individual owners of plug–in hybrids perpetuates at the fleet level and to what extent favorable fueling behavior could contribute to reaching climate targets.

Computer models are needed in order to assess these problems. Different modelling communities however evaluate these from different angles (see left side of Figure 1.1). The integrated assessment community uses climate change mitigation models to analyze cost–effective transition pathways of different regions and sectors, such as the vehicle sector, compatible with a global warming of 1.5 to 2°C. The industrial ecology community uses life cycle assessment in order to trace the environmental impacts that occur throughout the lifetime of individual products, such as vehicles. Both model families have their own advantages and shortcomings. Climate change mitigation models have a comprehensive regional, temporal and sectoral character, usually modelling national or global mitigation pathways of relevant economic sectors with time frames to 2050 or even 2100. However, in order to keep the complexity of these models in check, they often do not capture the consequences of changes in demand or output in one sector on the emissions of other sectors.[19–21] Furthermore, specific processes that influence or cause emissions are often modelled in an aggregated way.[7] Life cycle assessment models, on the other hand, are usually more geographically and temporally confined, and trace the environmental impacts of individual products through different sectors with great process–specific detail. While life cycle models are unable to evaluate systemic climate change mitigation, models of climate change mitigation can only illustrate a limited range of mitigation pathways. Therefore, linking both modeling schools could help to overcome their inherent weaknesses and combine their strengths[19,20,22] for evaluating not yet explored climate change mitigation pathways of vehicle systems that consider emission reduction opportunities along the whole supply chain.[7] To date it is unknown what insights may be gained from this integration and how it might influence optimal scenarios of climate change mitigation of vehicle fleets. These insights would in turn improve our understanding of future emissions of low–carbon vehicle systems.

1.2 Scope and content of this thesis

In order to address the above described problems, this thesis investigates several specific questions:

1. How large is the contribution of vehicle production to total vehicle life–cycle emissions and how can it be mitigated (Chapter 2)?

2. What is the impact of fueling plug–in hybrid vehicles and how can it help in meeting climate targets (Chapter 3)?

3. To what extent are the above (and other) processes captured in models of climate change mitigation (Chapter 4)?

4. What insights can be gained from integrating detailed processes with models of climate change mitigation? More specifically, how would pricing of these process emissions affect optimal scenarios of climate change mitigation of the US vehicle fleet (Chapter 5)?

These questions are answered in Chapters 2 to 5 of this thesis (Figure 1.1), while Chapter 6 discusses the findings and concludes this thesis. Three of these chapters have been published as peer–reviewed articles, and one is in the process of being submitted.

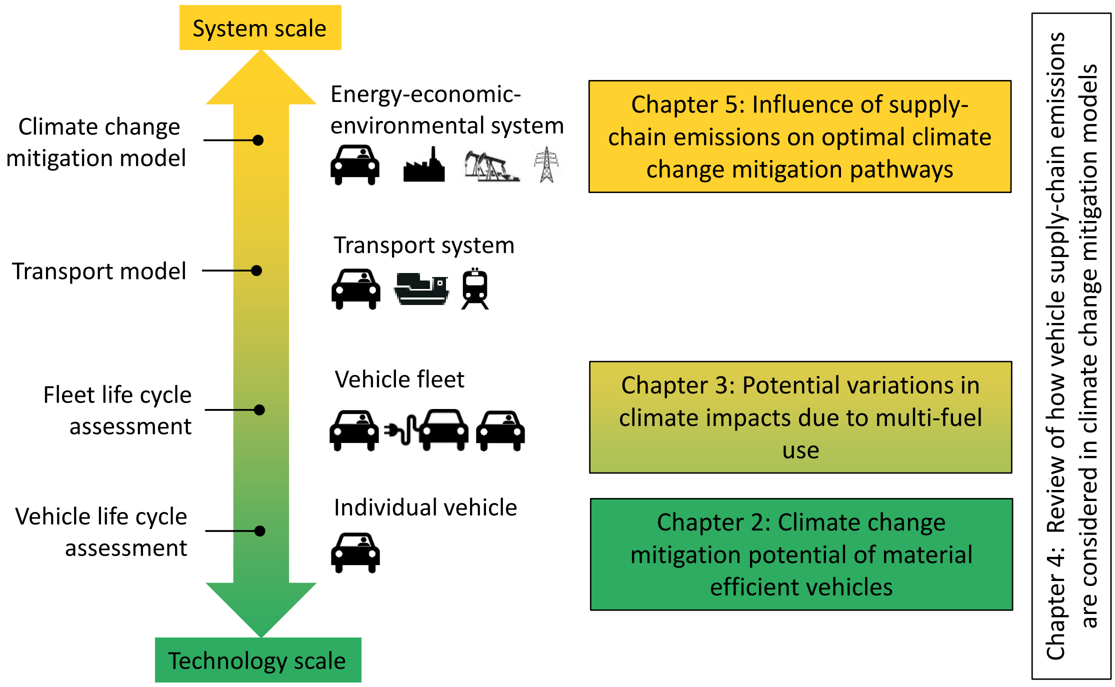

Figure 1.1: Overview of the thesis. The text boxes represent the different chapters of this thesis. The color of the text boxes indicates the level of assessment, with green indicating individual–technology scale and yellow indicating systemic scale.

The first paper is presented in Chapter 2 and investigates the environmental impacts of material production and vehicle assembly. It is further assessed to what extent these impacts can be mediated by material efficiency. This mitigation potential is then compared to that of renewable energy supplied to the vehicle sector. I find that material efficiency can reduce life–cycle emissions of individual vehicles considerably, by up to 57%. This is comparable to the pollution reduction potential of sourcing renewable energy of up to 83% per vehicle. The most promising material efficiency measures are the ones that not only reduce virgin material needs but also on–board energy requirements. Further, material efficiency can cut in half the emissions footprint of already highly efficient vehicles sourcing low–carbon electricity. This makes material efficiency both an important short– to medium–term measure until stronger deployment of renewable–energy sourcing vehicles is achieved, but also a suitable long–term strategy for achieving deep decarbonization of vehicle systems.

Chapter 3 takes a closer look on the fueling behavior of drivers of plug–in hybrid electric vehicles. Plug–in hybrids can be driven both on electricity and liquid fuels. For effective climate change mitigation it is however important that fuel use is minimized, while low–carbon electricity use is maximized. Fueling behavior depends on convenience of charging, electric range, and consumer education among other factors. I illustrate twenty–one scenarios of different combinations of technological progress, cost development, electricity carbon intensity, policy intervention and fueling behavior under three socio–economic settings. It is found that fueling behavior of hybrid drivers can substantially influence energy–related emissions of the US vehicle fleet, on average by 21% in 2050, with a range of 5 to 43% across scenarios. This behavior can therefore be decisive in meeting climate targets. Several options for nudging consumers toward environmentally favorable fueling behavior are discussed.

In Chapter 4, I am investigating how various processes, including the ones analyzed above (vehicle production and fueling behavior), are included in models of climate change mitigation. In particular, I review about 400+ items of fourteen popular climate change mitigation models in order to find out how passenger vehicles, their supply–chain emissions and mitigation options are considered and in what detail. I find that their representation can be enhanced by explicitly linking physical outputs from different economic sectors directly to the passenger vehicle sector. Furthermore, processes that strongly influence vehicle life–cycle emissions should be modelled in more detail. Specifically, processes related to vehicle production and assembly are often not considered at all, or modelled in the industry sector, simply following GDP growth, without an established link to the private vehicle sector. Another area that requires attention is the simplified modelling of fueling behavior of drivers of multi–fuel vehicles, i.e. vehicles that can be driven on more than one energy source. Establishing the mentioned linkages and paying more attention to process detail would allow for a more complete internalization of emissions in technology mix optimization procedures. This in turn could reveal technology mixes that incur lower costs and/or lower emissions, and thus help identify not yet explored climate change mitigation pathways for the passenger vehicle sector. This comprehensive review establishes an important theoretical basis for the final chapter.

Chapter 5 integrates the detailed vehicle life–cycle model developed in Chapter 2 with a climate change mitigation model for the US energy–economy system. I analyze different scenarios towards very high shares of electrified vehicles and renewable energy generation that are required to meet the US nationally determined contribution under the Paris Agreement. In these scenarios a carbon tax is raised on emissions from passenger vehicles. The scenarios however differ in terms of the scope of the carbon tax. Different cases in which emissions along the entire vehicle supply chain are priced are compared to a counterfactual scenario in which only direct tailpipe emissions are priced. It is found that whole–supply chain pricing leads to both, lower tailpipe emissions as well as lower supply–chain emissions, compared to pricing tailpipe emissions only. These scenarios also exhibit higher shares of electric vehicles. Given the current debate about 'dirty' batteries and electricity, this finding is surprising and indicates that very high electric vehicle penetration leads to a win–win situation for climate change mitigation, assuming a gradual decarbonization of electricity supply. The results further indicate that the US government should concentrate investments towards pure battery electric vehicles and largely disregard competing technologies. Hydrogen fuel cell vehicles could offer a suitable alternative if costs of producing fuel cells and hydrogen from renewable feedstocks would fall significantly.

2 Material efficiency and climate change mitigation of passenger vehicles

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Abstract

A transition to electric vehicles and renewable energy is currently underway but may not be rapid enough in order to reach ambitious climate change mitigation targets. Therefore, additional, preferably instantaneous, measures are needed for quick emissions reductions, which is where material efficiency (ME) could constitute a promising solution. ME strategies include but are not limited to vehicle lightweighting through material substitution, increased recycling of materials, reuse and remanufacturing of vehicle components, vehicle downsizing (switching to a smaller vehicle) and more intensive use by means of increased vehicle occupancy through sharing practices. While recent analyses have focused on a narrow subset of these, we find striking differences in the overall potential of different strategies to decrease vehicular carbon footprints. Downsizing and more intensive use offer the largest mitigation potential but strongly depend on consumer behavior and are highly sensitive to modeling assumptions. Combined, the analyzed strategies can achieve emission reductions of up to 57% over the life cycle of a single vehicle, which is comparable to up to 83% achieved through a shift to low–carbon energy supply. ME can cut carbon footprints of already efficient vehicles charging renewable electricity by half again. This makes ME both an excellent short–term solution for climate change mitigation targeting the light vehicle sector but also an important complementary strategy to the long–term transition towards electric vehicles and renewable energy supply.

2.1 Introduction

Climate change mitigation requires a rapid transition towards low–carbon energy supply and demand.[23,24] The shift to electric vehicles and renewable energy supply is already underway in many regions of the world and can potentially lead to significant emissions reductions.[25] However, vehicles and power plants have long lifetimes, typically around 10+ and 40+ years,[13] causing considerable lag in the turnover of the current stock of equipment.[14,15] In addition, alternative vehicle technologies face several barriers, such as lacking infrastructure, high battery cost, and consumer skepticism.[26] As a result, sizeable reductions in GHG emissions may not be achieved for decades to come[27,28] which could threaten compliance with the 1.5°C and 2°C global warming targets. Therefore, additional measures are needed that can accelerate reductions in GHG emissions, which is where ME promises to be a viable solution. Measures, such as lightweighting or downsizing, can be more easily integrated with existing automotive supply chains[29] and their implementation often requires short lead times.[30] We therefore analyze to what extent ME strategies could decrease emissions from conventional and electrified light vehicles and compare these to possible emissions cuts from renewable energy supplied to the light vehicle sector.

2.1.1 Material efficiency for vehicles

ME strategies are broadly defined as a set of technical measures and/or policy interventions that can lead to a significant reduction in the use of materials.[16,17,31] Common ME strategies described in the literature include lightweighting, recycling, remanufacturing, downsizing and more intensive use.[31] There can be synergies or trade–offs between GHG emissions from materials and from operational energy use. On the one hand, vehicle downsizing can reduce material use and simultaneously improve fuel economy. On the other hand, materials used for lightweighting usually require more energy to produce than steel. The potential effects of ME strategies can be described at a more detailed technology scale, or at a broader economy–environment scale.[7] Below we define each strategy and discuss some of the existing literature on each measure starting from the lowest scale (individual technology) and ending at the highest (systemic) level:

- *Lightweighting* usually refers to a substitution of heavier materials, such as steel, with lighter materials, such as aluminum, increasing a vehicle's fuel economy. However, this often entails increasing emissions from vehicle production.[32] Yet, higher production impacts can be mediated by powertrain resizing for performance equivalency[32] and by deploying recycled materials.[33] Life cycle assessments (LCAs) of individual vehicles and entire fleets have focused on the effects of electrification and lightweighting under regional conditions.[34–36] Economy–wide studies recently incorporated the effects of lightweighting on fuel economy improvements of the vehicle fleet, often in combination with other strategies, such as fuel economy or biofuel targets, but have not taken into account the increase in emissions from materials production.[37,38]

- *Recycling* is defined here as the use of recycled materials in the production of vehicles. Recycling of end–of–life vehicles is quite common in many countries around the world[39] but recovered materials often are not functionally recycled, meaning that they are used for lower–quality applications. Kim et al.[33] assessed to what degree open– and closed–loop recycling could offset increased vehicle production emissions from lightweigting an individual vehicle. Employing a global fleet–model, Modaresi et al.[40] capture the effects of vehicle lightweighting and recycling on total industrial emissions. Oda et al.[41] estimate the future global availability of secondary steel for construction and transport equipment. Certain whole–system models represent recycling technologies albeit not specific to vehicles. For example, the AIM/Enduse model considers recycling of paper and electronics.[42]

- *Remanufacturing* commonly requires disassembling, refurbishing, repairing, cleaning and reassembling of used vehicle components, such as engines or tires, to produce a 'like–new' product. This can reduce the life–cycle energy embodied in a diesel engine by about 70–90% compared to a newly manufactured one.[43,44] However, remanufactured components may not benefit from efficiency improvements in the same way as new ones do, if at all, causing a trade–off between savings in embodied energy and higher use–phase energy needs.[43] Sato et al.[45] estimate the energy and emission benefits from reuse and recycling in the Japanese automotive sector and find a potential reduction of 2.8 kg CO_2 per kg of vehicle. McKenna et al.[46] estimate the overall potential for energy savings from reuse practices in the German automotive sector to be 2.5–5% of the sector's total energy use in 2010. The effects of increased recycling and reuse at a global scale are demonstrated in IEA's Energy Technology Perspectives.[47]

- *More intensive use* is defined here as an increasing vehicle occupancy. Chester et al.[48] demonstrate the sensitivity of life–cycle emissions per passenger kilometer due to changes in vehicle occupancy. Based on an integrated transport land–use model, Yin et al.[49] find that ridesharing could lead to a 25–75% increase in vehicle occupancy in the Paris region. Integrated and economic models impose fuel and/or carbon taxes onto the vehicle sector,[50,51] which can reduce demand of personal motorized transport. This demand reduction in turn can be an implicit result of more intensive use (carpooling or ridesharing) or mode switching, or trip avoidance.
- *Downsizing* in a broader sense can be defined as a switch from a larger vehicle segment to a smaller one, e.g. from a light truck to a sports utility vehicle (SUV). Dhingra and Das[52] apply the downsizing concept in a narrower sense to study the effects of reduced size on efficiency and life–cycle emissions of an individual engine. The U.S. Annual Energy Outlook is based on an integrated energy model which captures the effects of taxes and fuel economy standards on segment switching within the US vehicle fleet.[38]

In conclusion, the engineering–type literature has focused on a narrow portfolio of ME strategies and vehicle types and is often conducted at an individual–technology level, and sometimes at fleet level. Integrated models often take a national or global perspective at the expense of resolution and thus, apart from downsizing and lightweighting, do not explicitly consider ME, and do not establish the link between service demand, material demand and emissions embodied in materials. Here we set out to bridge the two perspectives by analyzing an extensive set of ME strategies applied to a broad array of vehicle types available in the global market and by explicitly considering emissions embodied in material production under different energy supply scenarios.

2.1.2 Carbon emissions return on investment

The oil crises during the 1970s required highly economical usage of energy sources and thus popularized the use of the energy return on investment (EROI) indicator. EROI measures the amount of energy delivered by a technology ('energy out') per unit of life–cycle energy required to deliver that energy ('energy in'), and is therefore useful for comparing the 'energy pay–off' of technological alternatives.[53–55] EROI has been used ambiguously in the past due to the many different ways of measuring energy, such as primary versus final energy.[54,55] In addition, EROI counts every unit of energy input and output equally, be it sourced from renewable or fossil fuel energy carriers.

However, the pressing challenge of climate change mitigation[56] calls for a novel unambiguous indicator that accounts for the carbon intensity of energy sources. Carbon emissions return on investment (CEROI) measures the life–cycle GHG emissions benefit during vehicle operation ('Δ carbon out') per unit of additional life–cycle GHG emission burden during vehicle production ('Δ carbon in'). To the best of our knowledge this indicator has not yet been described or tested in the literature. Only Kim et al.[33] and Patterson et al.[57] presented a related indicator, emissions payback time (EPBT), investigating after how many years additional vehicle supply chain emissions from lightweighting and electrification would pay off through reduced operational emissions. Shanmugam et al.[29] developed a sustainable return on investment (SROI) indicator for vehicle lightweighting, analyzing the trade–off between external costs to society and costs to manufacturers.

By introducing the concept of CEROI and providing a first application of the concept, we aim at filling another gap identified in the literature. Specifically, we analyze the CEROI of vehicle lightweighting under both current and low–carbon electricity supply.

2.2 Methods and data

2.2.1 Life cycle assessment

For our analysis we choose four common vehicle segments (microcars, passenger cars, mini-vans/SUVs, and light trucks) as well as six mature and emerging powertrain technologies (internal combustion engine vehicles running on either gasoline or diesel (ICEV–g/–d), hybrid electric vehicles (HEV), plug–in hybrid electric vehicles (PHEV), battery electric vehicles (BEV), and hydrogen fuel cell electric vehicles (HFCEV)), representing a good approximation of both existing and potentially popular future vehicles types in the global market. While today there is also a considerable number of ICEVs running on compressed natural gas, these vehicles may not play a prominent role in the future according to IEA scenarios.[47]

As shown in Equation 2.1, vehicle carbon footprints (from hereon 'footprint', E) are evaluated on a life–cycle basis considering embodied emissions from vehicle production, i.e. vehicle supply chain emissions (F_{vc}), and emissions from production and use of energy carriers, i.e. energy cycle emissions (F_{ec}).

$$E = F_{vc} + F_{ec} \tag{2.1}$$

Vehicle supply chain impacts are calculated using a detailed and comprehensive LCA model, largely based on data points from the GREET2 model[58–60] and the ecoinvent life cycle inventory database v3.5, model 'allocation, cut–off by classification'[61] (see Section A.1.1 for details). The vehicle supply chain is divided into two phases: (1) material production, F_{mat}, and (2) vehicle assembly, F_{ass} (Equation 2.2). The former includes all processes from raw material mining to the finished material in the form of metal sheets, ingots and billets, or plastic pellets, resins and slabs. The second phase includes all material transformation processes needed to produce the final vehicle, including battery assembly, metal and plastic forming, welding, gluing, painting and other processes. As shown in Equation 2.3, emissions from material production equate to the Hadamard product (indicated by the $\circ$ symbol) of X_{mat}, a matrix that contains the material composition of vehicle archetypes, and f_{mat}, a matrix containing life–cycle emission factors of material production (cf. Table 2.1). Material emission intensities under low–carbon energy supply are based on the work by Vandepaer et al.[62] and have been provided by the authors on request. Vandepaer et al. derived emission factors of virgin low–carbon materials by integrating future low–carbon energy mixes from integrated assessment modeling into the respective life cycle inventories of these virgin materials.[1]

Similarly, emissions from vehicle assembly are derived as the Hadamard product of energy spent on vehicle assembly, X_{ass}, and the life–cycle emission factors of the energy mix used for the assembly stage, f_{en} (cf. Table 2.2, Equation 2.4).

$$F_{vc} = F_{mat} + F_{ass} \tag{2.2}$$

$$F_{mat} = X_{mat} \circ f_{mat} \tag{2.3}$$

$$F_{ass} = X_{ass} \circ f_{en} \tag{2.4}$$

Energy cycle emissions include emissions from vehicle operation as well as upstream processes, such as oil drilling, fuel transportation, electricity generation and transmission and are derived following Equation 2.5. Operational energy use factors, X_{en}, are based on drive–cycle simulations using FASTSim (Future Automotive Systems Technology Simulator, cf. Section 2.2.3).[66,67] Life–cycle emission factors of the energy carriers used during the operational phase are specified in Table 2.2. We assume an average vehicle lifetime mileage, parameter α, of about 180,000 km.

$$F_{ec} = X_{en} \circ f_{en} \times \alpha \tag{2.5}$$

Our functional unit is one person driving a vehicle over its entire lifetime of 180,000 km. Impact results are therefore presented as footprints per passenger over the vehicle

[1]For further information on the integration of energy mixes from integrated assessment models into LCA, please refer to the work by Cox et al.,[63] Beltran et al.,[64] and Knobloch and colleagues.[65]

lifetime, E_{pp}, in t CO_2e person^{-1} (Equation 2.6). This means that our results present the footprint of each passenger over the entire vehicle lifetime, having the advantage of capturing the reductions in footprints from increased vehicle occupancy. Footprints can also be expressed as emission intensities per vehicle–kilometer (cf. section A.3). We estimate an average global occupancy of 1.5 passengers per vehicle.[68] Therefore, vehicle footprints derived from Equations 2.1–2.5, are divided by the amount of passengers per vehicle, parameter β (1.5 in the default case and 2.0 in the more intensive use scenario).

$$E_{pp} = \frac{E}{\beta} \tag{2.6}$$

Table 2.1: Life–cycle emission factors of average global production processes of materials under current and future low–carbon energy supply per unit material. The last column indicates the reduction in GHG emissions due to low–carbon energy.[33,58,60,62,69,70]

		Current	Low–carbon	Unit	Reduction
Automotive steel	virgin	2.46	2.04	kg CO_2e kg^{-1}	17%
	recycled	0.98	0.82		
Stainless steel	virgin	4.67	3.22	kg CO_2e kg^{-1}	31%
	recycled	1.87	1.29		
Cast iron	virgin	1.85	1.73	kg CO_2e kg^{-1}	7%
	recycled	0.61	0.57		
Wrought aluminum	virgin	11.90	4.80	kg CO_2e kg^{-1}	60%
	recycled	1.79	0.72		
Cast aluminum	virgin	11.90	4.80	kg CO_2e kg^{-1}	60%
	recycled	1.79	0.72		
Copper, elec. grade	virgin	5.22	2.67	kg CO_2e kg^{-1}	49%
	recycled	1.00	0.51		
Plastics	virgin	2.13	2.11	kg CO_2e kg^{-1}	1%
	recycled	1.40	1.39		

2.2.2 Definition of vehicle archetypes

Vehicle archetypes represent differences in vehicle segment, technology and production design. We model four vehicle segments (microcar, passenger car, minivan/SUV, light truck), six technologies (ICEV–g, ICEV–d, HEV, PHEV, BEV, HFCEV), and two production designs (conventional and lightweight). The conventional ICEV–g light truck and passenger car are modelled off of the Ford F–150 and the Toyota Corolla, each being

Table 2.2: Life–cycle emission factors of average global energy supply under current and future low–carbon energy supply.[7,60,61,71–73]

	Current	Low–carbon	Unit	Reduction
Electricity grid mix	750	60	g CO_2e kWh^{-1}	92%
Assembly energy mix	503	151	g CO_2e kWh^{-1}	70%
Heat, coal	659	659	g CO_2e kWh^{-1}	0%
Heat, natural gas	218	218	g CO_2e kWh^{-1}	0%
Hydrogen	460	460	g CO_2e kWh^{-1}	0%
Gasoline	328	328	g CO_2e kWh^{-1}	0%
Diesel	304	304	g CO_2e kWh^{-1}	0%

the worldwide highest–sold vehicle in their segment in 2018.[2] The microcar is modelled off of the Suzuki Alto, the highest–selling car in India between 2004 and 2018.[3] The minivan/SUV has been modelled off of the Wuling Hongguang, which is the most popular vehicle in China.[4] Several data points on performance, weight and dimensions of each of these vehicles have been collected from manufacturer homepages and additional online sources. When different options exist, we average their characteristics. For example, the Ford F–150 is sold as a two– and a four–wheel–drive option, considerably differing in curb weight, fuel tank capacity, driving range, fuel consumption and vehicle dimensions. Since sales shares between the two options are unknown, we average between them. The selected vehicles, which are all ICEVs, serve as the foundation for other powertrains. To model alternative powertrains off of ICEVs, components are added, removed or scaled as needed.[74] The masses of individual components are determined using variable and fixed masses from Bauer et al.[75] The resulting component and total vehicle masses are illustrated in Figure 2.1b. The vehicle mass breakdown by material is derived from the GREET2 model[58,60] and illustrated in Figure 2.1c and d. For more details, please refer to Section A.1.2 and a technical documentation by Wolfram et al.[68]

2.2.3 Drive–cycle simulations

Vehicle characteristics are used as input data for drive–cycle simulations in FASTSim.[67] Specific inputs include vehicle mass, motorization, energy storage, vehicle dimensions,

[2] https://www.best-selling-cars.com/global/2018-full-year-international-global-top-selling-car-models/

[3] https://economictimes.indiatimes.com/industry/auto/cars-uvs/maruti-suzuki-alto-crosses-35-lakh-cumulative-sales-mark/articleshow/63171749.cms

[4] https://www.goodwood.com/grr/road/news/2018/4/axons-automotive-anorak-chinas-best-selling-cars/

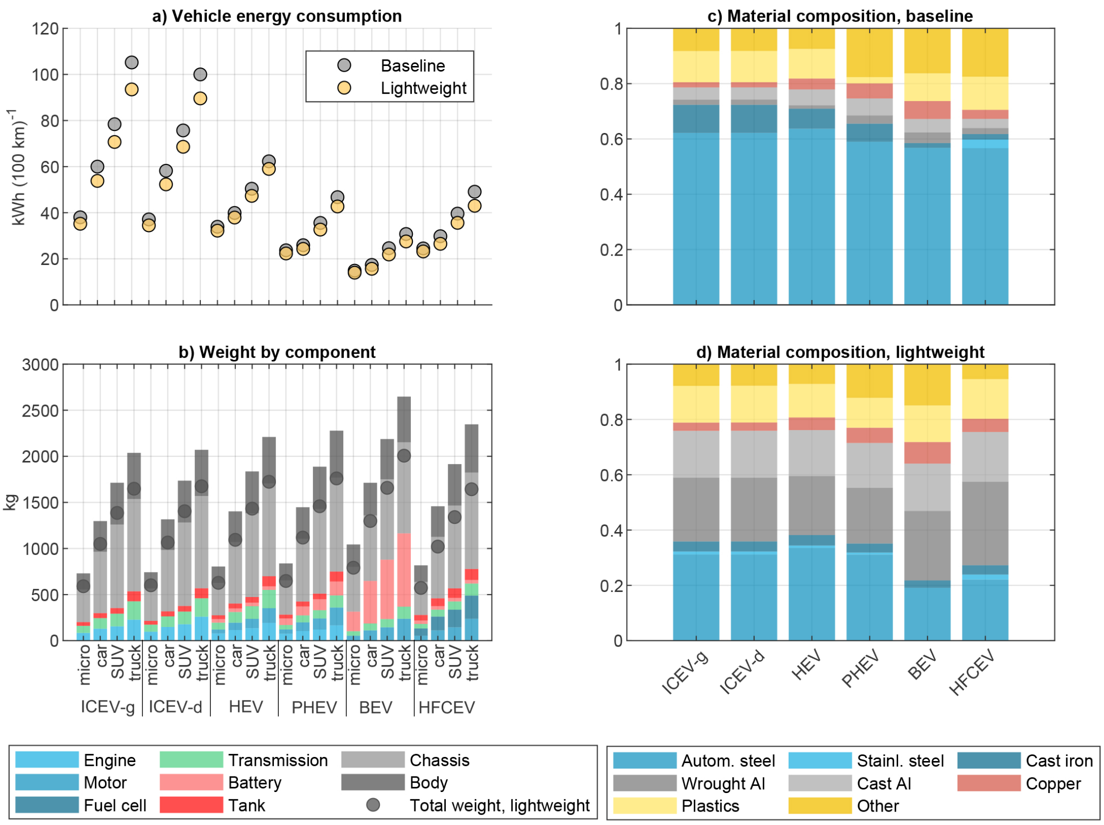

Figure 2.1: Characteristics of vehicle archetypes. a) Drive–cycle energy consumption of baseline and lightweight vehicles. A PHEV utility factor of 0.5 is assumed. b) Baseline vehicle weight by component. Circles indicate total weights of lightweight vehicles. c) Material composition of baseline vehicles. d) Material composition of lightweight vehicles. Underlying data used to create this figure can be found in a data repository at http://doi.org/10.5281/zenodo.3896664.

and drag coefficient for each vehicle segment and powertrain. Operational energy use is determined over EPA's US06 drive cycle. While various drive cycles are used across different countries, they all exhibit some divergence between official and real–world fuel consumption.[76] FASTSim however automatically corrects any drive cycle for real–world conditions.[77] This built–in correction increases energy consumption by about 30–40% depending on technology. For lightweighted vehicle archetypes, we assume that power components are resized for performance equivalency in accordance with the literature. Specifically, peak power is reduced incrementally until the acceleration of conventional and lightweighted vehicle archetypes match.[66] Additional weight reduction can be achieved through downsizing of components, which is a consequence of primary weight savings by material substitution. For the powertrain, we assume an additional 50% weight reduction compared to the 100% initial reduction.[32]

2.2.4 Modelling of ambitious material efficiency strategies

Analyzed strategies include (1) vehicle lightweighting through material substitution, (2) material recycling, (3) components remanufacturing, (4) more intensive use, and (5) downsizing. In addition, we analyze the effects of a simultaneous implementation of all ME strategies (6) as well as a combined implementation of all strategies but lightweighting (7). The implementation levels of these measures should be regarded as ambitious, yet plausible, and are roughly in line with the storylines of very optimistic climate change mitigation scenarios, such as SSP1[78] and LED (low energy demand).[79]

- *Lightweighting:* Compared to the baseline material composition, we assume an increase in the content of aluminum by 10–28% and a reduction in the steel content by 25–31%, depending on powertrain. These assumptions are largely based on the aggressive lightweighting scenario in Burnham et al.[60] (refer to Section A.1.2 for details). We further investigate the trade–offs of lightweighting, i.e. the relationship of additional carbon invested upfront (in the vehicle supply chain), and carbon saved in the energy cycle, which we term ‘carbon emissions return on investment’ (CEROI).

- *Recycling:* The recycled content is assumed to amount to about 11–85% by weight depending on material (refer to Section A.1.2 for details), thereby reducing material–related energy expenditures. These rates are already high and can be seen as upper boundaries as materials in end–of–life vehicles are usually downcycled for use in less demanding applications.[17,80] Emission factors of recycled materials are illustrated in Table 2.1.

- *Remanufacturing*: We infer from Liu et al.[44] that each kg of remanufactured equipment reduces energy needs of material production by 98% and assembly energy needs by about 40%. We assume that the share of recovered materials through remanufacturing amounts to roughly 9–19% by weight depending on powertrain and component. These rates are based on current practices in Japan where the combined rate of remanufacturing and recycling is already very high, about 82% by weight[45] (see Section A.1.2 for details).

- *Downsizing* is defined as customers switching to a smaller vehicle segment, i.e. light truck→van/SUV; van/SUV→passenger car; passenger car→micro car. No further downsizing is available for micro cars in our model. Downsizing reduces vehicle weight by 16–44% and fuel consumption by 9–37%, depending on vehicle segment and powertrain (cf. Figure 2.1). Nudging consumers to drive smaller cars would require an immense effort to reverse the current trend of vehicles becoming increasingly bigger.[77]

- *More intensive use* implies an increase in vehicle occupancy from 1.5 to 2.0 passengers, lowering vehicle– and energy–cycle emissions per passenger by a constant 25%, regardless of energy mix, powertrain or vehicle segment. Such increase in vehicle occupancy is in line with the LED scenario[79] and would require very high usage rates of ridesharing services.

2.2.5 Carbon emissions return on investment

Among all of the ME strategies analyzed in this work, only lightweighting is suited for a CEROI analysis because of the trade–off between inputs (increased vehicle supply chain emissions) and outputs (reduced energy cycle emissions). All other measures either yield reduced vehicle supply chain emissions at constant energy cycle emissions (remanufacturing and recycling) or complementary emission reductions in both the energy cycle and the vehicle supply chain (downsizing and more intensive use), which mathematically does not allow for a CEROI calculation. We therefore define CEROI as the fraction of additional vehicle supply chain emissions, ΔF_{vc}, and reduced energy cycle emissions, ΔF_{ec}, due to vehicle lightweighting (LW) compared to the baseline (BL) vehicle (Equation 2.7).

$$CEROI = -\frac{\Delta F_{out}}{\Delta F_{in}} = -\frac{\Delta F_{ec}}{\Delta F_{vc}} = -\frac{F_{ec}^{BL} - F_{ec}^{LW}}{F_{vc}^{BL} - F_{vc}^{LW}} \tag{2.7}$$

2.3 Results

2.3.1 Vehicle carbon footprints

Under current energy supply, the ICEV–g light truck has the highest total footprint with 46.7 t CO_2e person^{-1} (Figure 2.2a). With 10.6 t CO_2e person^{-1}, the PHEV micro car can achieve the lowest footprint when applying all ME strategies, and is closely followed by its ICEV–d and HEV counterparts. PHEVs, despite their higher weight, achieve a higher fuel economy than HEVs due to their more efficient powertrain (larger electric motor and smaller combustion engine). Due to the 'dirty' electricity mix (global average of 750 g CO_2e/kWh), the BEV only achieves 11.6 t CO_2e person^{-1}.

Assuming a low–carbon energy supply mix, the footprint of the ICEV–g light truck falls from 46.7 to 44.6 t CO_2e person^{-1} (Figure 2.2b), as the vehicle supply chain benefits from the lower–carbon energy supply. An increasing share of renewable electricity is used to produce materials and assemble vehicles (Section A.1.1). Meanwhile, production of gasoline is left unchanged, meaning that the carbon intensity of gasoline remains constant. In contrast, BEVs fully capitalize on the low–carbon energy supply, cleaning up both the energy cycle and the vehicle supply chain. Hence, the lower end of the range of footprints shown in Figure 2.2b is fully dominated by BEVs. For example, the BEV micro car reaches a footprint of 2.9 t CO_2e person^{-1}, which further falls to 1.7 t CO_2e person^{-1} after applying all ME strategies.

2.3.2 Contribution of energy cycles and vehicle supply chains

The relative contribution of vehicle supply chains and energy cycles to total footprints strongly varies, depending on powertrain, vehicle segment, energy supply and implemented ME strategies. Under current energy supply, the vehicle supply chain can contribute as little as 9% ('ICEV–g micro all but lightweighting') or as much as 34% ('BEV car lightweighting', compare Figure 2.3a and 2.3e). Assuming low–carbon energy, these two extreme points become even more extreme with a 5% contribution from the vehicle supply chain to the ICEV–g footprint, and a 73% contribution to the BEV. The decreasing energy cycle contribution to the footprint of the ICEV–g is due to the assumption that

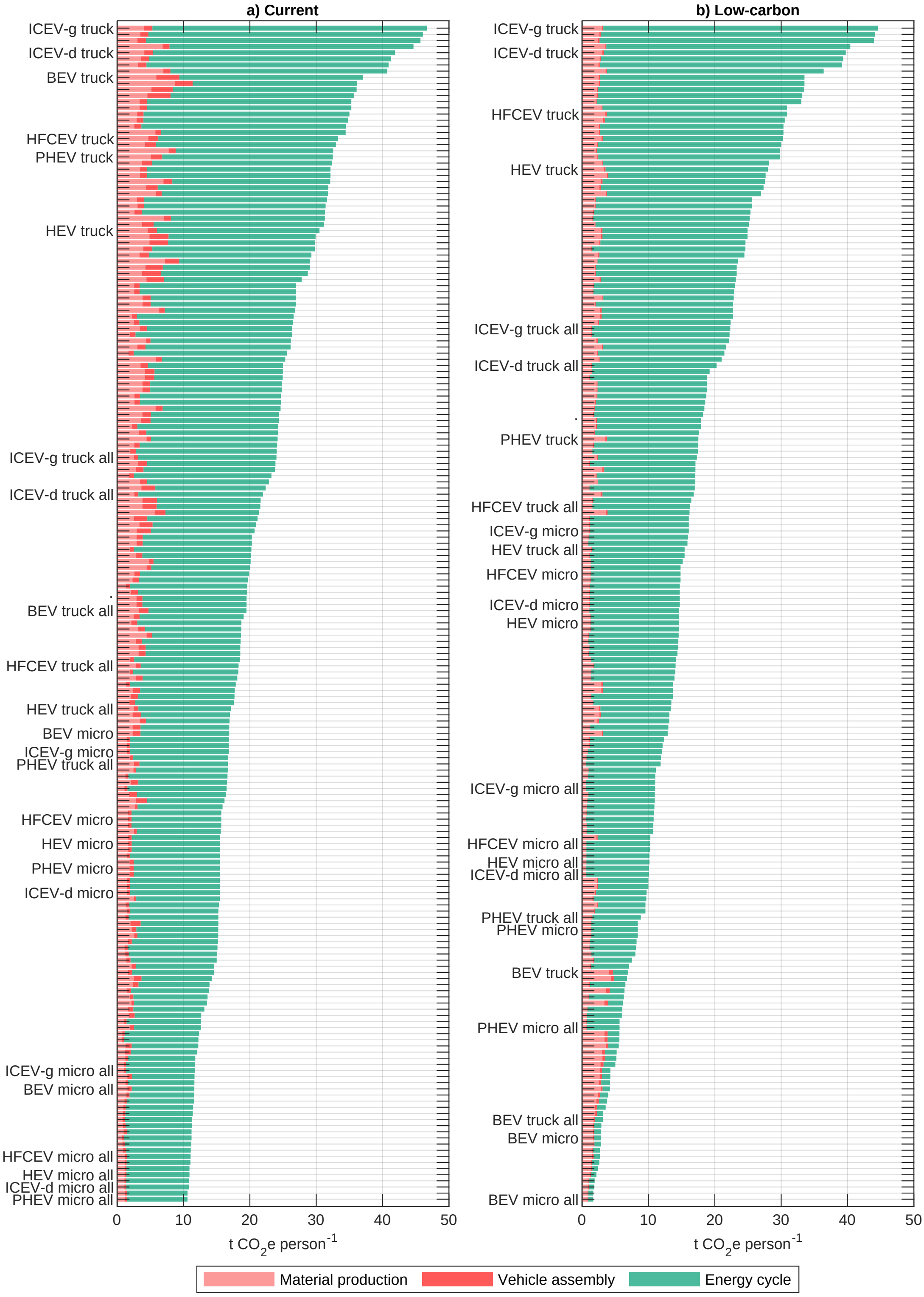

Figure 2.2: Vehicle carbon footprints in ascending order under current global energy supply mix (a) and low–carbon energy supply mix (b). Labels are shown for micro cars and trucks only, and for no ME and all ME strategies. Underlying data used to create this figure can be found in a data repository at http://doi.org/10.5281/zenodo.3896664.

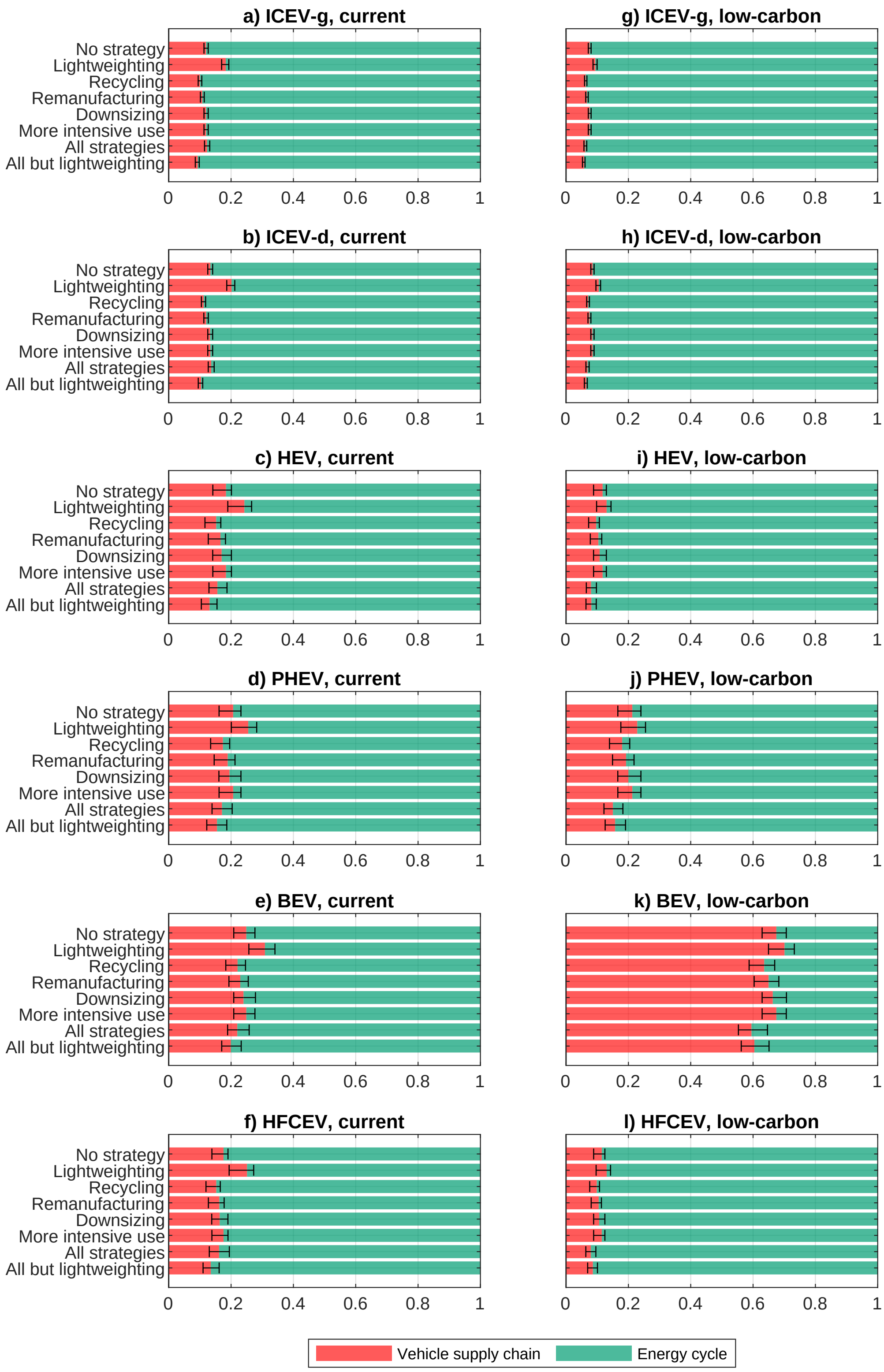

Figure 2.3: Share of vehicle supply chain (= material production + vehicle assembly) emissions to total vehicle carbon footprints (= vehicle supply chain + energy cycle). Left: Under current global energy supply mix. Right: Under low–carbon energy supply mix. Whiskers indicate the range of results across vehicle segments. Underlying data used to create this figure can be found in a data repository at http://doi.org/10.5281/zenodo.3896664.

the carbon intensity of crude oil remains unchanged. Therefore, mitigation of energy cycle emissions cannot be achieved for gasoline or diesel, whereas the vehicle supply chain can still source low–carbon energy and therefore reduce impacts. As a result, for ICEVs and HEVs the emissions share of the vehicle supply chain decreases while the energy cycle share grows (compare pairs a–g, b–h, and c–i of Figure 2.3). Fully relying on electricity as a power source, only BEVs can truly capitalize on the 'cleaner' grid so that energy cycle emissions strongly shrink. As a result, mitigation of the energy cycle is even greater than that of the vehicle supply chain, which still depends on fossil fuels to a much larger degree. Hence, the share of vehicle supply chain emissions further increases for BEVs, while the energy cycle share grows smaller (compare Figure 2.3e and k). The changes for PHEVs and HFCEVs can go in either direction but are minor since reductions in vehicle supply chain and energy cycle emissions are about equal under low–carbon energy (compare pairs d–j, and f–l of Figure 2.3).

2.3.3 Mitigation through material efficiency

We find striking differences in the overall potential of different ME strategies to reduce footprints (vehicle supply chain + energy cycle emissions). Under current energy supply, lightweighting achieves modest, and sometimes slightly negative, footprint reductions ranging from − 3 to + 4% (− 0.8 to + 2.0 t CO_2e person^{-1}). Reductions are particularly high for ICEV–g, ICEV–d, BEV and HFCEV vans, SUVs and light trucks. Reductions for micro and passenger cars are typically found at the other end of the range and can be slightly negative, which indicates a small increase in footprints (more in Section 2.3.4). Although lightweighting can reduce energy chain emissions (by 5–12% or 0.7–4.6 t CO_2e person^{-1}), vehicle production impacts can simultaneously increase (by 21–49% or 0.6–2.6 t CO_2e person^{-1}), which explains the small or sometimes negative reductions in total footprints. Figure 2.4 shows the absolute mitigation potential of ME for vans/SUVs while Figures A.1–A.4 show absolute and relative mitigation results for all powertrains.

Recycling and remanufacturing can mitigate vehicle supply chain impacts by about 6–20% or 0.2–1.3 t CO_2e person^{-1}, whereas energy cycle discharges are not affected. As a result, total footprints are only marginally reduced, by about 1–4%. The benefit of recycling is constrained by the limited recycled content in vehicles, which is a result of the high performance required of materials in this application. As a result, most materials from end–of–life vehicles are downcycled. Remanufacturing components, such as engines, also prevents the deployment of new, more efficient ones, causing a trade–off between production and operational pollution. This opportunity cost has not been modeled here and would further diminish the abatement potential from remanufacturing. In order to avoid overestimating the GHG mitigation potential of remanufacturing we therefore limited the degree of its application (Section A.1.2).

More intensive use and downsizing can yield the largest impact mitigation. While more intensive use can reduce footprints by 25% or 3.9–11.7 t CO_2e person^{-1}, downsizing offers reductions on the order of 17–38% or 3.1–11.4 t CO_2e person^{-1}. Both strategies act positively on both the energy cycle and the vehicle supply chain.

All strategies taken together can cut footprints by 29–57% (4.6–22.7 t CO_2e person^{-1}) with particularly high reductions for larger vehicle segments and conventional powertrains. Implementing all strategies except for lightweighting leads to similar overall footprint alleviation (27–54% or 4.3–21.1 t CO_2e person^{-1}) but differs in the sense that it acts more strongly on the energy cycle and less so on the vehicle supply chain.

Footprints can also be cut by switching from the current energy supply to low–carbon energy supply, by 4–83% (0.8–30.2 t CO_2e person^{-1}) in particular, which is comparable in magnitude to the overall potential of above analyzed ME strategies (28–57% or 4.6–22.7 t CO_2e person^{-1}). While footprint reductions from low–carbon energy supply are very heterogeneous, with large reductions for BEVs and low reductions for ICEVs, footprint reductions from ME are strongly homogeneous among all technologies (Table 2.3). This shows that ME is a very suitable mitigation strategy not only for electric vehicles but for all technologies. In addition, by comparing the last two rows of Table 2.3, we can assert that even when taking future low–carbon energy supply as a starting point instead of the current one, a further substantial drop in footprints is possible thanks to ME.

The corresponding results for ME under low–carbon energy are illustrated in Figures A.2 and A.4. Most notably, lightweighting becomes a more important strategy

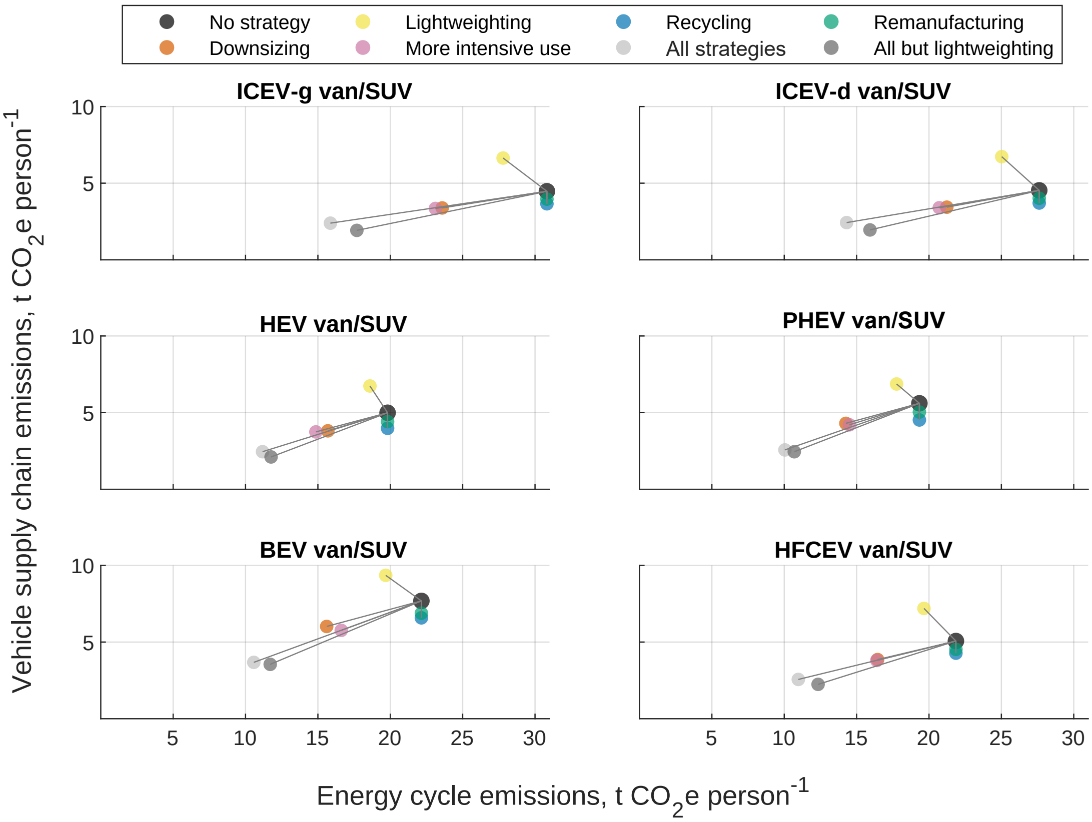

Figure 2.4: Effect of different material efficiency strategies on energy chain and supply chain emissions of vans and SUVs under current energy supply. 'Recycling' is partially covered by 'Remanufacturing' and 'More intensive use' is partially covered by 'Downsizing'. SUV=sports utility vehicle; ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel. Underlying data used to create this figure can be found in a data repository at http://doi.org/10.5281/zenodo.3896664.

Table 2.3: Individual and combined potential of material efficiency strategies and low–carbon energy supply to reduce vehicle carbon footprints. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle.

	ICEV	HEV	PHEV	BEV	HFCEV
Material efficiency	30–57%	30–45%	32–49%	31–52%	29–50%
Low-carbon energy	4–6%	6–8%	45–46%	80–83%	5–7%
Combined	35–59%	35–50%	63–74%	90–92%	35–55%

as it can yield footprint reductions ranging from 0.4–10% or 0.01–4.1 t CO_2e person^{-1} compared to – 3 to + 4% or – 0.8 to + 2.0 t CO_2e person^{-1} under current energy supply (more details in Section 2.3.4).

2.3.4 Trade–offs of lightweighting

Generally, lightweighting can lead to favorable results, meaning that additional GHG emissions in the vehicle supply chain are more than compensated for by GHG savings in the energy cycle. Figure 2.5 shows that lightweighting leads to a CEROI roughly ranging between 0.6:1 and 1.8:1, with a median of about 1.2:1, when current average energy supply is assumed. This means that on average one additional kg of CO_2e invested during vehicle production shrinks energy cycle emissions by about 1.2 kg CO_2e. However, in some cases, increased GHG emissions in the vehicle production phase outweigh savings in the use phase, leading to a CEROI below 1:1.

Assuming low–carbon energy supply, however, a CEROI of about 25:1 and higher can be achieved. This is largely due to the assumed constant carbon intensity of gasoline and diesel, while vehicle production benefits from low–carbon energy supply. Thus, it 'pays off' to 'invest' more carbon upfront. If the carbon intensity of crude oil further increases in the future,[81] the CEROI could become even higher, meaning that for gasoline– and diesel–powered cars lightweighting could be even more favorable than illustrated by our computations.

2.3.5 Sensitivity of results

Our results indicate that the mitigation potential of ME exhibits significant variation over different vehicle technologies and segments as well as energy supply. Here we further highlight the sensitivity of selected results to two fundamental model parameters, vehicle occupancy and vehicle lifetime. For example, assuming a longer vehicle lifetime of 210,000 km instead of 180,000 km, an increase of about 17%, increases total life–cycle emissions of the ICEV–g truck under current energy supply by 15%, while the footprint of a micro BEV under low–carbon energy supply is increased by only 7%. Conversely, a shorter lifetime of 150,000 km reduces use–phase emissions and increases the share

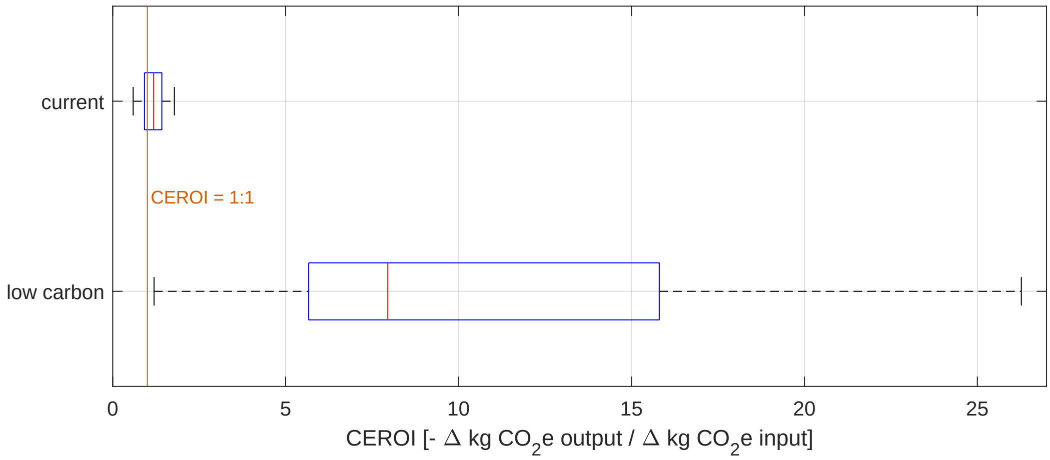

Figure 2.5: Carbon emissions return on investment (CEROI) of lightweighting different vehicle types under current and low–carbon energy supply. Whiskers indicate the range of results across different vehicle segments and technologies. Underlying data used to create this figure can be found in a data repository at http://doi.org/10.5281/zenodo.3896664.

of vehicle production emissions further, for example from 73% (Figure 3k) to 77% in the case of a lightweight BEV car under low–carbon energy. Meanwhile, assuming that more intensive use increases ridership from 1.5 to 1.75 passengers per vehicle, instead of 2.0, a 13% difference, increases respective life cycle emissions of all vehicle types in the more intensive use scenario by the same percentage regardless the emissions intensity of energy supply.

2.4 Discussion

2.4.1 Discussion of results, limitations and future work

Our results indicate that downsizing and more intensive use can potentially yield the largest footprint cuts. However, their successful implementation relies strongly on consumer behavior and is therefore highly uncertain. Today's potential for downsizing and more intensive use is significant. For example, with 1.5 passengers per vehicle,[82] vehicle occupancy in the US is quite low. In addition, the US share of SUVs and light trucks almost tripled between 1975 and 2017,[77] suggesting that larger vehicles are a recent consumer preference rather than a necessity. However, nudging consumers toward more efficient practices will require political intervention. Such intervention could trigger rebound effects, which can reduce or even negate achieved emission reductions. For instance, more efficient vehicles have been found to be driven further than less efficient ones (direct rebound).[83] In addition, cost savings from owning and driving more efficient vehicles may be spent on increased air travel or other highly polluting activities (indirect rebound).[84] None of the mentioned mechanisms have been analyzed in this work however, since our model lacks the necessary economic considerations.

Our results and modeling assumptions are largely consistent with the literature cited throughout this paper. For example, Elgowainy et al.[85] estimate that a current ICEV LDV emits about 280 g CO_2e/vkm over its lifetime, which falls right into the range of our reported 140–389 g CO_2e/vkm,[5] depending on vehicle segment. Depending on powertrain, lightweighting reduces vehicle weight by 18–24%, which is consistent with Bandivadekar et al.,[86] who find that about a 20% vehicle weight reduction is possible with aggressive material substitution. Secondary weight reduction is particularly high for BEVs due to the high initial weight of the large battery, a finding that is confirmed by Hofer and colleagues.[87] Ambrose et al.[88] estimate that vehicle production could contribute as much as two thirds to the life cycle GHG emissions of a future BEV charged by renewable electricity, while here we find a range from roughly two thirds to three quarters (Figure 2.3k).

The individual contributions to GHG mitigation from lightweighting, recycling and remanufacturing are modest. This is at least true under current global energy supply, whereas regional conditions could support stronger mitigation effects. For instance, economies whose energy supply is 'cleaner' than the global average, can produce lower carbon aluminum and thus enable stronger emission benefits from lightweighting.[36] We show that larger emission reductions are also possible globally in a hypothetical future with low–carbon energy supply. For recycling, an economy–wide perspective considering downcycling of materials recovered from end–of–life vehicles may reveal stronger system–wide climate benefits[40] compared to our results. Conversely, the potential of remanufacturing may be lower than estimated in this work if a fleet model is employed which considers efficiency improvements of vehicle vintages. The reason therefore would

[5]Convert results from Figure 2.2 as follows: g CO_2e/vkm = t CO_2/person × 1/180,000 vehicle/vkm × 1.5 persons/vehicle × 1,000,000 g/t

be that remanufactured engines do not benefit from efficiency improvements as new ones do, therefore leading to trade–offs between operational and embodied energy and carbon.[43] In addition, we assume that remanufacturing restores vehicle components to 'like–new' conditions, which is not necessarily the case in reality.[17] To alleviate the effects of these two issues, we limit the degree to which remanufacturing is deployed (Section A.1.2).

Even stronger reductions in vehicle footprints may be possible through additional deployment of other low–carbon technologies not analyzed in this work. For instance, carbon capture and storage could save the majority of carbon dioxide discharged from coal and natural gas power plants,[89] while biofuels,[90] synthetic fuels,[37] and other low–carbon fuels[85] could further alleviate pollution from combustion processes. Similarly, emissions from steel production could be further decreased by direct iron reduction using renewable hydrogen.[91,92] However, many, if not all of these technologies are not yet commercially available, which makes their future deployment uncertain.

2.4.2 Relevance for integrated modeling

Integrated energy models can be broadly defined as models of national or global energy demand and supply within the broader economic–environmental system.[93–95] These models are commonly used to investigate emission pathways as a function of mitigation efforts[79,96–98] and have become more and more detailed in the way they portrait mitigation mechanisms and consumer behavior.[99–101] The industrial ecology literature has pointed out that explicit linking of service demand to material demand constitutes another important building block towards a holistic evaluation of climate change mitigation pathways.[102–104] Following this new direction of research, we apply industrial ecology methodology in order to derive important data points for use within or in combination with integrated models. Most notably, we have defined 48 different vehicle archetypes representing the global vehicle market. These archetypes can be readily used to replace or detail existing descriptions of global average vehicles in integrated models and may be further customized to represent regional differences. Integrated modeling teams may choose to only incorporate vehicle fuel consumption or fuel cycle figures, or consider the complete vehicle life cycle, including material production, vehicle assembly and ME options. Doing so could significantly change the technology mix optimization procedure in integrated models and could illustrate yet unknown mitigation pathways for the light vehicle sector and its supply chain. Further research on the optimal level of vehicle–technological detail in integrated models is needed.

2.4.3 Policy implications

In order to stay within reach of climate targets, an annual personal footprint budget of roughly 1–2 t CO_2e has been hypothesized by environmental and consumer organizations.[105,106] This ambitious threshold is currently involuntarily met only by the poorest of nations, whereas rich countries by far overshoot that target.[107] Here we show that stringent ME and low–carbon energy application can achieve a personal vehicle footprint roughly as low as 2 t CO_2e over the vehicle lifetime. Assuming an average vehicle lifetime of about 15 years, that value translates to an annual footprint of 130 kg CO_2e per person, which would make up 13% of a personal carbon budget of 1 t CO_2e per year, leaving the majority of the budget for other purposes, such as housing or diet. This indicates that the current demand level of personal motorized transport is compatible with ambitious climate targets only under two major conditions: (1) consumers must switch to more energy– and material–efficient vehicles, e.g. smaller or shared electrified vehicles, and (2) the energy used to charge these vehicles must be highly decarbonized.

Various policy measures exist which can help consumers switch, such as taxes or feebates. Yet, as a prerequisite for consumers to make that transition, appropriate vehicles must be offered by manufacturers, which in turn may need incentives to do so, such as tighter fuel economy and low–carbon fuel standards. In order to reduce vehicle supply chain–emissions next to energy cycle–emissions, however, requires existing regulatory frameworks to be complemented by an additional vehicle production standard, which regulates emissions embodied in vehicle production. Alternatively, existing standards could be replaced by a life–cycle standard which regulates all upstream and direct emissions. Tailpipe emission regulations in different countries around the world are targeting 95–99 g CO_2e per vehicle–km between 2020 and 2025. Some vehicle options already achieve these targets today, even under real–world conditions (see Section A.3), highlighting the scope for further tightening of existing standards.

Smaller, material–efficient vehicles may offer important side effects for sustainability, such as reduced stress on road and parking space, lower consumer costs, higher energy security, and increased safety for non–motorized road users.

Finally, in line with Shanmugam et al.,[29] we note that lightweighting, recycling and remanufacturing may be more easily integrated within traditional automotive supply chains compared to fuel–side initiatives, and depend less upon consumer acceptance, if at all, compared to consumer–oriented policies. Despite their lower potential to reduce vehicle footprints, these measures should therefore be implemented regardless.

2.4.4 Conclusions

This work is the first to provide a comprehensive overview of the potential of ME to mitigate vehicle emissions under a vast range of conditions. We also offer the first analysis of the carbon return on investment of vehicle lightweighting. Our results indicate striking differences in the overall potential of different ME strategies to abate footprints. When implemented together, ME can yield sizeable reductions of up to 57%, comparable to mitigation of up to 83% achieved through low–carbon energy supplied to vehicles. Moreover, ME can halve the emissions of an electric car run on low–carbon electricity.

Our analysis illustrates the importance of considering specific conditions when choosing the most suitable portfolio of mitigation options. Lightweighting should not be seen as a 'one–fits–all' solution as its 'carbon pay–off' highly depends on other vehicle characteristics and energy supply of material production. Recycling and remanufacturing lead to modest reductions, while downsizing and more intensive use can have the largest reduction effect on footprints. However, policy incentives will be required in order to nudge consumers towards more efficient behavior. Rebound effects, which have not been evaluated in this work, can diminish the footprint alleviation potential of these strategies. An economy–wide approach will be needed to capture these effects. Conversely, our results offer a valuable starting point for economy–wide and integrated models, which usually lack the connection between climate change mitigation and material use.

According to our results, vehicle production would contribute a larger share of the life cycle impacts of electric vehicles in a low–carbon energy future. Hence, we argue that more attention should be paid to vehicle supply chain emissions in regulatory frameworks. For example, existing fuel economy and low carbon fuel standards could be complemented by vehicle production standards.

While low–carbon energy supply reduces footprints of electric vehicles more than that of other vehicles, ME is suited to reduce footprints of all analyzed technologies more equally. Thus we conclude that ME is highly suited as an immediate strategy to reduce emissions in the short term until full proliferation of plug–in and fuel cell electric vehicles in combination with renewable energy supply may be achieved. In addition, ME is a useful companion to the long–term transition towards low–carbon technology as it can further cut the footprint of low–carbon vehicles in half.

Author contributions

P.W. designed the approach, collected the data, performed the analysis and wrote the paper. All authors helped with study design, data collection and framing of the paper and provided feedback. E.H. supervised the work.

Code and data availability

The data that supports the results of this study as well as the MATLAB code used to generate the results can be found in an open repository on Zenodo: http://doi.org/10.5281/zenodo.3896664. FASTSim, which has been used for drive–cycle simulations, is freely available at https://www.nrel.gov/transportation/fastsim.html.

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3 Potential climate impact variations due to fueling behavior of plug–in hybrid vehicle owners in the US

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Abstract

With the expected rapid growth of renewable electricity generation, charging plug–in hybrid electric vehicles (PHEVs) from the grid promises ever higher reductions in CO_2 emissions. Previous analyses have found that the share that PHEVs are driven in electric mode can differ substantially depending on region, battery size and trip purpose. Here, we provide a first fleet–wide emissions mitigation potential of US–based PHEV drivers adopting high or low shares of electric driving. Specifically, we illustrate scenarios of different combinations of PHEV uptake, renewable electricity generation shares and PHEV fueling behavior. Across 21 analyzed scenarios, annual greenhouse gas (GHG) emissions of the light–duty vehicle (LDV) fleet could differ by an average of 21% (5–43% range) in 2050 depending alone on the fueling behavior of PHEV drivers. This behavior could further determine the discharge of about 1.3 (0.7–1.9) Gt CO_2 (or roughly one year of current emissions) over the next three decades, significantly influencing the feasibility of reaching an 80% emission reduction target in the LDV sector. Governments can nudge PHEV drivers towards environmentally favorable fueling behavior. We discuss several options for nudging, including charging infrastructure availability, battery design and consumer education.

3.1 Introduction

Since a record high in 2007, GHG emissions from the US electricity sector have fallen by almost a third in subsequent years.[108] This positive development has been contrasted by steadily growing GHG emissions from the transport sector in the same period,[108] despite substantial efficiency gains.[109] Thus, one promising measure to reduce transport

GHG emissions, especially in the LDV sector, is to increasingly electrify transport,[110] capitalizing on the falling carbon intensity of electricity.

However, only few of today's commercially available battery electric vehicle (BEV) models offer a sufficient range for long-distance trips on a single charge. With 515 and 595 km (320 and 370 miles),[111] only Tesla's Model 3 and Model S long range variants offer a driving range comparable to the 650–800 km (400–500 miles) that popular conventional cars provide today. Due to their significant price tag, both models may be reserved to a small percentage of the population however. A lack of charging infrastructure, load shedding and high cost of electricity can pose additional challenges, especially for developing countries, making it difficult to transition to fully electric cars.[112]

This is where plug–in hybrid electric vehicles (PHEVs) have an important advantage over BEVs: PHEVs can run on both electricity and gasoline. Once the battery is depleted, the driver can continue driving on gas. Even though the electric range of most of today's PHEVs is limited to below 48 km (30 miles),[113] one study finds that long–range PHEVs electrify as many annual miles driven as BEVs.[114] Another advantage is that the smaller battery of a PHEV leads to a smaller price increment over conventional cars. Thus, PHEVs could play a significant role in the future according to IEA projections.[47]

For the most effective mitigation of GHG emissions it is however crucial that PHEVs are mostly driven on electricity, and in areas with a suitably clean supply. Much analysis has therefore been devoted to the share of electric driving of individual PHEVs. For example, using data from the National Household Travel Survey, MacPherson et al. estimate that PHEVs are driven on electricity 60.2% of the time on average in the US, slightly lower than the US EPA's estimate of 63.5%.[115] This fraction is usually termed the utility factor (UF) of a PHEV.[116] MacPherson et al. also find that the regional heterogeneity of the UF ranges from below 0.6 in the Midwest and the Northeast to above 0.8 in Alaska (estimated from Figure 7 therein).[115] Ligterink and Eijk find an average UF of 0.33 in the Netherlands.[117] Including business travelers who hardly charge lowers the UF further to 0.24. Goebel and Plötz anayze data of 1,768 Chevrolet Volt's on–board diagnostics systems and find UFs ranging from 0.14 to 1.00, with a median of

0.80 and a mean of 0.77.[118] Similarly, Raghavan and Tal find UFs up to just under 1.0 for Ford C–MAX (32–km/20–mile electric range) and Chevrolet Volt (56–85 km/35–53–mile electric range) users, while Toyota Prius (18–km/11–mile electric range) drivers do not reach UFs higher than 50%.[119] The authors also observe that actual 'real–world' UFs are somewhere between 60–103% of EPA's estimates, which are based on drive–cycle simulations, indicating that EPA figures overestimate the UF of certain PHEV models.

Researchers observe a similar fueling behavior of other bi–fuel vehicle drivers. During a 10–year trial, Johns et al. find that alternative fuels, such as E–85 (a blend containing up to 85% ethanol and 15% gasoline by volume), compressed natural gas, or liquefied petroleum gas, accounted for only 30% of fuels used in bi–fuel vehicles, meaning that the majority of miles were fueled by gasoline.[120] They further find that convenience, informal communication with peers, as well as incentives and sanctions have a big effect on alternative fuel use.

Other important factors include (1) the timing of charging, (2) ride–sourcing and (3) ambient temperature. Regarding (1), Axsen et al. report that the UF of a PHEV is reduced if only off–peak charging is available compared to when charging is available at all times.[121,122] Despite the lower UF, GHG emissions from combustion and upstream processes were reduced, due to avoiding times of peak electricity generation, which is often dominated by more carbon–intensive energy sources. (2) The International Transport Forum estimates that the UF of ride–sourced PHEVs is almost half that of a private PHEV largely due to 'deadheading', i.e. empty trips of ride–sourced vehicles to the pick–up location of the next passenger.[123] (3) Finally, Wu et al. show that very low and very high ambient temperatures can significantly reduce the fuel economy of PHEVs and other powertrains.[124] Higher energy consumption reduces the electric range of PHEVs which can lead to reduced UFs. Climate change is likely to lead to more heat extremes in the future[125] which could further exacerbate this issue.

Systemic models, such as transport sector models, energy systems models or integrated assessment models are used to explore potential sectoral or holistic pathways of climate change mitigation. While these models increasingly improve their approximation of consumer behavior,[126,127] fueling and charging behavior is often modelled in a rather simplistic fashion.[7] For example, Karplus et al. define UFs exogenously in the EPPA integrated assessment model.[128]

To conclude, the fuel use behavior of PHEV drivers varies substantially, depending on trip purpose (e.g business vs. non–business trips), climate, electricity prices and availability. These extremes could be even more pronounced in the future, depending on the development of charging infrastructure, climate impacts on PHEV battery performance, and user education. While the fueling behavior (and sometimes the corresponding variation in climate impact) has been studied quite extensively for individual PHEVs or smaller fleets of government–operated bi–fuel vehicles, the authors are unaware of any study attempting to compute a fleet–wide estimate of well–to–wheel (WTW) GHG emissions at national level using a detailed transport scenario model. As such, we regard this to be the first study to analyze scenarios of climate impacts of the fueling behavior of US PHEV drivers considering various dynamics of the energy system.

3.2 Methods and data

3.2.1 Model overview

For our analysis, we use the LAVE–Trans (Light–duty Alternative Vehicle Energy Transitions) model.[129–133] LAVE–Trans is a transportation scenario model forecasting WTW GHG emissions from US light–duty vehicles (LDVs). WTW emissions include emissions of the entire energy chain from the production of energy carriers to their final use. Estimates are provided annually for the time period 2005 to 2050.

3.2.2 Vehicle choice

Technology choice is endogenized in LAVE–Trans through a nested discrete choice model in which six powertrain technologies are available: internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), PHEVs, BEVs, compressed natural gas (CNG) vehicles, and hydrogen fuel cell electric vehicles (HFCEVs). Consumers can further choose between two vehicle classes: passenger cars and light trucks. For each powertrain and segment, the model distinguishes several characteristics such as vehicle purchase price, fuel economy/fuel costs, driving range, charging and fuel station availability, model diversity, and maintenance cost. The model also accounts for available vehicle subsidies which are subtracted from vehicle purchase prices, and provides an option to model a carbon tax on energy carriers, increasing their price as a function of their carbon content and the magnitude of the tax. While fuel economy and CO_2 standards cannot be fully modelled, LAVE–Trans assumes by default that the costs of ICEVs increase in the future which can be primarily seen as an effect of increasingly stringent regulations.

The model however considers different consumer risk groups, i.e. innovators and early adopters (16%), early majority (34%), late majority (34%), and laggards (16%). These groups are distinguished by their willingness to pay for above mentioned vehicle characteristics. Each consumer picks the vehicle which provides them with the lowest disutility/cost. The probability distribution of different consumers picking certain vehicles is directly translated into vehicle sales shares in a given year. A vintage–based vehicle fleet stock module then translates the inflows of new vehicles and the outflows of retired vehicles into the current vehicle stock and the corresponding total travel demand for each year.

3.2.3 Vehicle types

Current PHEVs are modeled to have a 48–km (30–mile) all electric range (Figure 3.1a), which corresponds well to the sales–weighted average electric range of the nine highest sold PHEVs, each with cumulative sales above 15,000 units between 2011 and 2019 (estimated using data on electric range by model from EPA's fuel economy database[111] and vehicle sales data from the Alternative Fuels Data Center).[134] These nine models represent 81% of cumulative PHEV sales in that time period. In SSP5 we assume that PHEV electric range remains constant over the studied time frame, while increasing ranges are presumed in SSP2 and SSP1 (see section B.1.1).

Similarly, in SSP1 we assume that the driving range of BEVs increase up to 644 km (400 miles) shortly after 2030 (Figure 3.1b), which is at the lower end of the range that current gasoline cars provide. The sales–weighted average range of BEVs already increased

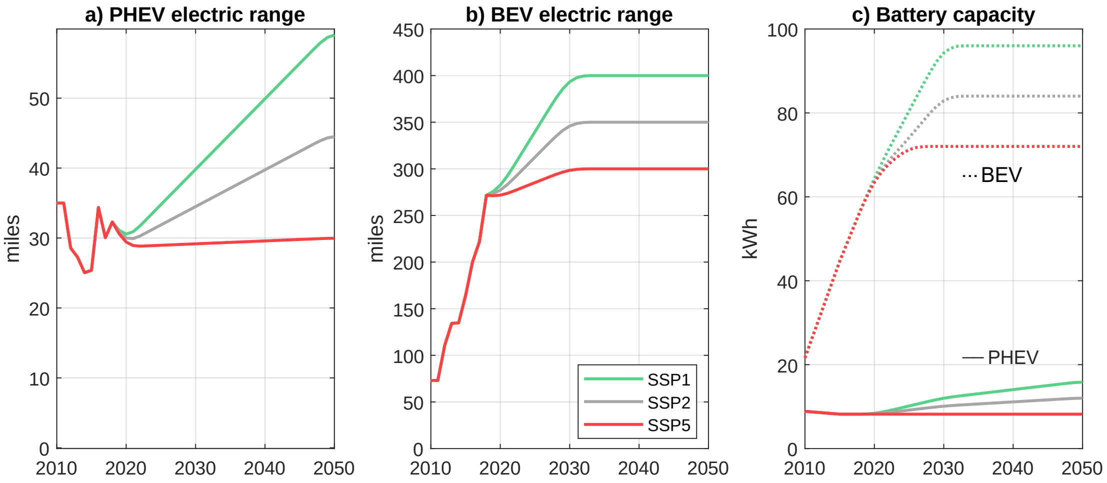

Figure 3.1: Estimated sales–weighted electric driving range and battery capacity of BEV and PHEV. SSP = shared socio–economic pathway; BEV = battery electric vehicle; PHEV = plug–in hybrid electric vehicle.

from 121 km (75 miles) in 2011 to around 435 km (270 miles) in 2019. Figure 3.1c illustrates the corresponding battery capacities, assuming a charging loss factor of 5%. Detailed cost estimates for all powertrains through 2030 are largely based on Wolfram and Lutsey.[73] Here we extend the time horizon to 2050 and update BEV and PHEV battery cost estimates in line with Lutsey and Nicholas,[135] BNEF,[136] Edelenbosch et al.[137] and Ziegler & Trancik[138] (see sections 3.2.5 and B.1.3 for more details).

3.2.4 Emissions factors

LAVE–Trans provides detailed emission factors for several energy carriers on a WTW basis, including gasoline, corn ethanol, cellulosic ethanol, biofuel from cellulosic pyrolysis, liquefied coal, liquefied gas, electricity, hydrogen, compressed natural gas, and liquified petroleum gas. Gasoline can be blended with several of these fuels. In this work, we adopt the standard assumptions of the LAVE–Trans model on gasoline according to which conventional gasoline is increasingly blended with other drop–in fuels. Specifically, the share of conventional gasoline falls from 94% in 2010 to 74% in 2050, while the shares of corn ethanol, cellulosic ethanol and liquefied coal increase accordingly. As a result, the carbon intensity of gasoline falls slightly from 318 g CO_2e/kWh in 2010 to 297 g CO_2e/kWh in 2050. Also the carbon intensity of the electricity mix falls over time, which is in line with recent developments.[108] Depending on the scenario, the decarbonization of the electricity grid differs in magnitude however (see next subsection and Figure 3.2a). Our model assumes average, not marginal emissions factors of electricity generation.

3.2.5 Scenarios of the energy system

We develop three main scenarios following the shared socioeconomic pathways (SSP) framework.[78] From the five available SSPs, we adopt SSP1, SSP2, and SSP5. These three scenarios differ in terms of challenges to GHG mitigation. SSP1 ('sustainability') faces the lowest mitigation challenges, whereas SSP2 ('middle of the road') faces medium challenges and SSP5 ('fossil–fueled development') faces high mitigation challenges. We do not adopt SSP3 or SSP4 for one major reason. The main difference between SSP3 and SSP5 is the differing degree of climate change adaptation challenges, while mitigation challenges are assumed to be similar (see Figure 1 in O'Neill et al.[78]). The same relationship exists for SSP2 and SSP4. Since we do not model climate change adaptation measures in this work, the pairs SSP2/SSP4 and SSP3/SSP5 can be regarded as equivalent and would not yield different modeling outcomes.

Electricity carbon intensity: In SSP1 we assume that the carbon intensity of the electricity mix falls from 561 g CO_2e/kWh in 2010 down to 50 g CO_2e/kWh in 2050 due to significant uptake of renewable electricity as well as CO_2 capture and efficiency improvements of remaining fossil–fueled power plants. SSP5 is characterized by a moderate reduction down to 400 g CO_2e/kWh in the same time period. As the name suggests, SSP2 follows the in–between path and reaches 225 g CO_2e/kWh (Figure 3.2a).

Battery costs: The costs of battery packs are assumed to decrease rapidly in SSP1. BEV batteries reach a floor price of 50 USD/kWh by 2050, while PHEV battery costs fall down to 100 USD/kWh (Figure 3.2b). PHEV batteries are assumed to decrease at a slower rate because they have a smaller storage capacity yet need to provide high power.[73,129] However the incremental cost of PHEV batteries over BEV batteries also falls over time. These assumptions are comparable to those made in recent publications. For example, Lutsey and Nicholas assume that BEV battery packs could reach 64–73 USD/kWh by 2030, while PHEV battery packs arrive at 86–88 USD/kWh.[135] Berckmans et al. calculate that BEV pack costs could fall down to 50–80 USD/kWh by 2030.[139] Estimating from

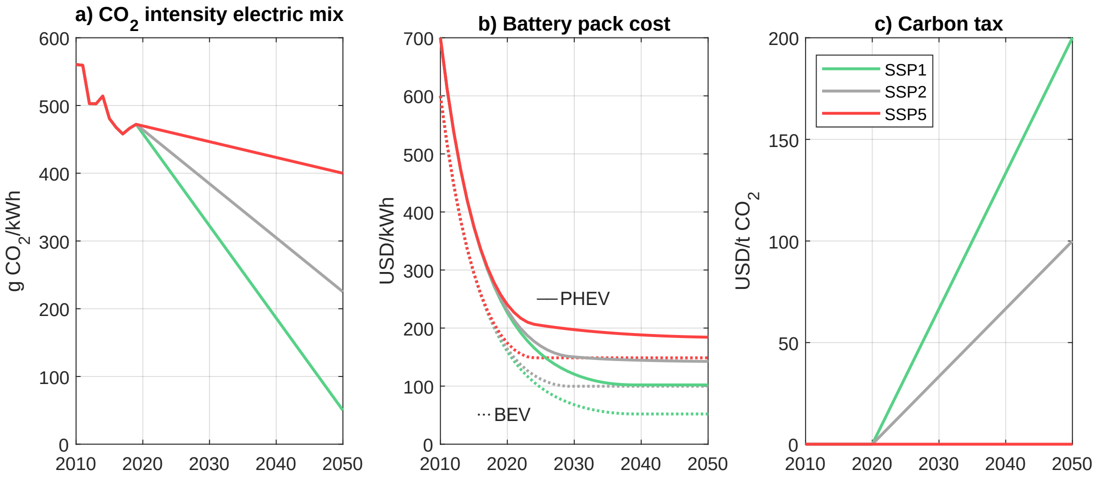

Figure 3.2: Select scenario input parameters. SSP = shared socio–economic pathway; PHEV = plug–in hybrid electric vehicle; BEV = battery electric vehicle.

Figure 1 in Edelenbosch et al., the authors assume pack costs of about 65 USD/kWh by 2030 and 50 USD/kWh by 2050 in their most optimistic scenario.[137] A recent consultancy report estimates a pack price of 73 USD/kWh by 2030.[136] The two latter sources do not mention differences in relative (USD/kWh) costs between BEV and PHEV battery cost. Also note that first industry claims of battery costs as low as 80 USD/kWh have been made as of 2020.[140] More pessimistic cost trajectories[73,137] for BEV batteries roughly translate to 150 USD/kWh by 2050, which we assume representative for SSP5. Accordingly, the middle–of–the road scenarios assumes 100 USD/kWh (for more details see section B.1.3).

Carbon tax: In SSP1 we further assume that a carbon tax is introduced in 2021, which linearly ramps up to 200 USD/ton CO_2 by mid–century. While no carbon tax is assumed in SSP5, SSP2 again follows the in–between path (Figure 3.2c). Consequently, prices of carbon–intensive energy carriers significantly increase in SSP1. For example, gasoline reaches 1.52 USD/liter (5.75 USD/gal) by 2050. Without the added cost of a carbon tax, the gasoline price moderately increases to about 1.04 USD/liter (3.93 USD/gal) in SSP5 which is somewhat higher than the assumed 0.90 USD/liter (3.40 USD/gal) in the reference scenario of the 2020 Annual Energy Outlook.[141] Electricity prices develop in similar ways in all three scenarios but react to different underlying mechanisms. In SSP1, the electricity price is less affected by the carbon tax due to strong reductions in carbon intensity of the electric grid (Figure 3.2a). However, the added cost of the massive expansion of renewable electricity still causes consumer electricity prices to increase from about 11 ct./kWh to about 16 ct./kWh by 2050. Due to the impact of the carbon tax, SSP2 and SSP5 experience similar price increases up to 18 and 16 ct./kWh by 2050.

Fueling behavior: For each SSP, we first illustrate a case in which PHEV UFs grow in accordance with larger battery capacities, that is up to 0.9 in SSP1, and up to 0.75 in SSP2, while battery capacities and UF remain constant in SSP5. We then illustrate cases in which the UF remains below these upper estimates despite growing battery capacities. Reasons therefore could be increased demand for ride–sourcing services, inadequate recharging infrastructure and potential restrictions for PHEV users to use all charging bays (for more details and some back–of–the–envelope calculations refer to section B.1.2). We conservatively estimate that these factors could reduce fleet–wide average UFs by about 20–25%.

3.3 Results

3.3.1 Vehicle market shares

Sales shares differ substantially in all three scenarios due to the different prevalent conditions described above. BEVs become fully cost–competitive in SSP1 and share the vast majority of the market with PHEVs (Figure 3.3a). BEVs also attain considerable shares in SSP2 but PHEVs are the dominating drive technology (Figure 3.3b). SSP5 sees a major uptake of HEVs accompanied by a moderate increase of PHEV sales (Figure 3.3c). Accordingly, cumulative sales of PHEVs reach 254 million units in SSP1, 242 million units in SSP2, and 210 million units in SSP5. Lower UFs lead to reduced PHEV sales in all scenarios (Figure 3.3d–f) as increased use of gasoline also raises total cost of ownership. The differences in vehicles sales between the cases with high and low UFs can be seen in detail in Figure 3.3g–i. The influence of these sales figures on the total vehicle stock and on fleet–wide energy demand are shown in section B.2.

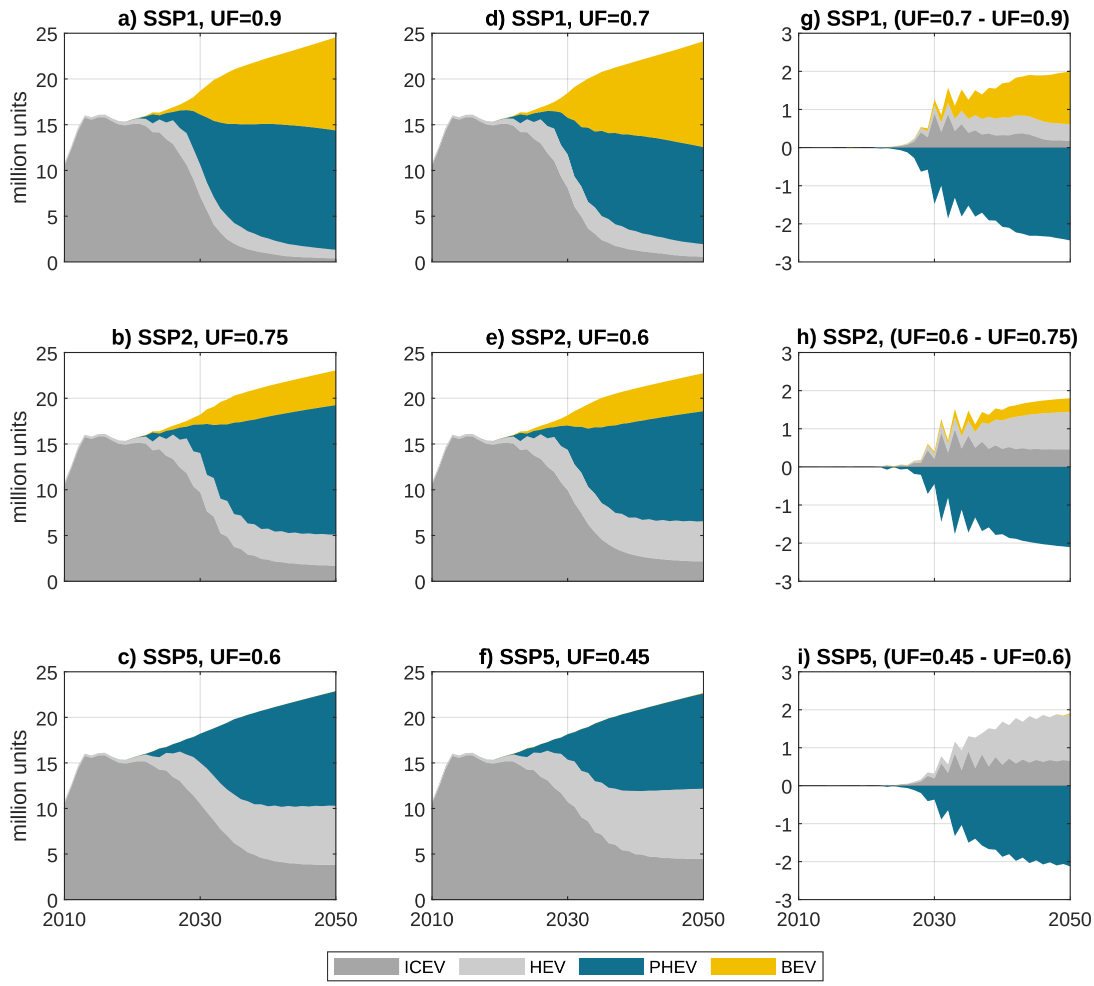

Figure 3.3: Vehicle sales under different SSPs with high UFs (a–c), and with low UFs (d–f), and differences in sales due to variations in UFs (g–i). SSP = shared socio–economic pathway; ICEV = internal combustion engine vehicle; HEV = hybrid electric vehicle; PHEV = plug–in hybrid electric vehicle; BEV = battery electric vehicle.

3.3.2 Fleet–wide WTW GHG emissions

Fleet–wide WTW GHG emissions are estimated at 1.38 Gt CO_2e in 2005 and follow a slight upward trend until about 2016, peaking at about 1.45 Gt, after which emissions are beginning to fall in all scenarios. Assuming increasingly favorable PHEV fueling behavior (UF = 0.9), emissions fall quickly in SSP1, due to the sharp increase of BEVs and PHEVs mainly fueled by low–carbon electricity. As a result, GHG emissions reach a low of 0.21 Gt by 2050 (green line in Figure 3.4a), which is 85% below 2005 levels. Cumulative emissions over the 2005–2050 period sum up to 43.3 Gt CO_2e. Although SSP5 (UF=0.6) is dominated by fossil fuels and relatively less efficient vehicles, a moderate reduction in emissions by 21% by 2050 relative to 2005 can be achieved, while cumulative emissions reach 53.6 Gt CO_2e. This is mainly due to the fact that HEVs are strongly penetrating the market. While HEVs, just like ICEVs, operate on gasoline, their ability to capture braking energy makes them significantly more economical compared to ICEVs. Meanwhile, further reductions are realized due to moderate sales of PHEVs as well as significant efficiency improvements of ICEVs (see section B.2.2 for more details). Nestled in between SSP1 and SSP5, SSP2 (UF=0.75) achieves a 52% reduction in emissions in the analyzed period, mainly due to a stronger uptake of PHEVs, while sales of HEVs and ICEVs are greatly reduced compared to SSP5. Cumulative emissions arrive at 45.8 Gt CO_2e.

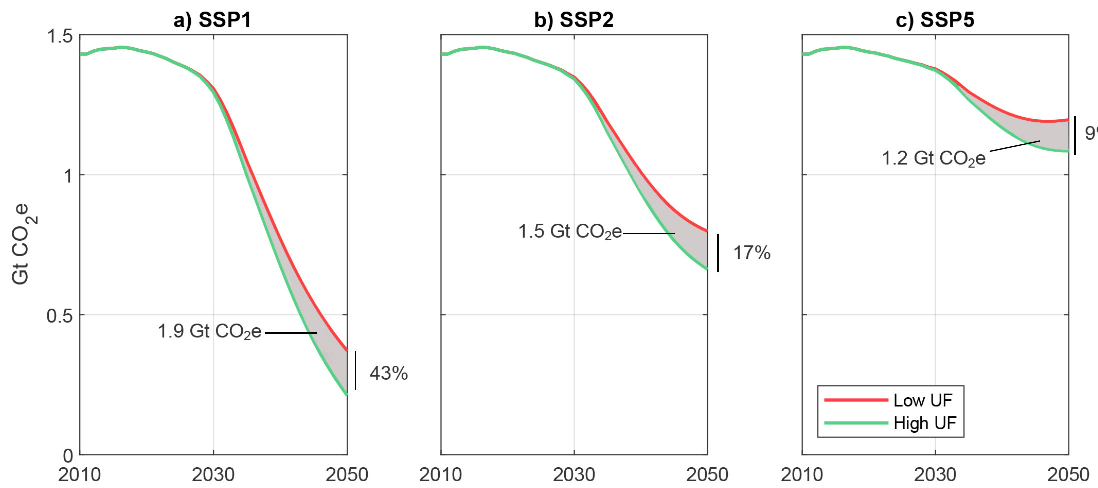

Figure 3.4: Well–to–wheel greenhouse gas emissions under the three SSPs with varying fueling behavior of plug–in hybrid vehicle drivers. SSP = shared socio–economic pathway; UF = utility factor.

3.3.3 The influence of PHEV fueling behavior

In the scenarios considered, fueling behavior of PHEV drivers can have a surprisingly high impact on fleet–wide emissions. For example, in SSP1, an increasingly less favorable fueling behavior of PHEV users (UF=0.7), can lead to missed reduction opportunities in the range of 1.9 Gt CO_2e (compare the grey area between the green and the red line in Figure 3.4a). With 1.2 and 1.5 Gt CO_2e this difference is similar in SSP5 and SSP2 (see grey–shaded areas in Figure 3.4b and c). The potentially strong influence of PHEV users is further highlighted by the fact that 2050 emissions arrive at 212 Mt in the case of SSP1/UF=0.9, and at 370 Mt in the case of SSP1/UF=0.7, a significant difference of

43% (Figure 3.4a). Conversely, the smallest influence can be observed in SSP5 with a 9% difference in 2050 emissions (Figure 3.4c).

3.3.4 Sensitivity analysis

Future fueling and charging behaviors are highly uncertain and their contribution to future climate impacts will depend on the uptake of different powertrain technologies, infrastructural development, and the carbon intensity of energy sources. In the last section we explored three plausible pathways of the US passenger vehicle market and the energy supply sector, and quantified their GHG and energy use implications. In this section we further alter some key variables to test the robustness of our results. Figure 3.5a shows the influence of three key variables on the relative difference in cumulative WTW GHG emissions between the cases with high and low UF. This difference is the area highlighted in grey in Figure 3.4a–c.

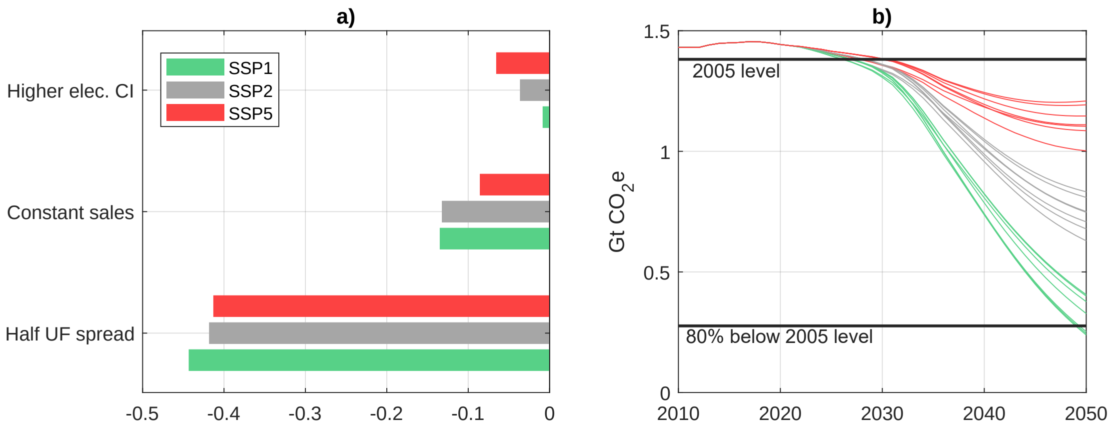

Figure 3.5: Sensitivity of the differences in cumulative well–to–wheel greenhouse gas emissions between SSP cases with low and high UFs (a). Range of scenarios and sensitivity cases illustrated in this work (b). CI = carbon intensity; UF = utility factor; SSP = shared socio–economic pathway.

Little surprisingly, by far the largest influence is due to the spread between high and low assumed UF. Lowering this spread by half, reduces the difference in results by almost the same amount (41–44%). As can be seen in Figure 3.3, LAVE–Trans assumes a substantial increase in future vehicle sales. Holding annual vehicle sales steady at the 2020 level of roughly 16 million units per year, implies a cumulative reduction of total vehicle sales over the 2020–2050 period by 14–20%, depending on scenario. Accordingly, differences in cumulative emissions change by 8–13%. Keeping the carbon intensity of electricity in SSP5 at the 2020 level, would reduce differences in cumulative emissions by about 7%. The influence of these parameters is also reflected in the various diverging emissions pathways as shown in Figure 3.5b. Only three cases reach the 80% reduction in GHG emissions relative to 2005 hypothesized by several authors.[37,129,142] All of these cases require socioeconomic development in line with SSP1 and favorable PHEV fueling behavior (UF=0.9). The base case (SSP1/UF=0.9) reaches an 84.7% reduction. From there, lower vehicle sales reduce emissions further but only by 0.5 percentage points, while a slighlty higher carbon intensity of electricity (reaching 59 instead of 50 g CO_2e/kWh by 2050) would offset emission reductions by 0.6 percentage points. We caution the reader that further significant variation could be introduced by changing the vehicle choice parameters in LAVE–Trans,[133] which is not something we have done in this work.

3.4 Discussion

3.4.1 Implications for the US carbon budget

In this work we find that the fueling behavior of PHEV drivers can determine the discharge of up to 1.9 Gt CO_2e over the next 30 years. These results are not insignificant when one considers that US fuel economy standards led to a cumulative reduction of about 17 Gt CO_2 of combustion emissions over the last 43 years.[109]

Further, implications for emission reduction targets and the carbon budget are substantial as well. Estimates of the US carbon budget can range from about 80–150 Gt CO_2 (see section B.1.4). In the scenarios depicted here, WTW emissions of the LDV fleet consume between 43–55 Gt, which is about one third to one half of the available budget. (These estimates also include upstream emissions. Excluding these reduces cumulative emissions to about 41–51 Gt CO_2.) This stresses the fact that it will be an immense effort to stay within the US carbon budget and even high shares of BEVs/PHEVs and renewable electricity generation may not be enough to meet ambitious climate targets if not accompanied by other measures. Achieving favorable fueling behavior of alternative vehicle drivers can be one such measure. Below we discuss some key factors that could encourage PHEV drivers to electrify the majority of their driving.

3.4.2 Nudging consumers

Electric charger availability: In a 2008 survey of nearly 2,400 households in the US, more than half of the respondents stated that they already had the ability to charge a PHEV at home (within 7.5 meters/25 feet of the vehicle) but had little opportunity to charge at work or at other locations.[143] The availability of EV chargers not only at home but also at work, along highways and in commercial areas, has been found to significantly increase UFs. For example, Davies and Kurani find that a PHEV with a (24–km) 15–mile electric range achieves a UF of 30% in absence of work charging, and 50% when work charging is available.[144] Axsen et al. find that the availability of work charging increases the UF of a PHEV with a 32–km (20–mile) electric range from 45% to 55%, and similarly for a PHEV with a 64–km (40–mile) electric range from 70% to 79%.[121] Heywood et al. cite a report prepared by EPRI which concludes that the UF of PHEVs with 16– and 64–km (10– and 40–mile) ranges varies between 27–50% and 65–80% depending on whether charging is available only at home or whether it is also available at work and at commercial locations.[37]

Arguably, work chargers are even more critical for PHEV commuters than for BEV commuters. Due to the short electric range of PHEVs, it is crucial that PHEVs can be recharged at work before returning home. In a 2013 survey by Tal et al., 70% of Prius (18–km/11–mile electric range) drivers indicated they required work charging, and so did 33% of Volt drivers (56–85-km/35–38-mile electric range), but only 5% of Leaf (BEV with 117–121-km/73–75-mile electric range) drivers.[145] Wu et al. confirm that finding and report that workplace charging opportunities significantly increase UFs for PHEVs with an electric range below 64 km (40 miles).[124] Zoepf et al. also confirm that ubiquitous availability of conventional chargers can double UFs, but add that fast charger availability does not lead to a significant increase in UFs.[146] A report by the National Academy of Science further stresses that the federal government should ensure that all BEV and PHEV drivers can charge their vehicles at all public charging stations, raising the convenience of electric charging.[26]

There is a range of incentives and technologies whose impact on PHEV fueling behavior seems inadequately studied, including the effect of incentivizing home charger installation, public charger reservation services through smartphone apps, removing differences in plug–design between different charger networks, the development of wireless charging, and vehicle–to–grid or vehicle–to–home applications. The optimal amount of public chargers is another key uncertainty left for future research.

Consumer education: Perhaps the most important incentive for charging a PHEV is the price difference between electric charging and gasoline fueling as well as the ability of the PHEV user to obtain that knowledge. Sun et al. showed that electricity prices significantly affect the timing of charging.[122] EPA's online fuel economy database[111] helps consumers compare annual energy costs of most commercially available vehicles in the US market, including PHEVs and BEVs. EV Explorer[147] combines the data from EPA's fuel economy database with the mapping functionality of Google Maps. As a result, users can compare their annual cost of driving a BEV, PHEV or ICEV based on their exact home and work locations, number of days of commuting, local gasoline and electricity prices, and charger availability. In addition, several smartphone apps have been developed with hundreds of thousands of EV charging locations on file, and useful information on charger availability, charging status, wait times, and wait lists. Furthermore, reducing driver aggressiveness can save up to 35% of energy use in the short term and up to 21% in the long term (Table 8.2 in Heywood et al.),[37] and can thus increase the electric range of PHEVs and their UF. Employers could link financial incentives to economical driving of their employees, or pay for fuel economy training courses.

Battery design: Zoepf et al. find that high charger availability has a stronger impact on UFs than larger battery capacities.[146] Regardless, it seems advisable that PHEVs offer at least an electric range comparable to the average daily US travel distance, which is about 43 km (27 miles).[110] Sun et al. showed that PHEV drivers tend not to charge when PHEV electric range is below drivers' daily driving distance.[122] Doubling the electric range from 18 to 35 km (11 to 22 miles), which is near the average daily distance driven, can raise the UF of a Prius from about 0.28 to about 0.42, an increase of about 50%.[146]

3.4.3 Limitations and future work

In this work we estimate the GHG emissions potential of PHEV drivers adopting more or less environmentally favorable fueling behavior. The most important limitation of this work is the fact that LAVE–Trans is not able to model these behavioral changes endogenously as part of its discrete choice module. Instead it relies on exogenously defined UFs. The aim of this work is to demonstrate an upper range of potential climate impacts of variations in PHEV fueling behavior, which is why we choose to model cases with high and low, yet plausible, and externally set, fleet–wide UFs. In a sensitivity analysis we reduce the spread between high and low assumed UFs and note the resulting changes. Surprisingly, the results are still substantial, with GHG emission differences between high and low UFs at the gigaton–scale.

Further, so–called 'composite vehicles', simplified representations of a larger, diverse group of vehicle types, are commonly estimated in vehicle choice models. It has been shown that this practice can distort vehicle sales mix estimations considerably, which is why future work should either use a broader range of vehicle options or use correction methods as described in Yip et al.[148]

Finally, since LAVE–Trans is not a full–scale energy model, additional variables had to be defined externally, such as the total amount of annual vehicle sales, carbon taxes, electricity emissions, and battery pack prices. In order to reduce the bias in our work we provide different scenarios with various sensitivity cases, displaying a total of 21 different GHG emission outcomes (Figure 3.5b).

Despite modeling limitations present, our results demonstrate that fueling behavior of PHEV owners can have significant impact on fleet–wide emissions and can therefore be decisive for reaching climate targets. Future research may be directed at improving the empirical basis of our work regarding the factors that could influence fleet–wide UFs of future PHEV fleets. Further work may address the importance of fueling behavior of bi–fuel vehicles in other regional markets or at global scale. Integrated models should pay more attention to charging and fueling behavior and may revise implicit or potentially over–simplified assumptions.

Author contributions

P.W. designed the approach, collected the data, performed the analysis and wrote the paper. E.H. helped with framing and writing the paper, and provided feedback.

Data availability

LAVE–Trans is freely available at https://www.nap.edu/download/18264. The most important input data and model outputs are available as supplementary files at https://doi.org/10.1021/acs.est.0c03796.

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4 Representing vehicle–technological opportunities in integrated energy modeling

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Abstract

Light–duty vehicles (LDVs) are responsible for more than one tenth of global energy use and CO_2 emissions and are therefore an important focus in pollution mitigation efforts. Integrated energy models (IEMs) are frequently used to explore cost–optimal climate change mitigation measures for energy supply and demand sectors, such as LDVs. Options include fuel and powertrain switching through efficiency standards, taxation, and technology mandates. This review provides an overview on how LDVs are modeled in 14 popular IEMs. We find that the representation of mitigation options can be enhanced by linking emissions and physical outputs from industry, agriculture, and energy conversion directly to the vehicle life cycle and by more carefully reflecting important factors that influence LDV life cycle emissions. This would allow for a more complete internalization of emissions in the technology mix optimization procedure of IEMs. The results highlight a range of mitigation options currently not considered in most integrated models, such as reducing embodied emissions in infrastructure and vehicle production, reducing methane leakage, or switching to less carbon intensive crude oil grades.

4.1 Introduction

Globally, light–duty vehicles (LDVs) are responsible for more than one tenth of total CO_2 emissions and energy use.[4–6] In order to explore holistic and cost–effective decarbonization pathways for the LDV sector, several scenarios have been produced based on integrated energy models (IEMs), analyzing the effects of CO_2 taxation,[47] technology mandates,[149] fuel economy standards,[150] renewable fuels standards,[37,151] or increased electric vehicle

(EV) research and development (R&D) efforts.[137,152] Further, these models can be used to study the effects of fuel taxation.[153–155]

Broadly, IEMs are models of the energy–economy system, often including modules of the climate and environmental damage. However, the definition of IEMs is not clear–cut. We therefore define IEMs as models that (1) entail the entire environmental–energy–economic system, (2) find an equilibrium state of energy supply and demand, either for the entire economy (general equilibrium), or for individual energy demand sectors (partial equilibrium), (3) provide explicit representation of single energy demand sectors and climate change mitigation technologies within these sectors, (4) are mathematically solved through optimization or simulation, and (5) allow exploration of future energy and emissions scenarios under different policy assumptions.[22,156,157]

IEMs are the most prominent tools for informing long–term national and supra–national energy and climate policies, and have therefore been used by the US Energy Information Administration (EIA) and the Intergovernmental Panel on Climate Change (IPCC) Working Group III to directly inform government and international agencies around the world, including the United Nations Framework Convention on Climate Change,[158] the White House,[149] and the European Commission.[159]

The recent engineering literature points to several technical and behavioral factors that can substantially influence energy use and GHG emissions of different LDV technologies. Examples include material choice in vehicle production,[160,161] construction of road infrastructure,[48,162] fueling behavior of multi–fuel vehicle drivers,[163,164] charging behavior of EV drivers,[165,166] and the divergence between real–world fuel consumption and official laboratory testing.[74,76] Generally, IEMs do not incorporate such fine–grained detail in their mitigation scenarios. An open question to date is whether these factors should be considered inside these models, or whether more bottom–up modeling should (a) replace or (b) complement IEMs or (c) be used to parametrize or constrain IEMs.

The factors that we are going to discuss (indicated with numbers 1–13 in Figure 4.1b) have the potential to significantly influence the outcomes of proposed climate change mitigation measures. Some factors constitute overlooked emission reduction opportunities, while others add new constraints currently not considered in several, if not all IEMs. Other factors, such as biofuel upstream emissions, are in fact included in almost all models but are in some cases not linked to the life cycle of LDVs, and are therefore not taken into account in decision–making routines of the transport and energy modules of these IEMs, consequently masking the full impact of biofuel technologies. This has lead to heavy reliance on biofuels in past integrated assessments [167, Figure 7 therein]. As an overall result, IEMs do not capture the complete mitigation potential or trade–offs with other sectors, raising the risk of misleading technology recommendations.

A growing body of literature suggests that assessments considering greater detail of (end–use) technologies and end–user behavior are better equipped to model real–world policies more accurately, while more carefully reflecting technological change and innovation.[19–22, 168–173] Policy and decision makers need to be aware of the simplifications that currently exist in IEMs and the resulting uncertainties around IEM outputs in order to take these into account in their decisions. Scientists should make an effort to understand to what extent these factors can negatively or positively influence the results of integrated decarbonization scenarios. To aid that process we identify a number of factors from engineering and transport models that are important for climate change mitigation and present a multi–scalar typology of these factors. We review 14 widely used IEMs to identify whether and how these factors are modeled in IEMs and to understand other relevant features of their transport modules, such as technological detail and technology cost assumptions (totaling nearly 400 factors and model items).

The reviewed IEMs have been selected based on a systematic search of relevant literature databases and previous reviews of IEMs, see section C.1 for details. Following that, we evaluate what policies at the nexus of LDVs, energy and climate have been analyzed using IEMs and which simplifications may have influenced the outcomes. We end by making some recommendations on how future scenario exercises that aim to analyze specific transport–energy–climate policies could make use of greater engineering detail.

4.2 A typology of factors influencing vehicle energy use and GHG emissions

Both, integrated and engineering models, assess energy use and GHG emissions of transport equipment albeit at different scales. IEMs simulate the entire energy–economic–environmental system while engineering models analyze individual vehicles or vehicle fleets, often from a life–cycle perspective (Figure 4.1a). Higher scale assessments draw a larger system boundary at the expense of process detail. Temporal and geographical scope differ as well. IEMs are usually global with time frames up to 2100, whereas most engineering models are geographically and temporally more confined.

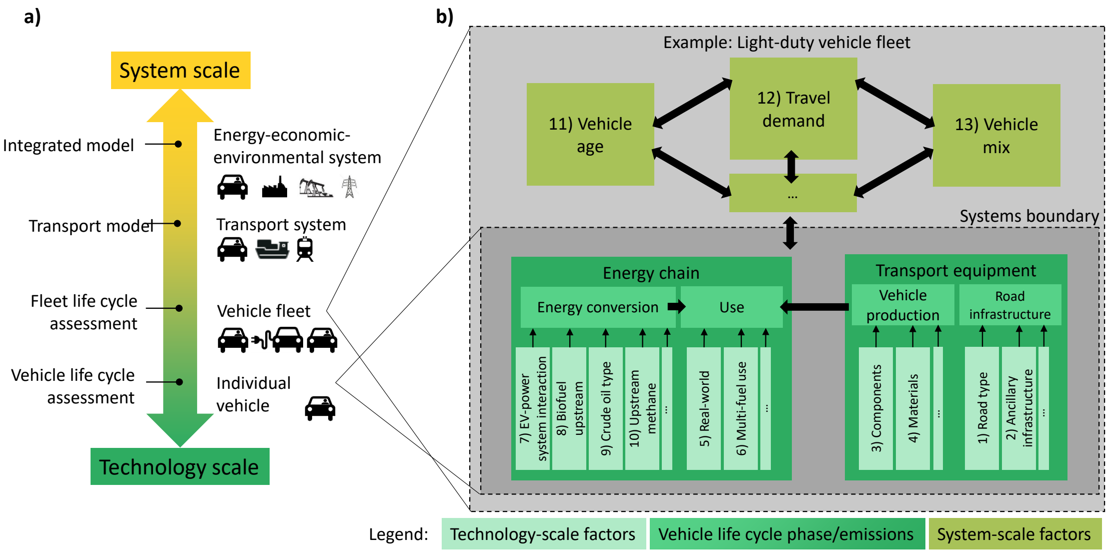

Figure 4.1: The range of different transport–related models at different scales (a) and a typology of different factors that influence vehicle life cycle GHG emissions at different scales and their interactions (b).

As mentioned before, the engineering literature points to several factors that can greatly influence the environmental performance of LDVs and therefore have implications for decarbonization efforts of the LDV sector. Although not exhaustive, the following selection addresses the most important factors (indicated with numbers 1–13 in Figure 4.1b) because – as we are going to discuss – they can influence the magnitude and variability of life cycle energy use and GHG emissions of different LDV technologies considerably. As such, they influence important trade–offs between these technologies and therefore affect the relative environmental performance of different technologies.

Whether or whether not factors are varied over time or geographies is generally not assessed in this review (except for 'vehicle age') because it would go beyond the scope of this review. We note that nevertheless such dynamic changes should ideally be included in a realistic assessment.

4.2.1 Road infrastructure

Roads influence operational energy consumption,[174] transport costs, and can induce additional travel demand.[175] Additionally, road construction itself is an energy– and material–intensive process. Different road types require more or less materials and therefore cause higher or lower embodied GHG emissions.[162,174] Chester and Horvath integrate the construction of different road types into the vehicle life cycle and find that roads cause 10–15% of the impact of road transport, the remainder being associated with fuel production and use and vehicle manufacturing.[48]

4.2.2 Ancillary infrastructure

Ancillary infrastructure may include all the additional infrastructure that is needed for LDVs besides roads, for example bridges, tunnels, parking lots, and alternative fuel stations. The availability of alternative fuel stations, for example, can strongly influence adoption rates of alternative fuel vehicles.[176] In addition, the provision of such facilities can have significant energy and carbon implications. For example, Lucas et al. report that charging infrastructure contributes 8–12% to total BEV and HFCEV life–cycle GHG emissions and energy use.[177] Further, a Norwegian standard road tunnel emits at least 31 kt CO_2 over its life cycle.[178] Chester et al. estimate that parking infrastructure increases vehicle life–cycle emissions from 230–380 g CO_2e km^{-1} by about 6–23 g CO_2e km^{-1}.[179]

4.2.3 Vehicle components

Vehicle production can contribute substantially to vehicle life cycle GHG emissions. Hawkins et al. identify that the embodied carbon in the production of BEVs is roughly double that of the production of a conventional vehicle.[9] Recent LCAs became more granular in that they describe the impacts of individual vehicle components. For example, Ellingsen et al. find a particularly high contribution of lithium–ion batteries to the production impacts of BEVs.[180] Others evaluate the production of electric motors and fuel cells[181,182] and Gawron et al. find that additional hardware can offset some of the life–cycle GHG emission reductions of automated vehicles.[183]

4.2.4 Vehicle materials

Between 1995 and 2014, automakers increased the use of lightweighting materials in vehicles sold in the US in order to comply with fuel economy standards,[160] yet meeting consumer demand for larger vehicles. Lightweighting materials may require higher energetic input.[17,160,161,184] With an increasing uptake of vehicle electrification and automation, as well as stronger use of lightweighting materials, and the associated material needs for batteries, sensors, etc., embodied emissions of future vehicle production may increase, depending on the degree of power sector decarbonization. Higher recycling rates could partially mitigate that trend.[36]

4.2.5 Real–world driving

Real–world driving describes the actual on–road behavior of drivers and the corresponding energy consumption. Significant divergence between official fuel consumption values based on drive–cycle testing and real–world fuel consumption has been found in several vehicle markets around the world. In the US, the ‘gap’ is around 30% on average[76] and even larger for alternative fuel vehicles.[163] This divergence is caused by several factors, such as driver aggressiveness, as well as climatic and traffic conditions.[185,186] Furthermore, vehicle efficiency technologies (e.g. start–stop) are optimized for drive cycles,[185,187] not for real–world driving.

4.2.6 Multi–fuel use

Several vehicle types exist that can run on two or three energy carriers, referred to as multi–fuel vehicles (MFVs), including bi–fuel vehicles, flexible–fuel (or dual–fuel) vehicles (FFVs) and plug–in hybrid electric vehicles (PHEVs). Existing literature has focused on the refueling behavior of PHEV drivers. The utility factor of a PHEV describes the ratio of distance driven on electricity to total distance driven and typically ranges from 0.3 to 0.76 depending on a vehicle's all–electric range,[188,189] and the region where the PHEV is driven.[115] Figure C.1 demonstrates the impact of different utility factors on PHEV energy chain emissions in different electric grid regions. Fewer literature analyzes the refueling behavior of other MFVs. Daley et al. found that government–owned FFVs are fueled with E85 (an ethanol–gasoline blend containing 51–83% ethanol by volume, depending on season and geography) only 24% of the time when available.[190] Huse showed that two thirds of MFV drivers purchase gasoline over ethanol even at price parity.[164]

4.2.7 EV–power system interaction

Interactions between the electric power system and the EV fleet are bilateral and complex. EVs are primarily users of electric energy and the anticipated uptake of EVs will likely induce an expansion of electricity generation capacity.[191] However, EV charging is reasonably flexible and can be controlled.[192] Depending on charging behavior and policy or market signals, EVs can help improve the stability of an increasingly renewable electric grid and reduce the costs of EV ownerhsip and electricity storage.[192,193] Hence, the introduction of EVs can impact the profitability of different generation sources differently. Alternatively, EVs can shift electricity peak demand and lead to grid congestion. Additionally, the environmental impact of EVs largely depends on the emissions intensity of the electric grid. In turn, incremental electricity demand from EVs also determines the marginal mix of electric generators employed. Depending on the electricity system in question, the time of year and the time of day, marginal emission rates can vary substantially and can be above or below average electricity emission rates.[165,194,195] Averaged over a whole year, emission factors of the marginal mix are often higher than emission factors of the average mix.[195]

4.2.8 Biofuel emissions

Many vehicle–related impact assessments consider the production of fuels, while certain inherent factors of that process are not considered.[20] For example, in the case of biofuels, these factors relate to the carbon uptake of feedstocks and land use and land–use change due to feedstock cultivation. Additional variation in overall emissions stems from field emissions, e.g. N_2O, and the large diversity in feedstocks and conversion technologies.[196,197] For example, many feedstock options can lead to overall GHG emission reductions compared to gasoline.[90,196] Some feedstocks, such as wheat and rapeseed, can even produce net–negative life–cycle GHG emissions [197, p. 878]. However, while US corn ethanol generally reduces life–cycle GHG emissions compared to gasoline, poor land management can lead to increased emissions.[12] Figure C.2 compares the energy chain emissions of corn ethanol and gasoline considering different sources of upstream emissions, including land use change, feedstock carbon uptake, crude oil upstream and midstream emissions, and gasoline sulfur content.

4.2.9 Crude oil grades

Similarly, in the case of gasoline, the GHG intensity of different crude oil grades can vary substantially. For example, Masnadi et al.[198] and Gordon et al.[199] show that the upstream carbon intensity of crude oil can easily vary by a factor of eight, from about 15 to 129 g CO_2e kWh^{-1}. This variation is largely caused by crude oil characteristics, geological factors, and the deployed extraction technology. For instance, Masnadi et al. found that carbon emissions per unit of energetic output can grow over tenfold with oilfield age.[200] Furthermore, crude oil density, and the amount of gas flaring (burning) and venting (directly emitting methane) are important factors that determine life–cycle GHG emissions of crude oil and oil products.[81,198,201]

4.2.10 Methane leakage

While there are many other upstream factors to consider, the last technology–scale item we wish to highlight is methane leakage (methane that escapes to the atmosphere).

Methane leakage is of concern during the extraction and transmission of natural gas, shale gas and coal for electricity generation,[202] and hydrogen production.[203] Assuming a natural gas leakage rate of 1–5% would add about 4–30 g CO_2e kWh^{-1} to the GHG balance of electricity generation from natural gas. In addition, biogenic methane leakage occurs during the electricity generation from hydropower through the decay of plants on the reservoir ground. Global average methane leakage from hydro power are found to be 4 g CH_4 kWh^{-1} (112 g CO_2e kWh^{-1} over a 100–year time horizon) with a large range from micrograms to tens of kilograms.[204] These emission sources are of importance for vehicles powered by natural gas[11] and hydrogen,[205] and potentially for EVs in regions with high shares of hydro power, coal and natural gas in the electricity mix.

4.2.11 Vehicle age

Due to increasing powertrain efficiencies, newer vehicles consume less fuel per mile and thereby reduce GHG emissions per mile. However, newer vehicles tend to be driven more frequently than older ones.[206,207] In addition, every new vehicle produced increases the amount of energy and emissions embodied in the stock of vehicles, thereby creating trade–off effects. The question whether replacing newer with older cars or extending the life of older cars yields reductions in overall GHG emissions, depends on a myriad of factors, such as the composition of the existing local fleet, the types of new vehicles that replace older ones, the timing of replacement, and the timing of scrapping schemes and other policies.[208] Figure C.3 shows the impact of ignoring vehicle vintages in modeling tailpipe emissions of the vehicle fleet.

4.2.12 Travel demand

Travel demand is influenced by fuel prices,[209] as well as personal income, employment levels, and population gains.[210] In addition, travel demand is strongly intertwined with vehicle demand and ownership, which may substantially change in the future due to increasing electrification, automation and sharing of vehicles. One of many open questions to date is whether increasing fleet electrification will entail a one–to–one substitution of conventional cars with EVs. On the one hand, households that own BEVs or PHEVs often own more vehicles per household,[206] pointing to an imperfect substitution. On the other hand, the development of long–range EVs and the growing EV charging network may lead to a perfect substitution in the near future. It is therefore inconclusive whether future trends may increase the number of vehicles needed to satisfy travel demand, and therewith increase energy and emissions embodied in vehicle production.

4.2.13 Vehicle mix

Relative cost differences between different LDV technologies is the strongest determinant of consumer vehicle choice, while driving range, model availability, infrastructure availability play a role among other factors.[211] EVs, especially BEVs, are assumed to grow substantially in numbers in coming decades due to forecast cost improvements of batteries.[47] A strong shift towards electrified, automated and lightweight vehicles will likely reduce energy chain emissions substantially, but may entail higher embodied emissions in the production of the required vehicle stock.[160,183] In addition, vehicles tend to become heavier in many markets,[187] and may continue so in the future. As a result – even though vehicles tend to become more efficient per mass – their overall energy consumption increases.

4.3 Decomposing vehicle energy use and emissions into factors

The factors listed above can be classified into technological and systemic factors, depending on the scale at which they influence LDV energy use and GHG emissions (Figure 4.1b). Technical factors occur at a technology–specific scale where they affect energy use and emissions of an individual vehicle or technology. We broadly distinguish between (1) energetic expenditures and emissions caused by the manufacturing of transport equipment and infrastructure, such as cars and roads, and (2) energy use and emissions from the production and usage of energy carriers, such as gasoline or electricity. Through the various vehicle life stages, different technological factors can influence each other. For example, the use of lightweight materials can increase emissions during vehicle production but reduce emissions during the driving phase. Systemic factors occur at a higher fleet–wide scale, i.e. they pertain to the entire vehicle fleet. Systemic factors also affect each other, for example, vehicle aging creates a demand for new vehicles (and perhaps new technologies), which alters the vehicle mix. Technological factors also influence systemic factors and vice versa. For example, an improved fuel economy of a new (individual) vehicle will also help to (marginally) improve the fuel efficiency of the entire fleet. On the other hand, demand for larger vehicles may influence the material composition of new vehicles. Life cycle GHG emissions from LDVs ($LCGHG_{LDV}$, e.g. kt CO_2e) can be decomposed into these factors:

$$LCGHG_{LDV} = \sum_{\text{technologies}} \underbrace{(\underbrace{Equipment}_{f(1,\,2,\,3,\,4)} + \underbrace{Energy}_{f(5,\,6,\,7,\,8,\,9,\,10)})}_{\text{Technological factors}} \times \underbrace{\underbrace{Activity}_{f(11,\,12)} \times \underbrace{Mix}_{f(13)}}_{\text{Systemic factors}} \tag{4.1}$$

where *Equipment* is embodied carbon in the manufacturing of transport equipment (e.g. normalized to g CO_2e km^{-1})[36,74,212] and is influenced by the factors one through four. *Energy* are all embodied emissions in the energy chain (e.g. g CO_2e km^{-1}). These emissions are influenced by the factors five through ten. *Activity* is the amount of vehicle travel (e.g. vkm), and is influenced by the factors eleven and twelve. Mix is the technology mix (%), factor thirteen. Summing over all available technologies yields total LDV life cycle GHG emissions. As described in the previous section, each of the factors can significantly influence energy use and emissions of LDVs and may offer potential for climate change mitigation, which has not yet been comprehensively assessed in IEMs.

4.4 Representing vehicle–technological opportunities in IEMs

In this section we present summarized findings of the in–depth review of fourteen IEMs, while detailed results for each individual IEM are given in Section C.5 and implications of our findings are discussed in the next section. In general, we find that technological detail and the representation of mitigation options can be enhanced (indicated by light and medium green boxes in Figure 4.2). The vast majority of models accounts for energy chain emissions, whereas few consider embodied carbon in vehicle production, and none account for embodied infrastructure emissions.

Regarding infrastructure construction, several models include emissions from relevant aggregate industries, such as cement production. Demand for cement is modeled as a function of GDP independent from transport infrastructure requirements, whereas a more detailed approach would be to link cement production directly to demand for transport infrastructure as a function of vehicle travel.[21] This approach would also allow for accounting of energy and emissions embodied in road infrastructure. Similarly, demand for ancillary infrastructure is only indirectly considered in overall GDP growth or within relevant aggregate sectors in most models. Some models consider the availability of fuel and charging stations as part of the vehicle choice procedure. However, none of the models assign emissions penalties for technologies' infrastructure needs.

Regarding the manufacturing of vehicles, most models consider some physical vehicle characteristics, such as engine power, battery capacity or masses of specific components but do not link these characteristics to specific material and embodied energy needs. Notably, a version of EPPA[37] distinguishes different metals and composites and changes in the material composition of the vehicle body, but these changes only affect fuel economy, not embodied energy use. Similar to the cement example above, demand for steel and aluminum is modeled as a function of GDP in several models, but not directly linked to demand for vehicle production.

Modeling of the energy chain is more detailed in all analyzed models, although opportunities for improvements exist. Real–world fuel consumption is explicitly considered in EPPA, GCAM, IMACLIM–R, GEM–E3, IMAGE and ETP–TIMES, while others estimate LDV fuel consumption from IEA's aggregate energy balances in a top–down approach. Energy intensities in AIM/CGE are even a little on the high side compared to EPA's adjusted average fuel consumption values, which are reflective of real–world fuel consumption.[189] The remaining IEMs assume too optimistic energy consumption values. PHEV utility factors are explicitly considered in EPPA, NEMS, GEM–E3, and ETP–TIMES, and have also been applied to versions of IMAGE[167] and TIAM–UCL.[213] Fueling factors for other MFVs are included in NEMS, IMAGE, and a version of EPPA.[37] A more stylized representation of fueling behavior of MFV drivers is achieved in most other models by considering either constant or dynamic degrees of biofuel and gasoline blending, assuming that biofuels can be used directly in ICEVs without prior modification.

Upstream emissions of energy conversion are usually considered in IEMs although a closer look reveals some room for improvement. For example, interaction of EVs with the power system is usually modeled as a unilateral one. For instance, the electricity mix influences EV charging emissions, whereas the timing of EV charging does not influence the amount of electricity generation nor the electricity mix. In the future, IEMs may integrate the response of the electricity system to EV charging from a lower–scale model, for instance an energy system model with a finer time–step resolution. Some models integrate land use modules, such as GLOBIOM or MAgPIE, which contain positive and negative emissions from agriculture, forestry and bioenergy and can be used to comprehensively assess life cycle emissions from different biofuel options when the agriculture and energy sectors are linked.[151] In NEMS, ETP–TIMES and versions of IMAGE[167] and MESSAGE[214] exogenous biofuel upstream emission factors have been linked to available LDV technologies in an ad–hoc fashion. POLES assumes that biofuel combustion is carbon neutral, while a version of EPPA[37] assumes that biofuel land use change emissions are negligible. Furthermore, a range of models provide a detailed representation of crude oil supply. For example, the Oil and Gas Supply module in NEMS distinguishes production of five different crude oil grades but the differences in their carbon content are not considered during the gasoline production stage. AIM/CGE and GCAM consider several sources of fugitive methane emissions during coal mining, natural gas production and distribution and crude oil production, while REMIND additionally considers biogenic methane release from hydro power.

The apparent strength of IEMs lies in the representation of systemic factors. Aging of the vehicle fleet, for example, is incorporated in all IEMs but AIM/CGE which does not employ a vintage formulation. Almost all IEMs calculate travel demand endogenously as a function of all or several of the following variables: projected fuel cost, personal income, vehicles per licensed driver, and employment rate. Potential future changes in vehicle demand and use patterns (e.g. the fact that EVs may or may not substitute

ICEVs on a one–to–one basis) is not considered by any model. Vehicle mix is endogenized in most models, for example through the use of discrete choice modules. However, vehicle technology choice differs vastly between IEMs, partly due to large differences in cost assumptions. Some models use dated EV battery cost estimates, while other models (GEM–E3, WITCH, IMAGE, DNE21+, TIAM–UCL, ETP–TIMES) use costs that are closer to latest empirically observed cost developments.[215] Others (EPPA, GCAM) use fuel cell cost estimates that are based on the assumption that fuel cell systems are fully learned,[129] whereas in reality the global production volume of automotive fuel cell systems is estimated at less than 1,000 units in 2015.[73]

While our focus is on the thirteen factors listed in Figures 4.1 and 4.2, we analyze several further items of IEMs. For instance, the range of considered technologies differs vastly across different IEMs. While the mainline IMACLIM–R model only considers HEVs and ICEVs, most other models include a broader range of major conventional and alternative technologies. For example, NEMS differentiates fourteen powertrains and recently added autonomous vehicles as part of the Annual Energy Outlook 2018.[216] Vehicle efficiency improvements occur in most models but are implemented as simple annual improvement factors. In Heywood et al.[37] EPPA utilizes efficiency improvement rates based on a soft link with the Autonomie vehicle simulation software. Efficiency improvement occurs through several measures such as engine downsizing, and reductions in weight and rolling resistance. As a result, rates of improvement are better aligned with physical efficiency limits and are therefore more robust and credible. The next section discusses how improvements to IEMs could enhance the potential of IEMs for effective policy formulation at the nexus of transport, energy and climate.

4.5 LDV climate change mitigation options in IEMs

One of the most common policies analyzed in IEMs is the introduction of a carbon tax on fossil fuels[217–219] (cf. Table C.23). In practice, a carbon tax is often implemented as a mark–up on the prices of sold transport fuels, thus implicitly taxing the actual real–world fuel consumption of the transport sector. Some IEMs however model the effects of carbon taxes based on official vehicle energy consumption, while others account

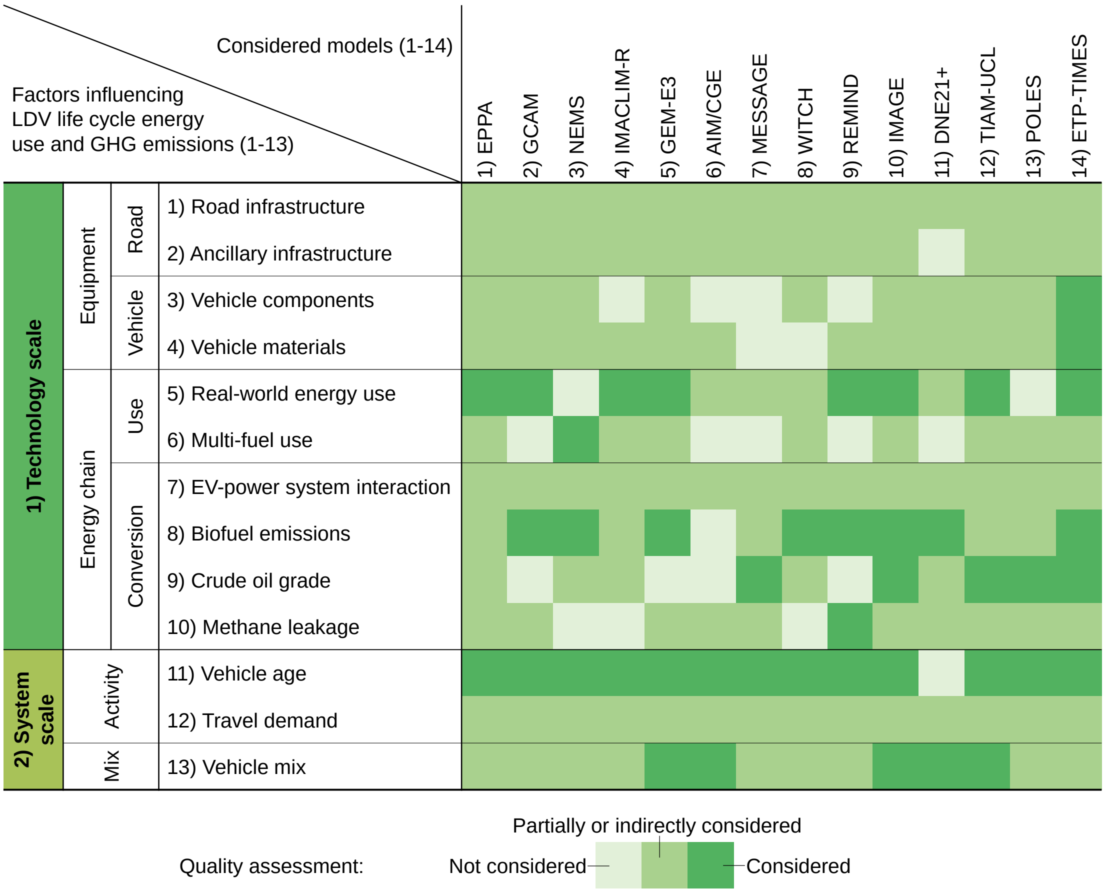

Figure 4.2: Review of integrated energy models applied to US light–duty vehicles and their coverage of various factors.

for real–world vehicle operation. Additionally, some modelers may apply taxes to direct tailpipe emissions only, while others apply taxes to emissions of the entire energy chain. As a result of these differing modeling practices, the impact of a carbon tax policy can be expected to differ substantially across IEMs, producing disagreement between IEMs and potentially leading to large uncertainties around anticipated policy outcomes.

In addition, several modeling teams analyze the GHG emissions reduction potential of the introduction of a renewable fuels standard. This standard is the first policy to regulate supply chain GHG emissions. Heywood et al.[37] (EPPA) find that, compared to carbon taxes and fuel economy standards, the renewable fuels standard could achieve the highest GHG emissions reduction over the analysis time frame. However, the authors do not account for land use change emissions from biofuel feedstock cultivation, which can produce considerable GHG emissions.[12,90,197] Including these emissions would lower the emissions reduction potential of the renewable fuels standard significantly. Additionally, including upstream emissions would allow for assessment of a wider spectrum of climate change mitigation measures. For example, measures aimed at reducing impacts of feedstock cultivation, such as switching from corn to cellulosic feedstock.[90] Other models, such as GEM–E3, WITCH, IMAGE, POLES, REMIND and the mainline MESSAGE version do in fact include a detailed description of LULUC emissions from biofuels, while POLES assumes that biofuel combustion emissions are carbon neutral. As a result, the technology mix in POLES may be skewed in favor of biofuel–using technologies, thus producing inaccuracies in forecast technology mixes and mitigation pathways.

Ó Broin & Guivarch[220] (IMACLIM–R) analyze the potential of modal switch and related infrastructure costs. They conclude that redirecting infrastructure investments from the LDV sector to the public transport sector could help lower costs of climate change mitigation. However, the authors do not include the physical requirements needed to sustain such infrastructure, neither for LDVs nor for public transport. While stronger use of public transport can effectively reduce direct emissions, the material requirements are especially high for public transport, potentially causing higher embodied emissions.[48] As a result, the GHG reduction potential and the cost effectiveness of this strategy is likely overestimated by Ó Broin & Guivarch.

Almost all model teams analyze the effects of increasing vehicle electrification, e.g. through government R&D policies. Most of these models, however, use dated baseline costs for electric vehicle batteries (notable exceptions include GEM–E3, WITCH, IMAGE, DNE21+, TIAM–UCL, and ETP–TIMES), which can be problematic because model results may overestimate the costs of employing clean technologies and therewith overestimate the costs of reaching a certain climate target, thus sending wrong signals to policymakers. Combined with the fact that some models (EPPA, GCAM) assume costs of fully learned fuel cell systems (which is not currently the case due to low production volumes), policymakers may focus on the deployment of alternatives to BEVs, which are sub–optimal not only in terms of carbon, but also in terms of other sustainability indicators, such as energy consumption and costs of ownership.[212] Figure C.4 demonstrates the effect of battery cost assumptions on EV penetration. For a more comprehensive list of analyzed policies in IEMs, refer to Section C.6.

No single IEM analyzed the potential effects of environmental standards or carbon taxes in vehicle production or infrastructure construction. Such regulation could limit the use of certain energy–intensive materials and promote the use of recycled materials and remanufactured components during vehicle production. As a direct consequence, manufacturers may be forced to use less energy–intensive materials and components in order to meet these standards. As an indirect consequence, manufacturers may reverse the trend of building ever bigger vehicles in order to still comply with future fuel economy standards. Resource conservation may be a co–benefit of smaller, and perhaps less powerful, cars.

Several political and industrial trends will likely increase the relative importance of indirect emissions in the future, for example increasing electrification, automation and lightweighting of the vehicle fleet, as well as increasingly stricter fuel economy and renewable fuels standards. Several of the analyzed factors (1–4, 7–10) influence these indirect emissions. Therefore, the importance of increasing efforts to properly model these factors is even more pronounced by mentioned anticipated trends.

4.6 Merging two worlds for prospective vehicle modeling

We have found that systemic factors (factors 11–13, Figure 4.2) are generally well described in IEMs, while there is potential to improve technological detail (factors 1–10). These findings add to those of Garcia et al.[221] who found that vehicle LCA often incorporates rich technological detail but neglects system dynamics, such as vehicle demand and vehicle choice and endogenous modeling thereof. Due to the gaps in both modeling schools, Creutzig et al.[20] and Pauliuk et al.[19] propose a coupling of engineering models and IEMs. This can be achieved by stronger ties between IEMs and engineering–type models, such as life cycle assessment, vehicle simulation, power plant dispatch modeling and vehicle and fuel choice modeling, or by directly integrating engineering data into IEMs in an ad–hoc fashion. A combination of the two modeling schools can help overcome the insufficiencies that persist in both worlds, improve overall analytical capabilities,[22] and reduce uncertainties around the LDV energy and emissions reduction potential and associated costs.

In addition, the links between the LDV sector and other sectors, such as electricity generation, oil production, agricultural production and specific industry branches should be made (more) explicit, for which higher sectoral detail is a prerequisite. For example, besides cement and steel production, which is already represented in many IEMs, further explicit industries may be considered, such as aluminum (for vehicle production) and bitumen (for road construction). The construction sector should explicitly distinguish roads, parking, charging and fuel infrastructure from other infrastructure projects. These links can be implemented in the same fashion as the electricity–demand–by–sector link, which is already in place in all IEMs. Doing so would help achieve a more realistic representation of the interdependencies of the different sectors.

Results from such a model could form the basis for improved and novel policy recommendations at the nexus of transport, energy and the climate. Two examples of such novel policies are vehicle manufacturing or infrastructure construction standards, as mentioned in the previous section. Another example is a 'smart' carbon tax[222] that accounts for the variation in life–cycle emissions of different crude oil grades which would lead to a more complete internalization of the externalities from oil extraction and refining.

To date, it is largely unexplored how life–cycle relationships (and behavioral aspects) may influence optimized national and global energy and climate change mitigation strategies.[22] Some exceptions exist in the literature that address the role of indirect emissions of energy supply (see Section C.3), but no such study has been prepared for energy end–use technologies, such as LDVs or transport in general. In this work, we provide an important starting point by identifying and qualitatively evaluating a number of potential areas for improvement regarding vehicle–technological detail in fourteen integrated models.

4.7 Challenges of the proposed approach

The proposed approach offers the merit of identifying additional climate change mitigation pathways in the LDV sector that have not been considered systematically in decarbonization scenarios. However, we acknowledge that IEMs are not LDV–specific models and it remains open whether all of the identified factors (1) *can* and (2) *should* be incorporated in IEMs. Regarding (1), we acknowledge that it may not be possible to include all the detail of engineering models in IEMs. Reasons therefore are for example the sheer vast range of biofuel and gasoline pathways, or the many different vehicle types and (sub–) components that are being modeled in engineering–type models, and the associated computational challenges of a full integration with IEMs. Regarding (2), all of the identified factors can potentially be of importance to consider, even more so since single factors can influence each other through the different vehicle life stages (Figure 4.1). However, some factors are more crucial than others when analyzing specific policies (cf. Section 4.5 and C.6). Therefore, a balance between a too simplified and too detailed representation of technologies in IEMs needs to be found.[219] In accordance with Pauliuk et al.[19] we note that beyond 2050, a more aggregate systems representation may be more suitable than a highly detailed model as technology descriptions and estimates of consumer behavior become highly speculative. Therefore, the most appropriate level of detail of the LDV sector within IEMs remains yet to be determined. Until then, it is at the discretion of the modelers to decide.

4.8 Moving forward

This review paper adds to the existing literature in several important ways: Firstly, we discussed the importance of a number of factors affecting life cycle energy use and GHG emissions of LDVs and provided a typology of these factors. Secondly, we performed an in–depth review of fourteen popular IEMs recently applied to US LDVs within a global setting with regards to which factors are considered in these models. Thirdly, we identified how future improvements to IEMs could enhance the potential for effective policy formulation at the nexus of transport, energy and climate. We regard some sort of integration of engineering data/models with IEMs and a more explicit linking of sectors and sub–sectors within IEMs as a crucial step for IEMs to maintain their status as central tools for informing national and supra–national energy–, climate–, and sectoral policies. IEMs are needed to integrate knowledge from different domains. At this point engineering–type models do not offer a viable alternative due to their lack of systemic aspects. Including these novel elements in IEMs can help to identify several climate change mitigation pathways that have not been systematically explored to date, but also help to identify potential emission shifting between the LDV sector and other industries. In addition, updating cost estimates, especially of EV batteries, would lead to lower–cost emission mitigation scenarios. Taken together, we expect that implications on climate policy are significant as climate action in the LDV sector may be more cost–effective than previously assumed. Therefore, future modeling exercises should make an effort to include a larger set of climate change mitigation strategies and re–evaluate the costs of climate change mitigation in the LDV sector. This paper indicates several possible avenues therefore. A collaborative effort across different modeling communities could help to create a suitable modeling framework for LDVs, or transportation in general. More transparent model documentations would be a first important step in that direction.

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Author contributions

P.W. and E.H. designed the approach. P.W. performed the review and wrote the paper. E.H. supervised the work and contributed to writing.

5 Pricing of indirect emissions accelerates low–carbon transition of US light vehicle sector

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Abstract

Large–scale electric vehicle adoption can greatly reduce emissions from vehicle tailpipes. However, previous research cautioned that it can come with increased indirect emissions from electricity and battery production commonly not regulated in transport policies. We combine integrated energy modeling and life cycle assessment to compare optimal policy scenarios that regulate the tailpipe only, versus both, tailpipe and indirect emissions, through pricing. Surprisingly, scenarios that also price indirect emissions exhibit higher, not reduced sales of electric vehicles, while yielding lower cumulative (tailpipe and) indirect emissions. This is because increased indirect electricity and battery emissions are more than offset by reduced indirect emissions of fuel production. The results show that carbon–pricing induced large–scale adoption of electric vehicles is a no–regrets strategy for climate change mitigation, given continued decarbonization of electricity supply. Whole–supply–chain policies are therefore needed to promote truly clean technologies.

5.1 Introduction

Global transportation is the single largest energy user and contributor to CO_2 emissions, chiefly driven by light duty vehicles (LDVs).[223] In order to curb emissions, many countries, including the United States (US), are increasingly promoting alternative fuel vehicles which are typically characterized by lower tailpipe emissions. However, concerns over potentially growing emissions from energy production and vehicle manufacturing have been voiced.[10–12] These emissions occur off–site, from generating the electricity to charge electric vehicles, in this work ∼66–86 g CO_2 per electric–vehicle km driven in 2020, to producing the vehicle, here ∼16–38 g CO_2 per vehicle–km driven in 2020 (Supplementary

Table 20 and Figure D.2). It has only recently been recognized that the emissions for producing gasoline can range significantly, from below ~15 to ~320 g CO_2/kWh in 2015,[198,224] compared to direct tailpipe emissions of about 250 g CO_2/kWh. Taken together, indirect emissions accounted for ~26% of the 1.5 Gt CO_2 caused by the US LDV fleet in 2020 (Supplementary Table 16).[6]

The introduction of the Low Carbon Fuel Standard in California suggests that precedent exists of policies that address at least part of vehicle life–cycle emissions. However, not a single transport policy exists to date that consistently regulates all sources of vehicle emissions along the entire supply chain. Fully regulating all emissions, for example through pricing, could significantly change the relative costs of different vehicle propulsion options, such as battery electric vehicles (BEVs) versus hydrogen fuel cell electric vehicles (HFCEVs) versus internal combustion engine vehicles (ICEVs). Changing costs, in turn, could affect production decisions of vehicle manufacturers, and purchase behaviors of consumers. The potential impact of these relationships is unknown though because neither model calculations, nor real–world policies have fully accounted for, or priced, indirect vehicle emissions to date.

Integrated energy models (IEMs) show that it will be very challenging to reduce emissions rapidly and far enough to reach the Paris goal.[23,79,98,225] However, there is concern that IEMs do not fully represent the impact of changes in one sector, such as electricity generation technologies, on emissions in other sectors, say industry or fuel supply.[7,19–21] For electricity generation, this has been investigated,[62,170,171,226–228] but not for vehicles. Our work is the first to fully account for, and price, all emissions that are directly (within the vehicle sector) and indirectly (in other sectors) caused by US passenger vehicles. We investigate whether this holistic emissions pricing influences the assessment of the benefit of competitive technologies.

To this end, we apply an interdisciplinary approach integrating industrial ecology methods with modelling of the entire energy–economy system. We link a detailed and comprehensive vehicle life cycle assessment (LCA) model to the Energy Information

[6]Supplementary Tables can be found at http://doi.org/10.21203/rs.3.rs-334331/v1. Final versions will be made available on the publisher homepage.

Agency's National Energy Modeling System (NEMS). NEMS is the federal government's main tool for evaluating energy and climate policies integrative of all energy demand and supply sectors. Among IEMs, NEMS has the advantage of representing the US passenger vehicle sector and its upstream sectors in remarkable detail (Section 5.7), which is a prerequisite for accurately accounting for all vehicle emissions across the entire supply chain of the vast portfolio of available technology options. Although *global* IEMs are the main tool for identifying optimal climate change mitigation pathways, they generally do not offer the same level of technological detail as national models do[7,19,20,229] which may limit their ability to identify optimal solutions across the range of options available in the real world. Further, while some integrated assessments account for materials used in electric power plants,[96,172] others call on the importance of considering efficient use of resources within integrated climate scenarios.[230] Yet, material and resource efficiency have not been thought of as pollution mitigation strategies in large–scale integrated energy scenarios and are therefore under–represented in the assessment reports of the Intergovernmental Panel on Climate Change.[231]

Here we address these knowledge gaps by applying a novel conceptual framework by Creutzig and colleagues.[232] We specify this framework for comprehensive climate change mitigation analysis of an important demand–side sector, the US LDV sector. Specifically, we illustrate a set of climate–change mitigation scenarios, primarily for the vehicle sector, but also considering responses in important upstream sectors, such as changes to material production, vehicle manufacturing and electricity generation. These responses are normally not captured in NEMS which is why we soft–link NEMS to a detailed LCA model (Section 5.7). We assume that the production cost of electric vehicle batteries and renewable electricity generators fall quickly, in line with recent estimates (Section 5.7). We further introduce a carbon price in the transport sector in 2021 which linearly increases up to 150 USD/t CO_2 (constant 2016$) by 2050 (Supplementary Table 9). This level is required for an LDV fleet commensurate with the US nationally determined contribution (NDC) under the Paris Agreement (Section 5.7). For simplicity and to provide insight, we run our cases with no carbon pricing on other sectors. The difference between scenario one and two is that either emissions from (1) the tailpipe, or (2) the entire vehicle supply chain are accounted, priced and optimized for. The implications are both surprising and significant. The strongest effect is that pricing indirect emissions would push the system to an even faster phase–out of gasoline–powered vehicles, leading to a scenario with both the lowest direct as well as indirect emissions.

5.2 Optimal vehicle choice

While scenario one (pricing only direct emissions) already leads to a quick phase–out of ICEVs (Figure 5.1a), the transition is further accelerated in scenario two (full accounting, Figure 5.1b). In addition, HFCEVs are avoided entirely in scenario two due to the high emissions penalty of producing hydrogen from natural gas. Reduced sales of ICEVs, HFCEVs and other powertrains (mostly hybrids and flex–fuel vehicles running both on conventional liquid fuels and biofuels) are compensated by increased sales of BEVs. This substitution pattern peaks around 2040 with about 2.4 million units (Figure 5.1c). Sales of ICEV light trucks experience the strongest decline, and are equally compensated by BEV cars and trucks. The cumulative amount of avoided ICEVs and HFCEVs amounts to nearly 29 and 9 million units. We explore a range of side cases in which (a) only energy–chain emissions instead of full life–cycle emissions are priced, (b) hydrogen production becomes carbon–neutral by 2050, (c) HFCEVs become cost–competitive with BEVs, as well as different combinations thereof. We display three of these cases in Figure D.6.

The mentioned substitutions of technologies lead to substantial reductions in cumulative life–cycle emissions through 2050 (– 1.6 Gt CO_2, Figure 5.2a and f), largely driven by reduced fuel combustion (– 1.4 Gt CO_2, Figure 5.2b and g) and decreased production of gasoline and hydrogen (– 0.5 Gt CO_2, Figure 5.2c and h). While increased sales of BEVs lead to growing electricity emissions (+ 0.25 Gt CO_2, Figure 5.2d and i), these are however relatively small compared to the reductions achieved in fuel production (– 0.5 Gt CO_2, Figure 5.2k). Finally, since BEVs are material intensive, an additional 30 Mt CO_2 embodied in vehicle production can be observed. However, increased production emissions could be more than compensated by ambitious recycling and reuse practices (+ 0.03 vs. – 0.5 Gt CO_2, Figure D.3). We explore a range of side cases (Figure D.6)

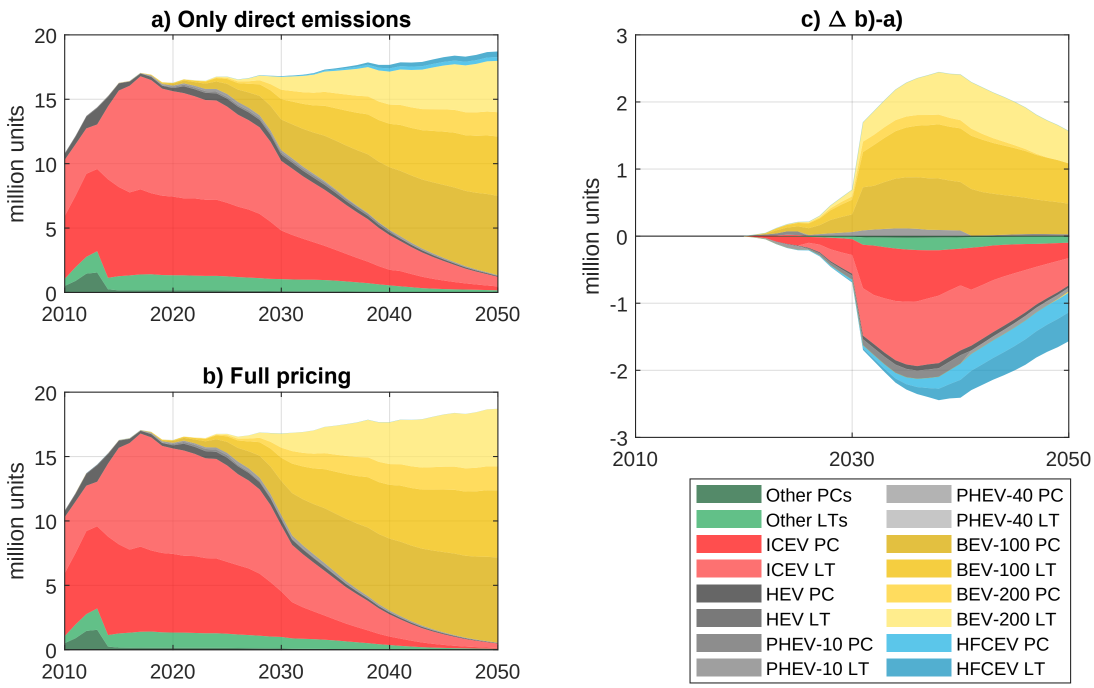

Figure 5.1: Optimal vehicle choice under direct–emissions–only pricing (a) and full emissions pricing (b). (c) Differences in vehicle choice between (b) and (a). PC=passenger car; LT=light truck; ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –100=100–mile range.

which show some variation in their potential for emission reductions (also see dotted lines in Figure 5.2) but the overall trend is robust among all cases. Accordingly, additional cumulative life–cycle emission reductions can vary between − 1.4 to − 1.7 Gt CO_2 across all cases (see dotted lines in Figure 5.2f) on top of emission reductions already achieved under pricing direct emissions only. In Figure 5.2k, the differences in emissions between ‘full pricing’ and ‘direct–emissions–only pricing’ are once more plotted by life cycle stage, while in Figure 5.2l, all sources of indirect emissions, i.e. production of fuels, electricity and vehicles, are categorized as such. It becomes apparent that ‘full pricing’ not only leads to reduced tailpipe emissions, but also to lower indirect supply chain emissions, at least after about 2035.

5.3 Fleet efficiency

The future of the Corporate Average Fuel Economy (CAFE) standard is currently highly uncertain and we therefore do not model changes to CAFE after 2025. While the Trump administration enacted the Safer Affordable Fuel Efficient (SAFE) standard in

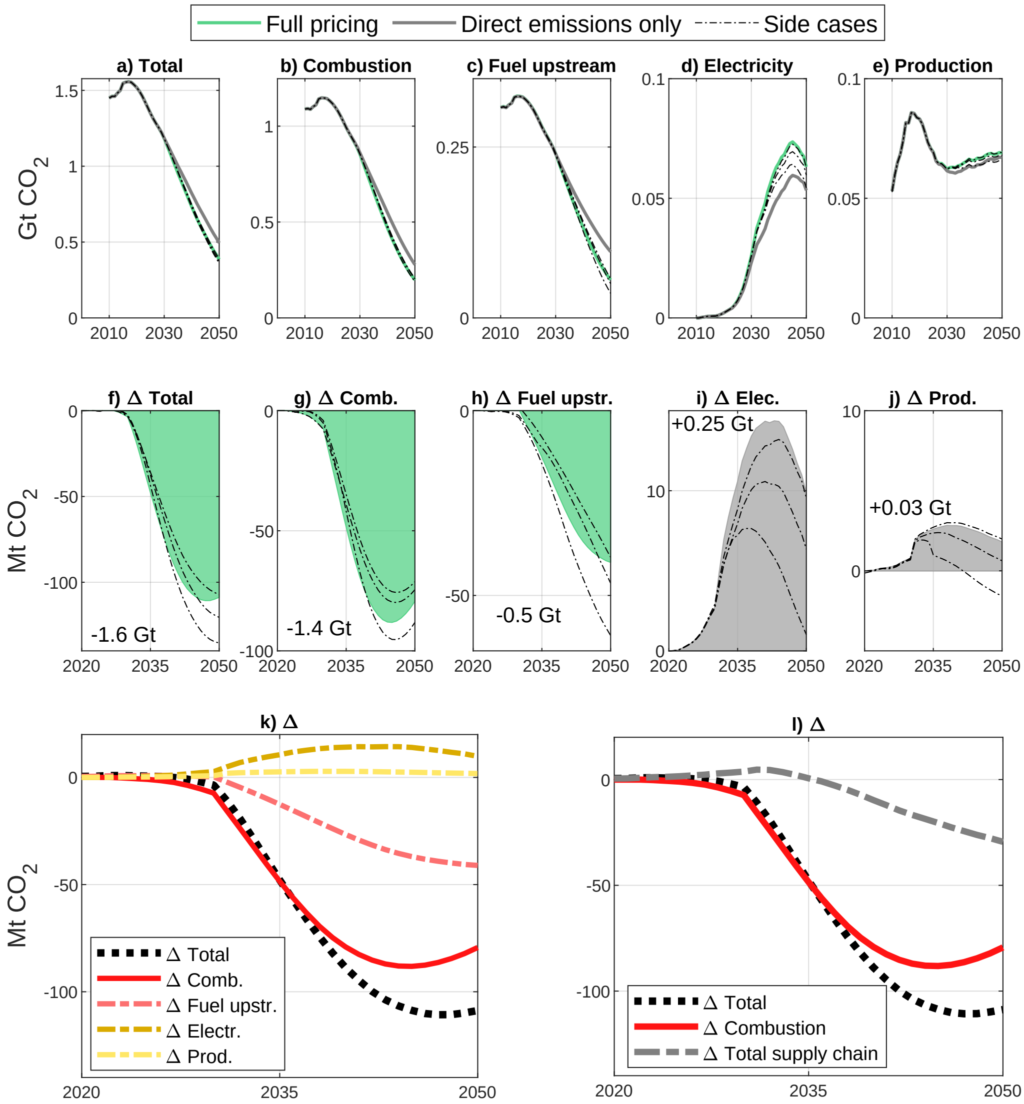

Figure 5.2: Life–cycle CO_2 emissions of the US light vehicle fleet, total (a) and broken down by life–cycle stage (b–e) when fully pricing emissions and when only pricing direct emissions. Differences in emissions between full and direct–emissions–only pricing (f–l). Dotted lines illustrate results from side cases (a–j).

2018, freezing the 2020 CAFE requirements through 2026, the Biden administration announced to re–introduce CAFE but further details are unknown at the time of writing. Despite the absence of a CAFE standard after 2025 in our model, average real–world fuel economy[233] of the fleet continues to improve greatly in all scenarios, even after 2025 (Figure 5.3). This can be explained by the strong market penetration of BEVs. When full life–cycle emissions are optimized for, average fuel economy is even higher compared to direct–emissions–only pricing due to the accelerated penetration of BEVs. Side cases with higher shares of HFCEVs however exhibit significantly lower average fuel economies

(Supplementary Table 12). Other fleet characteristics, such as average vehicle weight, lightweighting through material substitution, segment shares, and total travel demand, are less impacted by the different accounting approaches (Figure D.10).

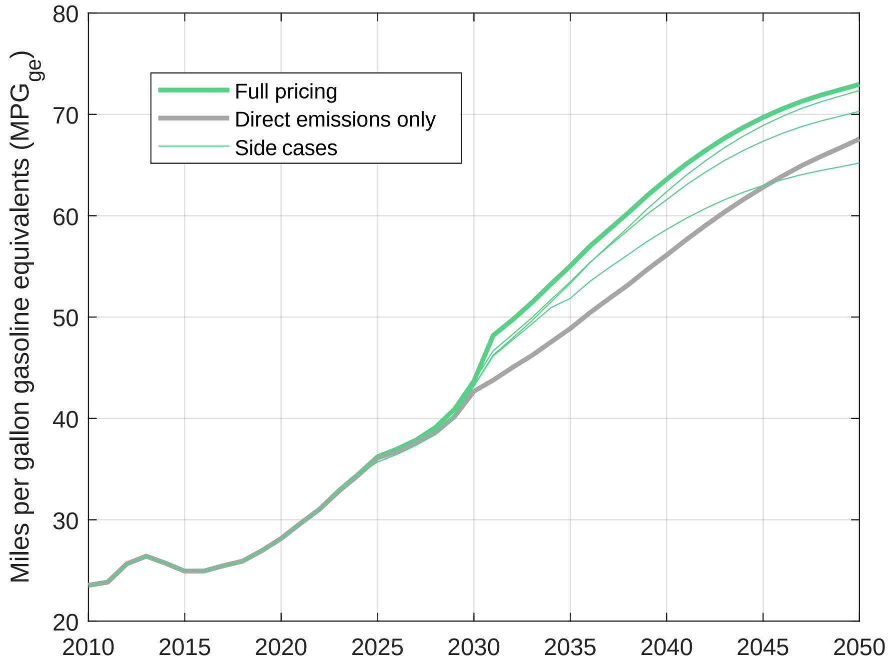

Figure 5.3: Average real–world fuel economy of the US light vehicle fleet when all emissions are priced and when only direct emissions are priced. The thin green lines show the range of results from the side cases.

5.4 Resource use implications

Fully pricing life cycle emissions would have important implications on resource use, too (Figure 5.4). For example, gasoline and diesel consumption would be reduced by 29% and 32% in 2050 (26–32% and 30–39% in the side cases) compared to optimizing for direct emissions only. Further, while hydrogen demand would generally be reduced by 99.9% (– 98.0 to + 327.0%), electricity use would increase by 18% (2–18%). Overall, a 7% reduction in energy consumption can be achieved (1–6%). Meanwhile, a slight increase in overall material demand by 2.1% (0.8–2.0%) can be observed, with the strongest relative increase for copper (4.7%, with a range between – 0.7 to + 5.0%). This is largely due to increased BEV sales (by 9.1%, with a range of – 6.1% to + 9.3%, Supplementary Table 17).

In absolute terms the difference between the two main scenarios ('full pricing' vs.

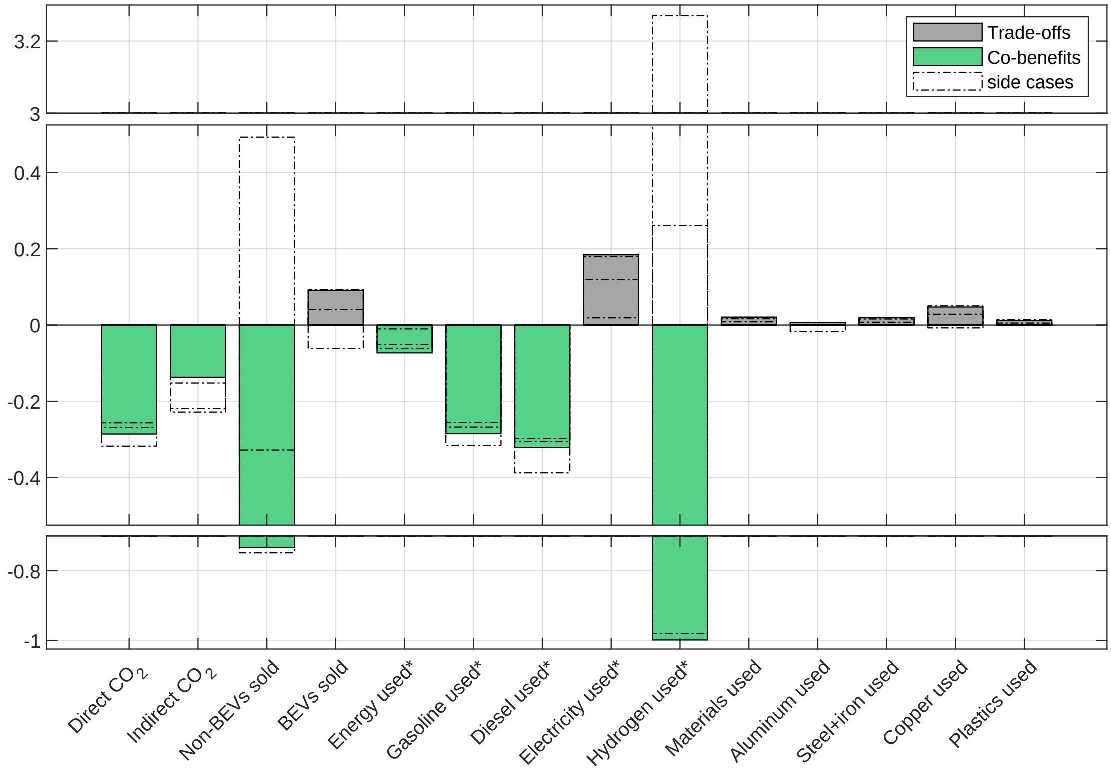

Figure 5.4: Normalized co–benefits and trade–offs of full pricing relative to direct–emissions–only pricing in 2050 (colored bars). The hollow bars show the normalized differences of the side cases relative to direct–emissions–only accounting in 2050. BEV=battery electric vehicle; *=on–board energy.

'direct emissions only') is a cumulative reduction of gasoline consumption by 0.15 trillion gallons or 0.6 trillion liters, roughly corresponding to three years of current (2019) annual US gasoline consumption (55 million gallons/0.2 trillion liters). Similarly, 0.8 PWh (trillion kWh) of hydrogen are saved, while electricity consumption increases by 3.2 PWh, roughly corresponding to the current annual amount of electricity end use in the US in 2019. Cumulative material use for vehicle production moderately increases by about 24 Mt, which is chiefly driven by the increased stock of material–intensive BEVs. This increased material demand is partially mitigated by a slightly decreasing average vehicle weight (Figure D.10a). Material substitutions due to vehicle lightweighting (Figure D.10b) lead to a minor increase of aluminum and plastics, and a reduction of steel and iron. Overall, the strongest absolute increase can be observed for stainless steel (+ 13.2 Mt), followed by copper (+ 3.1 Mt), aluminum (+ 1.6 Mt) and plastics (+ 1.2 Mt). Simultaneously, use of automotive steel and cast iron falls slightly by 1.0 Mt. However, more ambitious recycling and reuse practices have the potential to more than offset this increased demand of virgin materials by about 740 Mt (Section D.1).

5.5 Adequacy of analyzed decarbonization measures

Emission reduction required to halt climate change are sometimes framed through the carbon budget — the amount of emissions remaining until the atmosphere reaches an identified temperature threshold. Under the described cases, the US LDV sector would require 3–5% of the global carbon budget identified by the IPCC,[23] which is about as much as its share of current emissions (Supplementary Table 16).

5.6 Discussion

To date it is largely unknown to what extent indirect emissions shape optimal decarbonization pathways[22] and vice versa. Previous work focusing on electricity supply reported a limited role of indirect emissions in climate change mitigation scenarios.[170,171,226] Here we explore the role of indirect emissions in decarbonization efforts of the US passenger vehicle fleet and find that they can in fact significantly alter optimal climate change mitigation pathways. An important difference between the electricity supply sector and the LDV sector is that indirect emissions play a larger role, accounting for about a quarter of total life–cycle emissions already today. In our scenarios, indirect emissions make up almost half of total LDV sector CO_2 emissions in 2050 (44–49%) and about 24–29% of cumulative emissions over the 2010–2050 scenario time frame (Supplementary Table 16). For comparison, McDowall et al. report that indirect emissions would account for less than 10% of total life–cycle power plant emissions in 2050 in a decarbonization scenario of the EU.[170]

Although overall life–cycle emissions are reduced significantly under full emissions pricing, indirect ones can increase, most prominently from electricity generation and battery manufacturing due to strong penetration of BEVs. However, increased electricity emissions are more than offset by reduced gasoline supply–chain emissions stemming from exploration, transportation and refining of crude oil (Figure 5.2k). Increased emissions from material production and vehicle assembly could be more than offset by increased material efficiency efforts including more ambitious material recycling and reuse of components. While it is expected that direct emissions of BEVs are lower than those of ICEVs, it is surprising that in fact also non–tailpipe emissions are lower (Figure 5.2l). This sheds new light on the current public debate about 'dirty' batteries and electricity.[7] In fact, the simultaneous reduction of both direct and indirect emissions from the LDV fleet indicates a win–win situation, meaning that climate policy with very high shares of BEVs represents a no–regrets strategy. Our insights are therefore highly relevant for global climate and transport policies. Current policies, such as performance standards or emission pricing schemes, should be broadened in their scope in order to regulate all sources of vehicle emissions along the entire vehicle supply chain. Our scenarios further indicate that the US (and likely other nations with suitable low–carbon electricity grids) should target deployment of BEVs and largely disregard competing technologies. HFCEVs could offer a viable alternative if costs to produce fuel cells and low–carbon hydrogen would fall considerably in coming years.

Our work represents a first step towards a holistic inclusion of dynamic life–cycle relationships in integrated modelling frameworks. Future research could include further potentially important factors and processes, such as deployment of carbon capture and storage (CCS) at fuel refineries, differences in emission intensities of hydrocarbons, synthetic liquid fuels, net–negative emission pathways of energy production, and low–carbon steel production using hydrogen from renewable sources. Future research should also investigate to what degree results would differ in various regions of the world, or if other pollutants were internalized in optimal choice routines.

5.7 Methods

5.7.1 Demand–side framework

We address calls for a stronger research focus on demand–side solutions for mitigating climate change.[234] Specifically, we apply and specify a novel, transdisciplinary demand–side assessment framework focusing on an important emitting sector.[104] Our framework addresses the following key areas: (1) End–use context: we focus on demand–side solutions,

[7] https://www.bloomberg.com/news/articles/2018-10-16/the-dirt-on-clean-electric-cars

with the US LDV fleet as a case study. (2) Technology: we use industrial ecology methods to model full life cycle CO_2 emissions and costs of all major established and emerging vehicle technologies. This enables us to test the potential of different technological mitigation measures along the entire vehicle supply chain including powertrain switching, changes in material composition, recycling of materials, reuse of vehicle components, and feedstock switching for fuel and electricity production. (3) Policy instruments: Carbon pricing is applied to either tailpipe emissions, or the entire vehicle life cycle. (4) Climate change mitigation pathways: We present climate change mitigation scenarios of the US LDV sector and analyze the contribution of several mitigation measures towards the US NDC and a 2°C consistent US LDV sector. (5) Sustainable development: We highlight synergies with other sustainability indicators such as resource use, energy use and consumer cost.

5.7.2 Integrated energy modelling

Our tool of choice is NEMS which is the model behind the well–known Annual Energy Outlook.[141] Here we use a slightly altered version running on a server at Yale University (Yale–NEMS).[235,236] Yale–NEMS sets prices so that annual energy supply equals energy demand (general equilibrium) through 2050. The main energy demand sectors are residential buildings, commercial buildings, transport and industry. Projections of economic drivers are provided exogenously while world energy prices, world energy supply and demand, and US energy imports and exports are calculated endogenously. Yale–NEMS provides a full account of CO_2 emissions across all industries and a range of air pollutants from vehicles and power plants.

Transport sector modelling The transport sector includes several modes of travel, such as LDVs, aviation, trucking, shipping, and rail. The LDV submodule distinguishes twelve vehicle sizes, 86 fuel efficiency technologies, as well as sixteen alternative propulsion technologies including BEV–100 (100–mile electric range), BEV–200, PHEV–10, PHEV–40, HEV, and HFCEV. Various fuel pathways are modelled as well. The LDV submodule uses a discrete choice formulation to simulate both the behavior of vehicle manufacturers and consumers. Manufacturers make production decisions based on technology cost, CAFE requirements and potential regulatory costs, while consumers base purchase decisions on energy prices, charger and fuel station availability, vehicle purchase prices and a range of other vehicle attributes. Further details on the mainline NEMS and a direct comparison with other IEMs can be found elsewhere.[7] Here we make several refinements to Yale–NEMS' LDV submodule: We update vehicle costs in a bottom-up fashion using detailed cost estimates for all major vehicle components, such as engines, electric motors, transmissions, fuel cells, and hydrogen storage tanks.[73,129] Further, costs of lithium–ion batteries start out at about 465 USD/kWh in 2016 and reach floor costs of ∼83 USD/kWh over the modelled time horizon due to economies of scale and technological development. This cost development is within the range of recent estimates.[137]

Modelling upstream sectors The electricity market module considers all major fossil and renewable generators, including conventional, and advanced coal and gas power plants with and without CCS, nuclear, hydro, solar thermal, solar photovoltaics (PV), and on– and offshore wind power. In our scenarios we assume that overnight capital costs of solar PV and onshore wind power plants fall from around 1,245 and 1,230 USD/kW in 2019 down to about 370 and 540 USD/kW by 2050 due to economies of scale and technological developments. This cost development is within the range of recent estimates.[237,238] As a result, new power plant capacities are mainly provided by renewable electricity generators (Figure D.9a), while fossil–fueled power plants retire (Figure D.9b). Thus, renewables provide more than half of all electricity well before 2030 and more than three quarters by 2050. The remaining electricity demand in 2050 is mainly met by natural gas (16%) and nuclear power (6%), while coal is almost entirely phased out (1.5%, see Figure D.7 and Supplementary Table 18). A small percentage of electricity from coal is generated at CCS–equipped plants. Electricity is not only produced in the power supply sector but also in the residential and commercial end–use sectors — a feature that sets Yale–NEMS apart from other IEMs[229] — with the main technologies being rooftop solar PV and distributed natural gas. While electricity demand grows from almost four to more than six trillion kWh, an increase by more than half, electricity emissions fall from almost 2,400 to below 290 Mt CO_2, a reduction of 88%. As a result, the carbon intensity of the electricity mix falls by a factor of twelve, from 546 down to 45 g CO_2/kWh (Figure D.6 and Supplementary Table 18).

5.7.3 Determining a carbon price

We introduce a price on carbon in the transport sector in 2021 which linearly increases up to 150 USD/t CO_2 by 2050 (constant 2016$, Supplementary Table 9) — a level required to meet the US NDC under the Paris Agreement. The US is committed to reduce CO_2 emissions by 80% by 2050 relative to 2005. We assume that all sectors equally attempt to reduce their emissions by that percentage. According to the US EPA, direct CO_2 emissions from the US LDV fleet amounted to 1,180 Mt in 2005.[239] The growing carbon price leads to a significant cost increase of energy carriers, especially of gasoline (Figure D.8b). Combined with the cost reductions of electric vehicle batteries and renewable power plants, our assumed carbon price leads to reductions of direct CO_2 emissions on the order of 76–84% in 2050 relative to 2005, depending on the specific scenario (Supplementary Table 16).

5.7.4 Soft–linking Yale–NEMS with LCA

We soft–link Yale–NEMS to a detailed passenger vehicle LCA model[18] and iterate between the LCA model and Yale–NEMS until inputs and outputs converge between both models. The LCA model covers CO_2 emissions of all major technologies across the entire vehicle life cycle, including fuel production and combustion, electricity generation (Supplementary Table 5), material production and recycling (Supplementary Tables 4 and 7), assembly and reuse of vehicle components (Supplementary Tables 2, 6 and 8), and lightweighting through material substitution (Supplementary Tables 3 and 11).

Inputs from Yale–NEMS into LCA (1) In a first iteration we calibrate the LCA model to the US case by using the following Yale–NEMS outputs as calibration coefficients: (1) Vehicle baseline weights (without lightweighting, Supplementary Table 1),

(2) the expected degree of vehicle lightweighting (substitution of conventional materials with lightweight materials, Supplementary Table 11), (3) current and future on–road energy consumption (Supplementary Table 1), (4) current and future battery sizes (Supplementary Table 1), (5) current and future carbon intensity of electricity generation used to manufacture vehicles and charge BEVs (Supplementary Table 18), and (6) carbon prices (Supplementary Table 9). Taking these variables into account, the LCA model calculates per–vehicle life–cycle carbon emissions (Figures D.1 and D.2) and translates these into life–cycle carbon prices for each technology (Figure D.5 and Supplementary Table 10).

Inputs from LCA into Yale–NEMS The obtained carbon prices are then linked back to Yale–NEMS for consideration in the vehicle choice procedure of the LDV submodule. Specifically, carbon prices on indirect emissions are implemented in Yale–NEMS as a so–called 'feebate'. Feebates are regarded as one of the most effective policy instruments to reduce vehicle emissions.[240–242] Feebate systems impose a fee on vehicles with high CO_2 emissions and grant a rebate to low–carbon vehicles. Here we apply that design to both the production of vehicles and energy carriers separately. First, if the production of any alternative vehicle technology a is more carbon–intensive than the production of an ICEV, a fee is added to the purchase price of a, otherwise a rebate is granted. Second, if the production of the energy source that is used in a over a's lifetime is expected to create more CO_2 than the production of gasoline used in an ICEV, then an additional fee is added to a's purchase price, while a rebate is provided otherwise. For example: A fee is imposed on the production of BEVs, largely due to the energy– and material–intensive battery. This fee is increasing with the growing carbon price, from about 9–15 USD/BEV in 2021 to about 120–210 USD/BEV in 2050, depending on vehicle and battery size. A rebate is however granted due to the production of electricity that the BEV is expected to charge over its lifetime. This rebate is growing strongly each year as electricity quickly decarbonizes — from about 400 USD/BEV in 2021 to ~2,600 USD/BEV in 2050 (Figure D.5 and Supplementary Table 10). This way, these price mark–ups (or credits) become part of the decision–making process of vehicle manufacturers and consumers and influence both vehicle production and sales in Yale–NEMS. Note that due to the large uncertainties involved we do not attempt to estimate the costs of electric vehicle chargers[73] (especially when allocating a certain fraction of the cost of public chargers to individual BEVs and PHEVs), nor do we attempt to estimate how strongly consumers would discount future costs.[242] We do however acknowledge that these factors could influence consumer choice. Since we wish to present our results in isolation of these factors we leave it for future research to quantify the influence of these effects.

Inputs from Yale–NEMS into LCA (2) In a second iteration of the LCA model, total vehicle sales by technology and segment, and total energy use by energy carrier are extracted from Yale–NEMS and fed back into the LCA model. In addition, any vehicle characteristics that have been altered by the the life–cycle carbon price implemented in Yale–NEMS, such as vehicle weights (Figure D.10), are updated in the LCA model accordingly. As a result of the second LCA model run, total indirect emissions of vehicle and energy production over time are obtained (Supplementary Table 16). Tailpipe emissions and emissions from electricity use are taken directly from Yale–NEMS (Supplementary Table 16).

Author contributions

P.W. conceived and designed the experiments, performed the experiments, and analyzed the data. P.W. and S.W. contributed materials/analysis tools. P.W., K.G. and E.H. wrote the paper.

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6 Conclusions

6.1 Brief summary of results

This thesis contributes to a better understanding of future emissions of low–carbon vehicle systems in several ways. For example, this work confirms the importance of the infrastructure that enables a transition toward low–carbon vehicle fleets, such as wide–spread availability of renewable energy (Chapters 2, 3, and 5) and electric chargers (Chapter 3). This thesis further highlights the importance of material efficiency (Chapters 2 and 5) and fueling behavior (Chapter 3). Furthermore, it is highlighted that models of climate change mitigation commonly model these fine–grained processes in a more aggregated way, while omitting important linkages between the passenger vehicle sector and various other economic sectors (Chapter 4). This can lead to technology assessments that do not fully capture the emission benefits and trade–offs of various technological alternatives. This in turn can raise the risk of misleading technology recommendations (Chapter 5), which are an integral part of transport and climate change mitigation policies.

6.2 Policy implications

The results of this thesis can therefore inform future policies and guide investments into vehicle technology portfolios and their supporting infrastructure. Current policies generally fail to systematically consider all sources of emissions along the supply chain. For example, fuel economy standards have imposed increasingly stricter specific efficiency and tailpipe emission targets for light-duty vehicles. However, while these resulted in more efficient vehicles per mass, vehicles became heavier at the same time, which negated efficiency gains and led to increased vehicle production emissions. In addition, tailpipe emissions of electric vehicles are assumed to be zero even though no control mechanisms are in place that ensure that they are at least partially charged with renewable electricity. Therefore, electric cars can be used by manufacturers as 'balancing vehicles' while selling increasingly bigger conventional vehicles and still meeting average fleet emission targets. More recently, the Low Carbon Fuel Standard and the Renewable Fuels

Standard have been introduced to regulate supply chain emissions in addition to tailpipe emissions. However, their coverage is not comprehensive. For example, the Renewable Fuels Standard only regulates conventional and biofuels. California's Low Carbon Fuels Standard[8] also regulates electricity emissions but not vehicle production emissions, and is not implemented nation–wide in the US. This can lead to leakage effects, i.e. export of high–carbon energy sources from California to other regions. Leakage can also occur as a result of the current carbon tax landscape, which only covers certain regions and sectors in the US and worldwide. For example, some US states cover utility companies but not other polluting sectors, such as transportation or oil production. This perverse incentive makes gasoline–powered cars relatively more attractive compared to electric cars, therefore potentially leading to higher emissions in the transport sector. This work shows that a comprehensive consideration of all supply chain emissions in policy design would effectively incentivize car manufacturers and consumers to transition towards fuel and vehicle technologies with the lowest overall emissions. Therefore, policies should target *all* sources of vehicle emissions along the entire supply chain.

6.3 Recommendations for future research

This work offers a first step towards a holistic integration of detailed life–cycle relationships with climate change mitigation models (Chapter 5). It opens up several opportunities for additional improvements, for example:

- Modelling of novel vehicle technologies, such as longer range (300–400 miles) battery electric vehicles, plug–in fuel cell vehicles operating on both hydrogen and electricity, and automated vehicles.
- Including additional energy production pathways, such as carbon capture and storage at fuel refineries, differences in emission intensities of hydrocarbons, synthetic liquid fuels, and net–negative energy carriers.
- Representing additional material production pathways, such as low–carbon steel

[8]Similar regulatory approaches have also been implemented in British Columbia, the United Kingdom, and the European Union.

production using hydrogen from renewable sources, and the use of fly ash in concrete production.

- More accurate modelling of consumers, such as driving, charging, fueling and vehicle–purchase behavior, technology substitution, as well as overall vehicle and travel demand. These are in part determined by, and therefore require detailed modeling of, socio–economic factors, technology costs, energy prices, the expansion and maintenance of road networks, the distribution of (alternative) fuel stations, and the availability of sharing services and automated driving.

- Consumer preferences, technology costs, infrastructure and regulations in turn affect production decisions of vehicle manufacturers, which is another area that may require improved modelling. Manufacturers not only have to decide on which powertrains to produce but also on vehicle manufacturing techniques and design, including material choice, sourcing of virgin versus recycled materials, and purchasing new versus remanufactured vehicle components.

- A more complete linking of emissions and physical outputs from industry, agriculture, and energy conversion directly to the passenger vehicle sector. Modelling of interdependencies with other transport sectors, such as public transport, aviation and freight transport, needs attention, too.

- Including the impacts of traffic, ambient temperature and climate change on deployment and mitigation potentials of various technology options.

- Extending the study of life–cycle relationships in optimal climate change mitigation to other climate–relevant sectors, such as housing, industry or agriculture, and to other global regions.

- Internalizing additional pollutants, other than carbon dioxide, in optimal choice routines.

- Further research is also needed on the optimal amount of processes to be included in integrated models, and how specifically process models should be linked to large–scale integrated models. Increasing integration of models will further require stronger collaboration of different modelling communities. More transparent scientific publications and supporting technical documentations, as well as publicly available data and source codes will be of growing importance, too.

Performing the above mentioned steps could help to further improve our understanding regarding which technologies should be promoted in order to achieve climate targets in a cost–effective way without raising the risk of unintended consequences.

A Appendix to Chapter 2

A.1 Additional methods

A.1.1 Deriving life–cycle emission factors

Tables 2.1 and 2.2 in the main text specify the life–cycle emission factors of materials and energy carriers assumed in this work. In this section we discuss and/or derive the used coefficients. We start by discussing current and future emissions factors of materials and then proceed with deriving emission factors of energy carriers.

- **Virgin materials:** Future emission factors for virign aluminum, steel and other materials are based on the work by Vandepaer and colleagues.[62] The coefficients have been derived by assuming that low–carbon electricity is used to produce the materials. Since production of primary aluminum is very electricity intensive,[243] aluminum achieves a higher GHG emission reduction compared to the other materials. Other materials may further reduce their GHG intensity by employing yet immature, uncertain or untested methods. For example, the GHG intensity of steel could be further reduced by direct iron reduction using renewable hydrogen,[92] a method that is not currently cost–competitive.[91]

- **Recycled materials:** According to Kim et al.,[33] recycling of steel, cast aluminum, and wrought aluminum can reduce GHG emissions by about 68–82%, 88–97% and 90% relative to the production of virgin materials, while in the GREET2 model,[58] reductions of 53%, 79% and 79% are assumed. Here we assume reduction potentials of 60%, 85% and 85% which are well within the range of the above estimates. For recycled plastics we assume a carbon intensity of 1.4 kg CO_2e kg^{-1}.[69] For recycled copper we assume 1.0 kg CO_2e kg^{-1}, which is well within the range of estimates reported by Ekman and colleagues.[70]

- **Electricity mix:** For the current electricity mix, we assume a life–cycle carbon intensity of 750 g CO_2e kWh^{-1}. This value is based on Ecoinvent v3.5 (process: 'market group for electricity, medium voltage, GLO', model: 'allocation, cut–off by classification'). This emissions factor is weighted by the emissions factors of individual global regions based on their share of global electricity production. The value is similar to the 740 g CO_2e kWh^{-1} assumed by Knobloch et al.[65] and the 720 g CO_2e kWh^{-1} reported by Itten et al.[244] which is based on a global electricity mix of about 66% fossil fuels, 15% nuclear, 16% hydro, and 3% other renewables. We note that a more appropriate emission factor would weight the regional vehicle fleet stock with the regional electricity emission factors.[65] This would more appropriately capture the regional distribution of vehicle stocks, and their agglomeration in regions such as the EU, US, and China. A low–carbon mix of 60 g CO_2e kWh^{-1} is assumed which roughly corresponds to the 2050 electricity mix in the SSP2/RCP2.6 scenario in Pauliuk and colleagues.[72] The value is based on modeling from the MESSAGE integrated assessment model.[245,246]

- **Hydrogen:** Hydrogen is assumed to emit 460 g CO_2e kWh^{-1} over the fuel life cycle.[73] This value represents a central steam methane reforming process in 2020 using natural gas as a feedstock, and assuming pipeline transport of 7,000 km.[71] Onboard reforming is not consdidered. We do not assume reductions in carbon intensity due to carbon capture and storage or due to a switch to renewable feedstocks.

- **Vehicle assembly energy mix:** Based on the GREET2 model[60] we assume that vehicles are assembled using an energy mix of electricity (51%) and heat from natural gas (46%) and coal (3%). The electricity used is the grid mix described above (750 / 60 g CO_2e kWh^{-1}). From Ecoinvent we estimate the carbon intensity of heat using natural gas to be 218 g CO_2e kWh^{-1} based on the average of two processes: (1) 'market group for heat, central or small–scale, natural gas, GLO', and (2) 'market group for heat, district or industrial, natural gas, GLO' (model: 'allocation, cut–off by classification'). The carbon intensity of heat from coal is 659 g CO_2e kWh^{-1} (model: 'allocation, cut–off by classification', process: 'heat production, hard coal briquette, at stove 5–15kW, RoW').[61] Finally, the overall carbon intensity of the vehicle assembly energy mix equates to 750 g CO_2e kWh^{-1}

$\times$ 0.51 + 218 g CO_2e kWh^{-1} $\times$ 0.46 + 659 g CO_2e kWh^{-1} $\times$ 0.03 = 503 g CO_2e kWh^{-1} (current) and 60 g CO_2e kWh^{-1} $\times$ 0.51 + 218 g CO_2e kWh^{-1} $\times$ 0.46 + 504 g CO_2e kWh^{-1} $\times$ 0.03 = 151 g CO_2e kWh^{-1} (low carbon). We do not consider further carbon intensity reduction of coal and gas due to carbon capture and storage.

- **Gasoline:** The life–cycle carbon intensity of gasoline is estimated at a constant 328 g CO_2e kWh^{-1}. The combustion and upstream portions are estimated at 256 and 72 g CO_2e kWh^{-1}.[7] The combustion portion has been derived by assuming an energy density of 11.997 kWh kg^{-1} (lower heating value) and the average CO_2 emitted during complete combustion of 1 kg butane, C_4H_{10}, and complete combustion of 1 kg dodecane, $C_{12}H_{26}$. The upstream portion is based on Wolfram and Hertwich.[7] The effects of increasing or falling gasoline carbon intensities are not considered here and have been documented elsewhere.[37,81]

- **Diesel:** The life cycle carbon intensity of diesel is assumed a constant 304 g CO_2e kWh^{-1}. The combustion and upstream portions are estimated at 260 and 44 g CO_2e kWh^{-1}. The former value has been derived by assuming an energy density of 11.969 kWh kg^{-1} (lower heating value) and the average CO_2 emitted during complete combustion of 1 kg octane, C_8H_{18}, and complete combustion of 1 kg pentacosane, $C_{25}H_{52}$. The latter value is based on Ecoinvent v3.5 (process: 'diesel production, low–sulfur'; model: 'allocation, cut–off by classification').[61]

A.1.2 Modelling of material efficiency strategies

In this section we provide further details on the modelling of selected ME strategies. Table A.1 details the material composition of conventionally designed and lightweighted vehicles, based on Burnham et al./GREET.[60] With regards to recyclability however we chose to model aluminum– instead of carbon fiber–intensive lightweighting. The main premise for this modeling decision is that, although carbon fiber recycling technology exists, markets for recycled carbon fiber are not as established as markets for recycled aluminum, leading to a large fraction of carbon fiber not being recycled under current conditions.[9] In addition, cost of carbon fiber is currently much higher compared to other materials.[29] We therefore replaced any carbon fiber in the original data set with aluminum. More details on how this has been done can be found in a technical documentation available online.[68]

Table A.1: Material composition of conventional and lightweighted vehicle archetypes.[58,60,68]

	Autom. steel	Stainl. steel	Cast iron	Wrought Al	Cast Al	Copper, el. grade	Plastics	Other
Conv.								
ICEV–g	0.62	0.00	0.10	0.02	0.04	0.02	0.11	0.08
ICEV–d	0.62	0.00	0.10	0.02	0.04	0.02	0.11	0.08
HEV	0.64	0.00	0.07	0.01	0.06	0.04	0.11	0.07
PHEV	0.59	0.00	0.07	0.03	0.06	0.05	0.02	0.18
BEV	0.57	0.00	0.02	0.04	0.05	0.06	0.10	0.16
HFCEV	0.57	0.03	0.02	0.02	0.03	0.03	0.12	0.17
Lightw.								
ICEV–g	0.31	0.01	0.04	0.23	0.17	0.03	0.13	0.08
ICEV–d	0.31	0.01	0.04	0.23	0.17	0.03	0.13	0.08
HEV	0.34	0.01	0.04	0.21	0.17	0.05	0.12	0.07
PHEV	0.31	0.01	0.03	0.20	0.16	0.06	0.11	0.12
BEV	0.19	0.00	0.03	0.25	0.17	0.08	0.13	0.15
HFCEV	0.22	0.02	0.03	0.30	0.18	0.05	0.14	0.05

Assumed shares of recycled content in automobiles are shown in Table A.2. Vehicle–specific values were only available for automotive steel and aluminum in a US context.[58] For stainless steel we used an expert estimate[247] and for plastics we used an estimate from Toyota Motors who state that 20% of their plastics are either recycled or plant based.[10] For cast iron and copper we use the lower values reported by Graedel et al.,[248] which are not necessarily specific to vehicles but still represent best available estimates. The copper value has also been confirmed by an expert.[249] Materials from end–of–life vehicles often are not functionally recycled but 'downcycled' for use in other applications, for example steel extracted from an end–of–life vehicle often becomes construction steel.[17,80] We also note that currently there are differences in the maturity of recycling processes (and thus in recycling potentials) for standard components such as the vehicle body and more specialized components such as batteries and fuel cells.[250] Due to a lack of data

[9] https://www.compositesworld.com/blog/post/the-state-of-recycled-carbon-fiber

[10] https://www.plasticsmakeitpossible.com/plastics-recycling/what-happens-to-recycled-plastics/use-of-recycled-plastics-in-cars-is-shifting-into-overdrive/

(on partly immature technologies) we were not able to consider these differences and use plausible estimates of aggregate recovery rates instead.

Remanufacturing rates (Table A.3) have been estimated by using the following approach: First, typical remanufacturing rates for components of Japanese vehicles have been retrieved from the work by Nakamura and colleagues.[251] These were then mapped to the vehicle material composition of vehicle components from the GREET2 model.[58,60] The resulting remanufacturing rates were further adjusted by the longer vehicle lifetime assumed in our work. Specifically, while Japanese light vehicles have a typical lifetime of about 79,300 km, here we estimate an average vehicle lifetime of around 180,000 km. The adjustment is based on the premise that a longer vehicle lifetime is correlated with a lower remanufacturing rate. Further details are available in an accompanying technical documentation.[68]

Table A.2: Estimated recycled content in vehicles by weight.[58,247–249]

Autom. steel	Stainl. steel	Cast iron	Wrought Al	Cast Al	Copper, el. grade	Plastics
0.26	0.41	0.30	0.11	0.85	0.20	0.20

Table A.3: Assumed remanufacturing rates by weight.[68,251]

	Autom. steel	Stainl. steel	Cast iron	Wrought Al	Cast Al	Copper, el. grade	Plastics
ICEV–g	0.13	0.00	0.20	0.18	0.15	0.16	0.14
ICEV–d	0.13	0.00	0.20	0.18	0.15	0.16	0.14
HEV	0.14	0.00	0.20	0.18	0.15	0.18	0.13
PHEV	0.14	0.00	0.20	0.19	0.15	0.19	0.13
BEV	0.12	0.00	0.09	0.19	0.12	0.19	0.12
HFCEV	0.11	0.19	0.09	0.20	0.12	0.17	0.11

A.2 Absolute and relative reduction potential of material efficiency

The following Figures complement Figure 2.4 in the main text. While Figure 2.4 showed exemplary results for vans/SUVs the following figures show absolute and relative results for all vehicle segments. Figures A.1 and A.2 illustrate the **absolute** reduction potential of ME strategies under **current** and **low–carbon** energy supply, while Figures A.3

and A.4 demonstrate the **relative** mitigation potential assuming **current** and **low–carbon** energy.

A.3 Vehicle emission intensities

In the main text we express vehicle carbon footprints as absolute direct and embodied emissions per person over the vehicle lifetime (t CO_2e person^{-1}). An alternative metric that is commonly used in transport policy is the amount of direct emissions per driven kilometer (g CO_2e vehicle–km^{-1}). This metric neither considers vehicle supply chain emissions, nor upstream emissions of energy carriers, but tailpipe emissions only. Tailpipe emission regulations in Southern Korea, the European Union, Canada and the US are targeting 95–99 g CO_2e per vehicle–km between 2020 and 2025. To better compare our results against this metric we convert absolute personal vehicle footprints into emission intensities per vehicle–km by dividing absolute footprints by the assumed vehicle lifetime mileage of 180,000 km and multiplying by 1.5 persons per vehicle. This gives us an emissions intensity metric (g CO_2e vehicle–km^{-1}) which differs from the one applied in transport policy in the sense that it considers the whole vehicle life cycle impact. Table A.4 shows life–cycle emission intensities of select vehicle options under current and low–carbon energy supply. It can be seen that several vehicle options already are in the range of 95–99 g CO_2e vehicle–km^{-1}, even when taking into account real–world energy consumption, which – according to our simulations – is roughly 30–40% higher than US06 test–cycle energy consumption. For example, the ICEV–d micro car reaches real–world tailpipe emissions of 96 g CO_2e vehicle–km^{-1}. The last two columns show the ratio of life–cycle emissions divided by real–world tailpipe emissions.

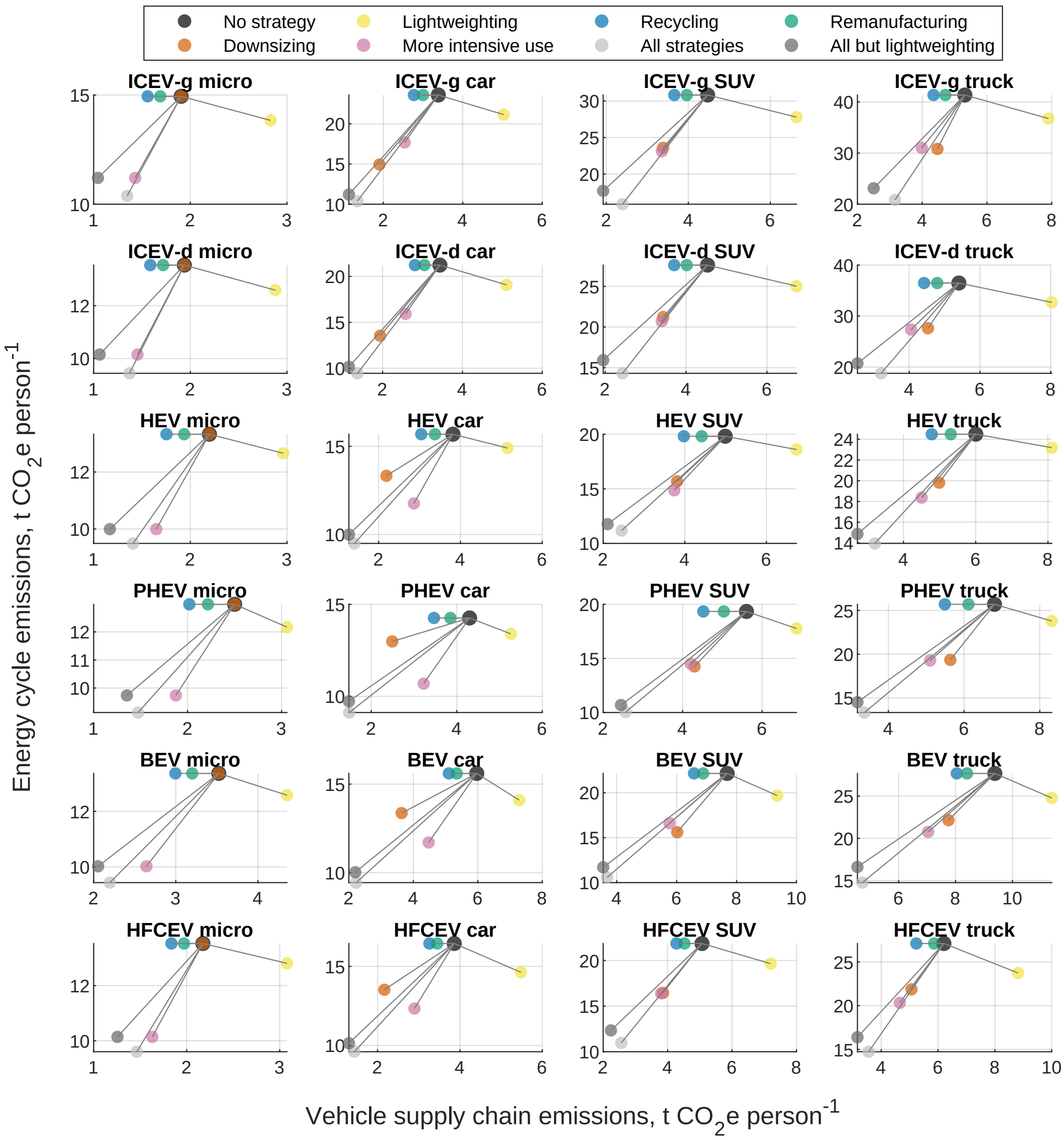

Figure A.1: **Absolute** effect of different material efficiency strategies on life–cycle emissions of various vehicle types under **current** energy supply. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel. Note: For micro cars, 'No strategy' is covered by 'Downsizing'.

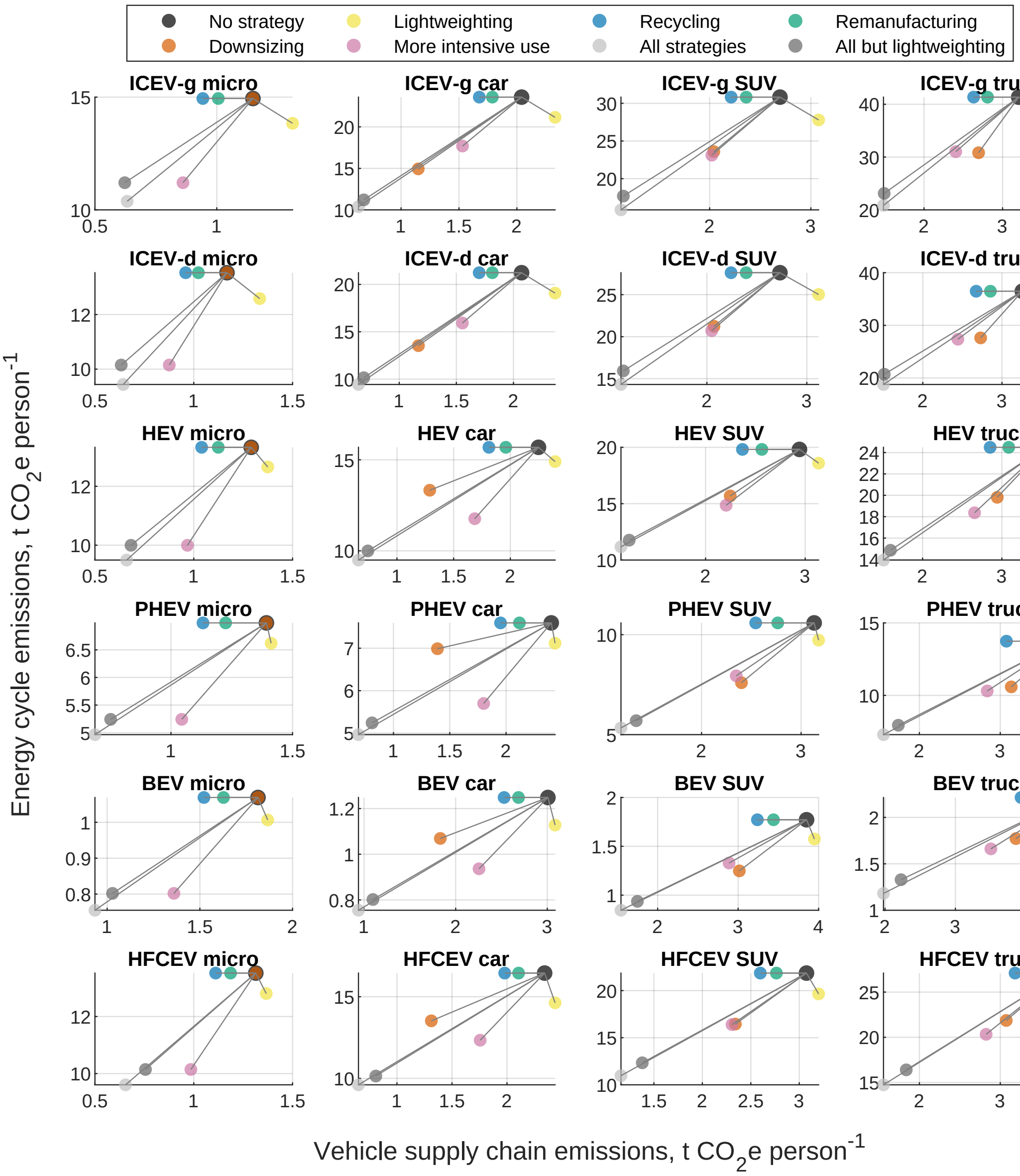

Figure A.2: **Absolute** effect of different material efficiency strategies on life–cycle emissions of various vehicle types under **low–carbon** energy supply. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel. Note: For micro cars, ‘No strategy’ is covered by ‘Downsizing’.

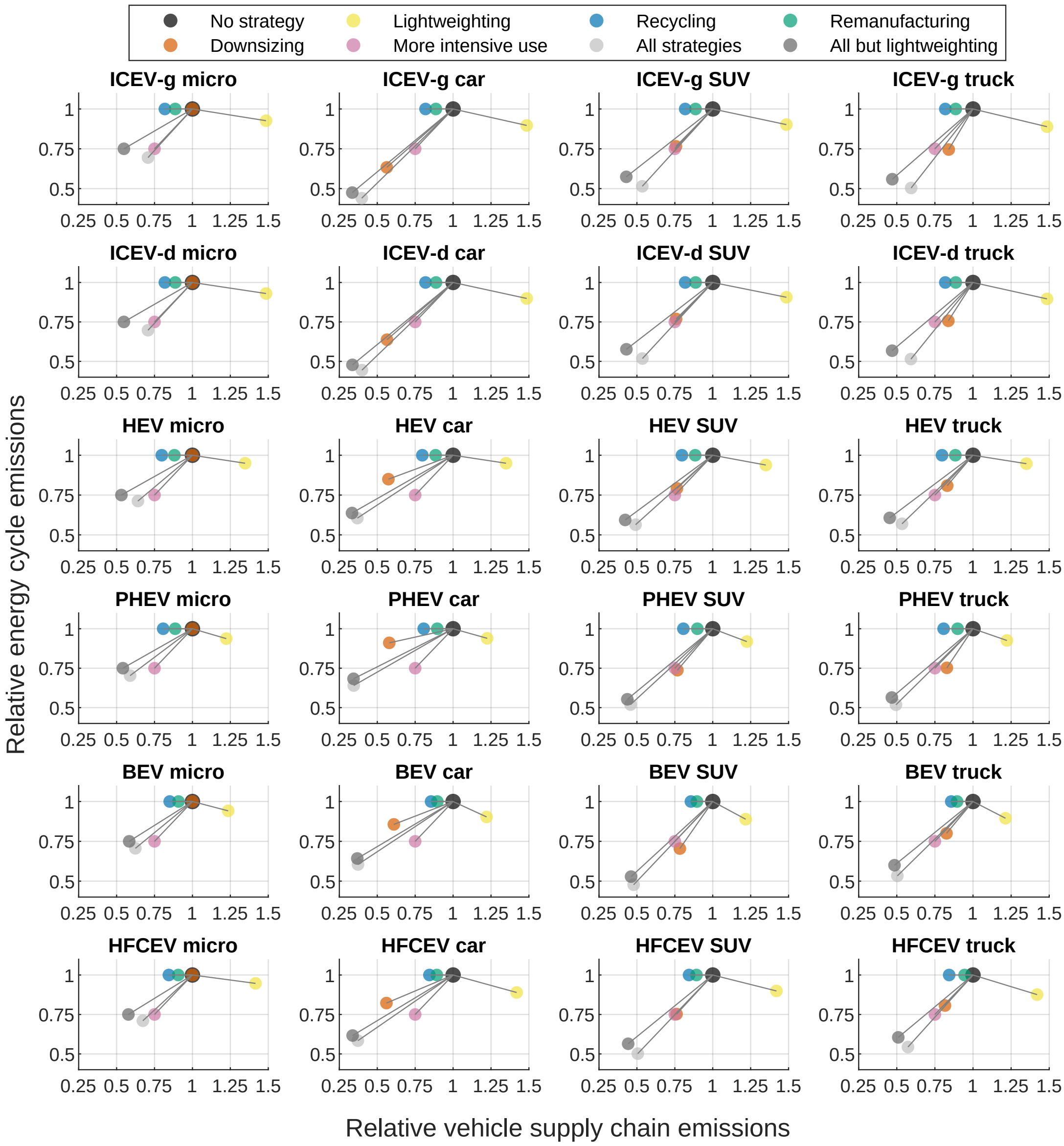

Figure A.3: **Relative** effect of different material efficiency strategies on life–cycle emissions of various vehicle types under **current** energy supply. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel. Note: For micro cars, 'No strategy' is covered by 'Downsizing'.

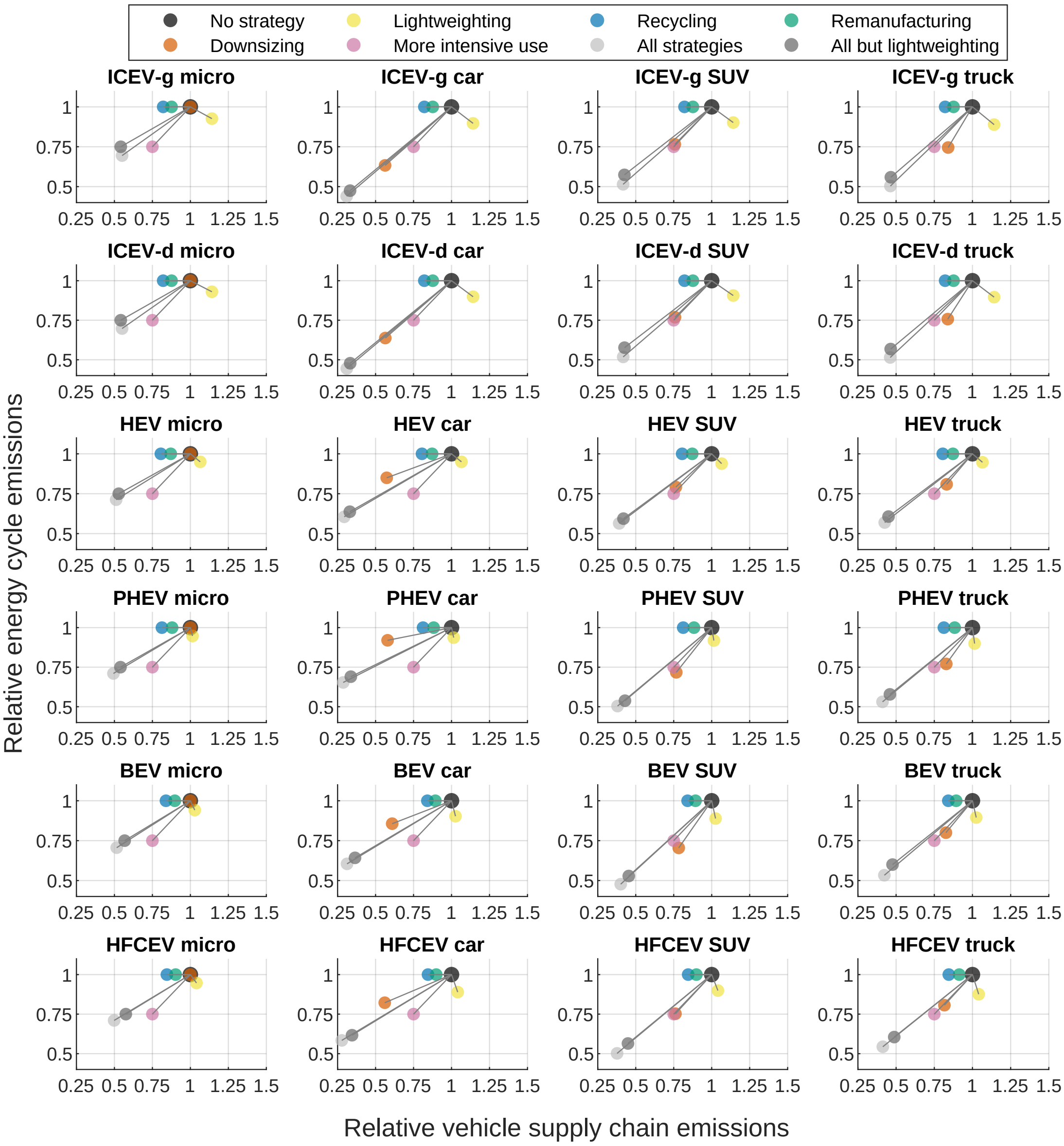

Figure A.4: **Relative** effect of different material efficiency strategies on life–cycle emissions of various vehicle types under **low–carbon** energy supply. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel. Note: For micro cars, 'No strategy' is covered by 'Downsizing'.

Table A.4: Life–cycle emission intensities of select vehicle options under current and low–carbon energy supply mix. All units are in g CO_2e vehicle–km^{--1}. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –d=diesel; BL=baseline; LW=lightweight.

		Life cycle		**Tailpipe (real–world)**		**Ratio**	
		Current	Low CO_2	Current	Low CO_2	Current	Low CO_2
ICEV–g micro	BL	140	134	97	97	1.4	1.4
	LW	139	126	90	90	1.5	1.4
ICEV–d micro	BL	129	123	96	96	1.3	1.3
	LW	129	116	90	90	1.4	1.3
HEV micro	BL	129	122	87	87	1.5	1.4
	LW	130	117	82	82	1.6	1.4
PHEV micro	BL	129	70	30	30	4.3	2.3
	LW	127	67	29	29	4.4	2.3
BEV micro	BL	141	24	0	0	–	–
	LW	141	24	0	0	–	–
HFCEV micro	BL	131	124	0	0	–	–
	LW	132	118	0	0	–	–

B Appendix to Chapter 3

B.1 Additional methods

B.1.1 Estimating future PHEV range

The BMW i3 REx is sometimes referred to as PHEV and sometimes as BEV with range extender (RE). Figure B.1 estimates the sales–weighted range of PHEVs with and without taking REs into account. The blue regression line includes sales of the i3 REx, while the grey regression line excludes the i3 REx. The blue line shows that the sales–weighted range of PHEVs varied between 40 and 56 km (25 and 35 miles) in the past with an average of about 48 km (30 miles). When considering REs (grey line), then the sales–weighted range is a bit higher and has an upward trend.

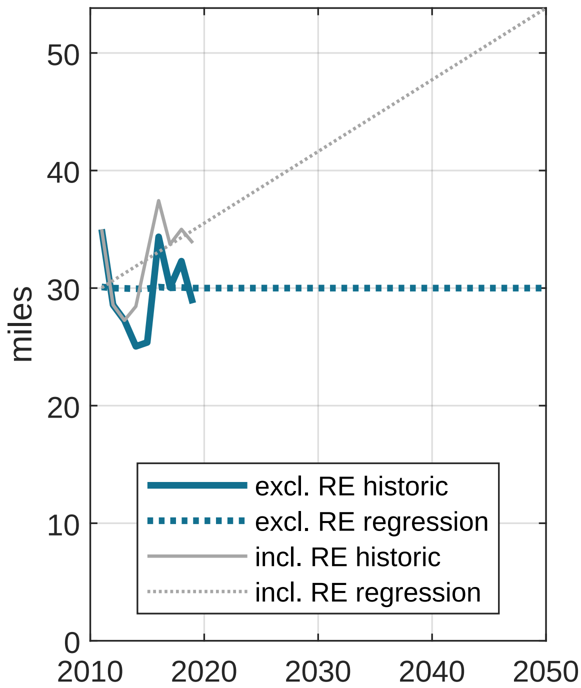

Figure B.1: Regression of PHEV range with and without RE. PHEV=plug–in hybrid electric vehicle; RE=range extender.

Here we assume the constant 30–mile range (blue line) for SSP5, mainly for two reasons: Firstly, the future of the range extended version of the i3 is uncertain. Some experts believe that the REx version may be discontinued due to recent advancements in the electric range of the i3 BEV without RE.[252] Secondly, most PHEV models announced for 2020/2021 do not come with an increased all–electric range over previous models,[253] indicating that future PHEVs may not necessarily offer longer electric ranges compared to current ones. Conversely, we assume that PHEV range in SSP1 closely follows the grey line and grows up to about 60 miles by 2050. In SSP2, PHEV range grows up to an intermediate 45 miles (compare with Figure 3.1a in the main text).

B.1.2 Scenarios of future UFs

In line with Plötz et al.,[114] MacPherson et al.[115] and EPA data[254] we estimate that a current PHEV with a 30–mile electric range yields a UF of about 0.6, while a PHEV–45 (45–mile electric range) reaches a UF of about 0.75, whereas a PHEV–60 can reach a UF of about 0.9. However, we also assert that certain factors could significantly reduce these UFs. For example, the International Transport Forum (ITF)[123] assumes that the UF of a current average PHEV–45 can be significantly reduced by about 45% if used as a ride–sourced vehicle (Lyft, Uber). Assuming that 20% of all future travel demand could be met by ride–sourced vehicles, a fleet–average UF of 0.75 could fall down to 0.7 ($.7 = .2 \times .75 \times (1 - .45) + (1 - .2) \times .75$). Furthermore, if future PHEV and BEV sales grow at a speed at which the deployment of electric charging infrastructure cannot keep up with, PHEV drivers may choose to drive more miles on gasoline. A limited network of chargers could potentially imply that certain chargers be reserved exclusively for pure BEVs.[11] If this effect would further reduce PHEV charging by 15%, the average UF of 0.7 could further drop to about 0.6 ($.6 = .7 \times .85$). These back–of–the envelope calculations need to be backed by more empirical data in the future, but nevertheless highlight the potential variation in average UFs of the PHEV fleet. Other influential effects may include potential future incentives for favorable fueling behavior, raising the UF, or increased use of PHEVs for business travels or as government vehicles, which in turn could lower the UF.

B.1.3 Estimating future battery costs

BEV batteries: As laid out in the main text, BEV battery packs are assumed to fall from about 600 USD/kWh in 2010 to 50 USD/kWh by 2050 in SSP1, 100 USD/kWh in

[11] https://www.carthrottle.com/post/experts-want-plug-in-hybrids-banned-from-public-chargers/

SSP2 and 150 USD/kWh in SSP5. The corresponding annual rates of cost reduction can be seen in Figure B.2a and b. The initial cost reduction rate is based on Nykvist and Nilsson[215] who report that costs declined by about 14% per year between 2007 and 2014. Cost reductions rates are assumed to fall more quickly in SSP5 and more slowly in SSP1.

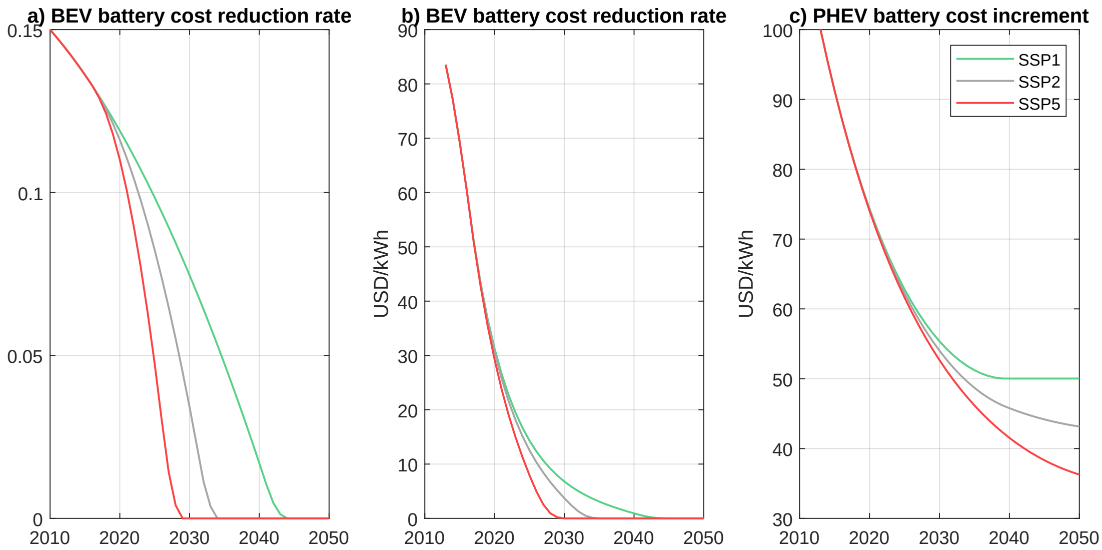

Figure B.2: Cost reduction rates of batteries. Relative (a) and absolute (b) cost reduction rates of BEV battery packs. Absolute cost increment of PHEV battery packs over BEV battery packs (c). SSP=shared socio–economic pathway. PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle.

PHEV batteries: As mentioned in the main text we assume that PHEV batteries are slightly more costly but their cost increment over BEV batteries falls over time (Figure B.2c). We further assume that this cost increment falls slower in SSP1, since investments are primarily targeted at BEV batteries, and faster in SSP5. More details can be found in a supplementary file at https://doi.org/10.1021/acs.est.0c03796.

B.1.4 Estimating a US carbon budget

Over the time period 2000–2050, a global carbon budget of roughly 1,000 Gt CO_2 yields about a 75% probability of staying below a global temperature increase of 2°C.[255] Assuming a grandfathering policy in which the US would be allowed to continue to emit 15% of global CO_2 emissions as has been the case historically,[12] the US would be assigned a carbon budget of 150 Gt CO_2. Assuming that annual per capita emissions were to

[12] https://www.globalcarbonproject.org/carbonbudget/19/highlights.htm

converge globally to equal levels by 2035–2050, the US carbon budget would shrink to roughly 80–100 Gt CO_2.[256] The US has pledged to reduce annual CO_2 emissions by 26–28% by 2025 and by 80% by 2050 relative to 2005 levels. As can be seen in Figure B.3, this commitment is roughly in line with the US carbon budget under grandfathering, assuming linear emission reductions.

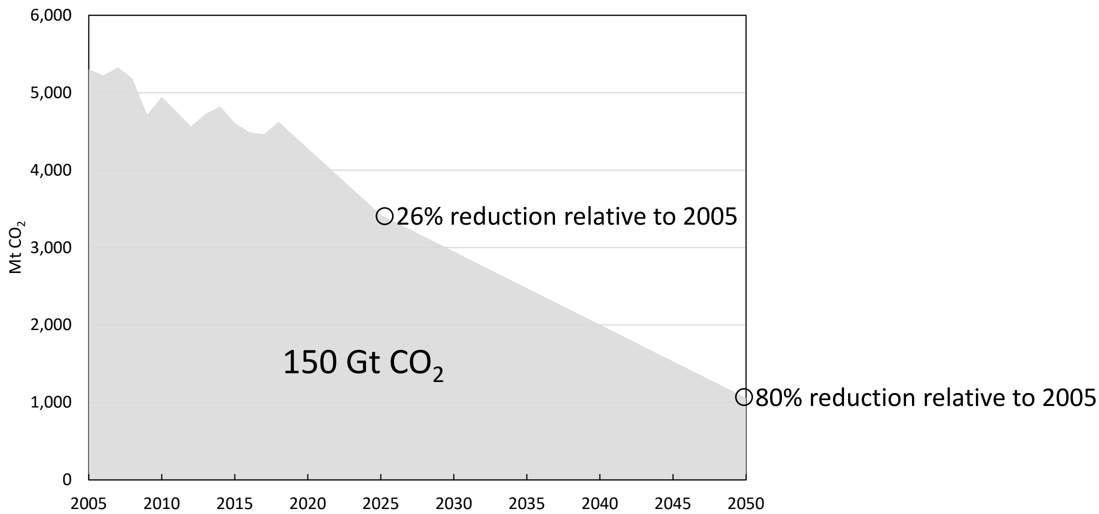

Figure B.3: Cumulative CO_2 emissions of the US following its nationally determined contribution (NDC) under the Paris Agreement.

B.2 Additional results

B.2.1 Vehicle stocks

(see next page)

B.2.2 Vehicle stock emission rates

(see next page)

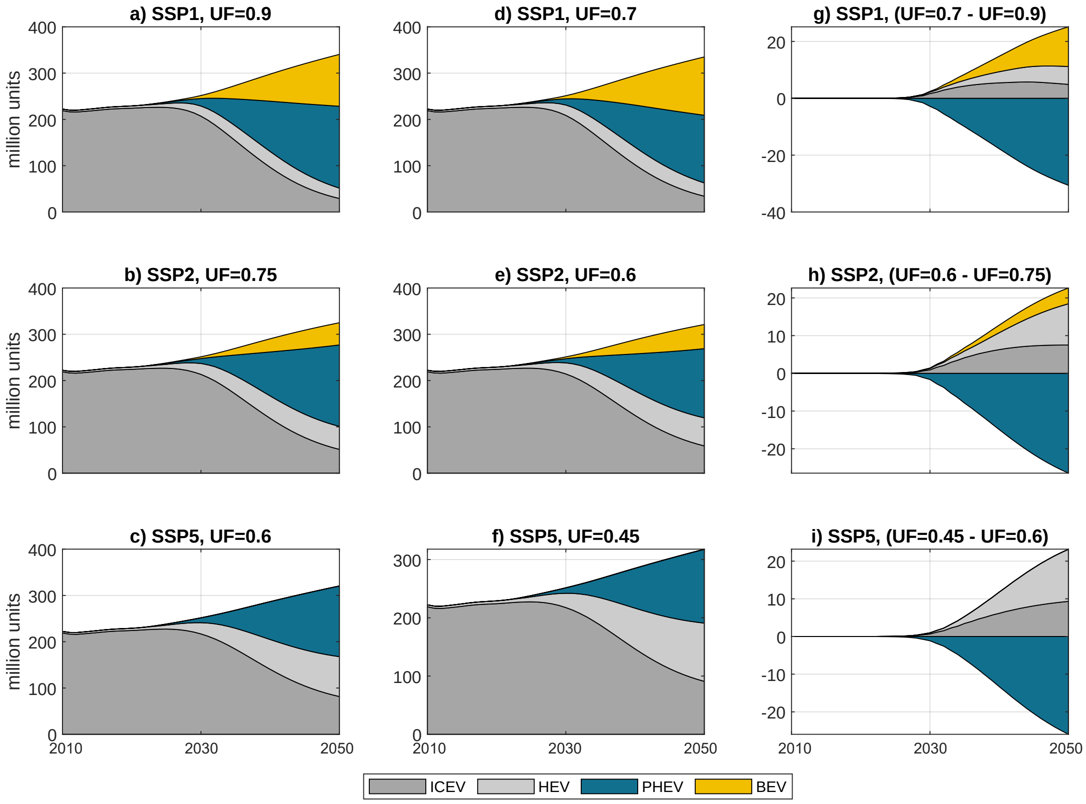

Figure B.4: Vehicle stocks by scenario. High UFs (a–c). Low UFs (d–f). Differences in stocks between scenarios with low and high UFs (g–i). SSP=shared socio–economic pathway; UF=utility factor; ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle.

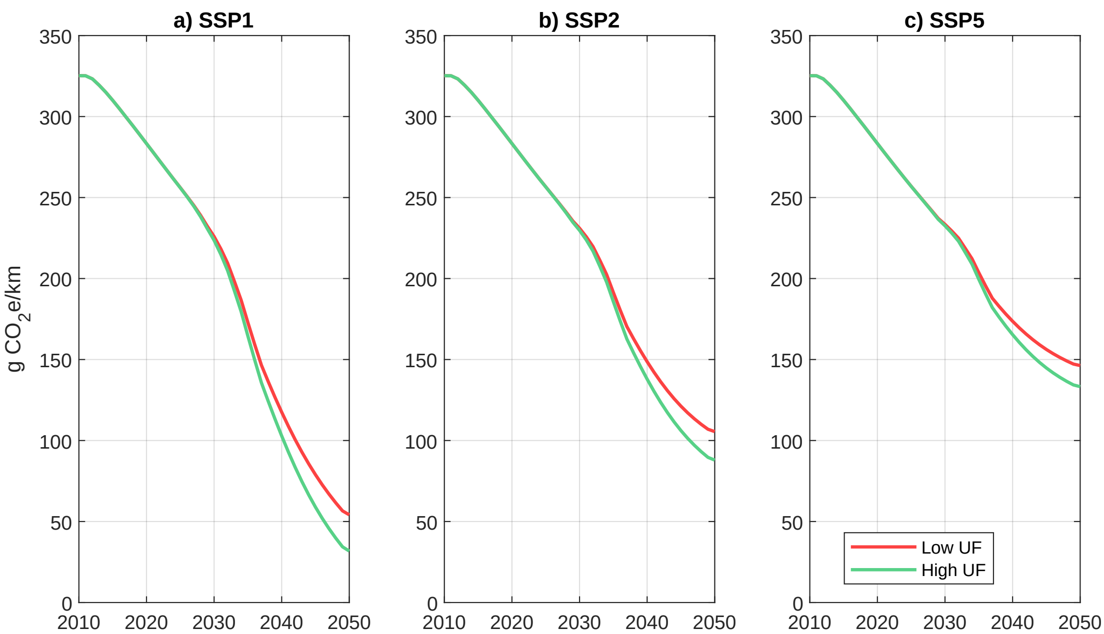

Figure B.5: Average emission rates of the vehicle stock by scenario and fueling behavior. SSP=shared socio–economic pathway; UF=utility factor.

B.2.3 Fleet energy use

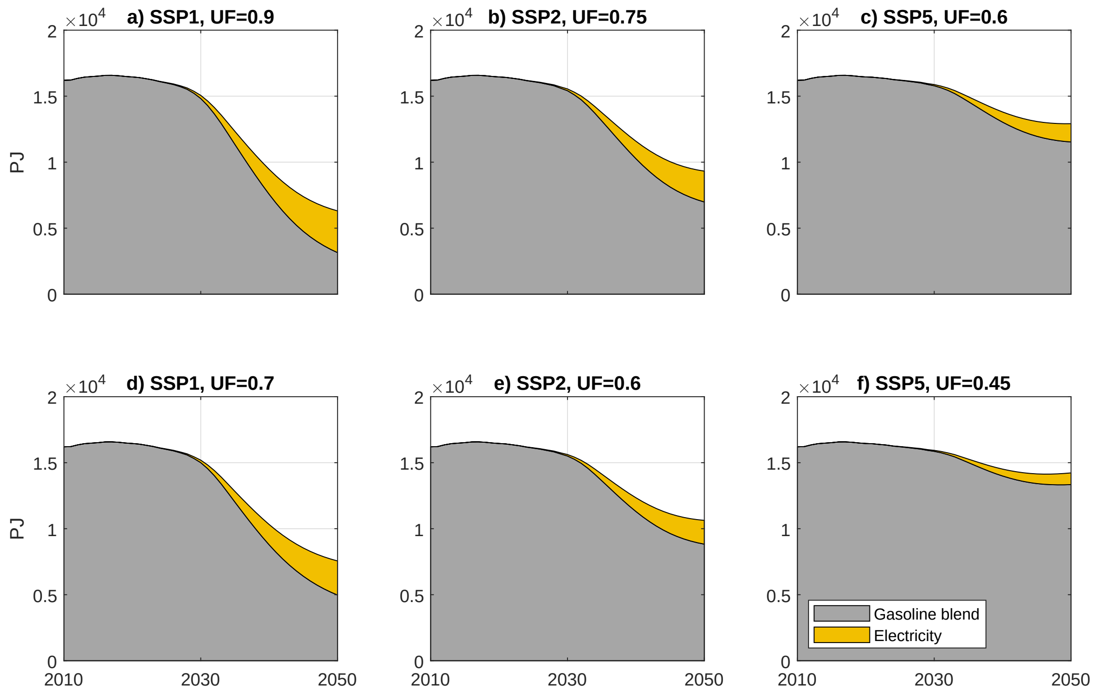

Figure B.6: Energy use by scenario and fueling behavior. SSP=shared socio–economic pathway; UF=utility factor; PJ=peta joules.

C Appendix to Chapter 4

C.1 Model selection and screening

As mentioned in the main text, we define IEMs as models that (1) entail the entire environmental–energy–economic system, (2) find an equilibrium state of energy supply and demand, either for the entire economy (general equilibrium), or for individual energy demand sectors (partial equilibrium), (3) are mathematically solved through optimization or simulation, (4) provide explicit representation of single energy demand sectors and climate change mitigation technologies within these sectors, and (5) allow exploration of future energy and emissions scenarios under different policy assumptions.[22,156,157]

In order to identify suitable IEMs we searched the ISI Web of Science, Scopus and Google Scholar databases using the following keyword string: *"Integrated energy model" OR "integrated assessment model" AND (passenger OR light–duty) AND vehicle AND energy AND (CO_2 or carbon or greenhouse).* We also searched the official websites of the US Energy Information Administration (EIA) and the International Energy Agency (IEA) and took previous model reviews into account. We identify a total of 14 relevant IEMs that address US LDVs within climate change mitigation scenarios. In order to evaluate whether the models consider different factors, the model documentations as well as different peer–reviewed papers applying the models have been screened using the keywords in Table C.1 prior to an in–depth review. In addition, we requested detailed feedback on model descriptions from each modeling team. We received detailed commentary from all modeling teams but DNE21+.

All works were assessed against whether or whether not the factors in Table C.1 were addressed. For all factors, a benchmark is defined based on the available engineering literature. For example, the work by Chester & Horvath[48] is identified as a state–of–the–art assessment for road types, because different road types are considered, their material and energy inputs are included and different life stages are distinguished. As stated in the main text, whether or whether not factors are varied over time or geographies is generally not assessed in this review (except for 'vehicle age') because it would go beyond the scope of this review. We note that nevertheless such dynamic changes should ideally be included in a realistic assessment.

C.1.1 Road infrastructure

- Considered — A complete life–cycle representation of energetic and material inputs into road infrastructure accommodating road vehicles, while distinguishing different road types. Life stages considered pertain to production, use and end of life. If applicable, impacts are split between different road transport modes, such as heavy–duty and light–duty vehicles.
- Partially or indirectly considered — (1) An incomplete representation of the above, or (2) a non–physical (monetary) representation of infrastructure investments, or (3) considered indirectly as part of aggregate industrial output driven by GDP without a link to transport.
- Not considered — Neither of the above.

C.1.2 Ancillary infrastructure

- Considered — A complete life–cycle representation of energetic and material inputs into ancillary infrastructure, such as parking lots, bridges, tunnels, street lighting, fuel stations and electric chargers. Life stages considered pertain to production, use and end of life. If applicable, impacts are split between different road transport modes, such as heavy–duty and light–duty vehicles.
- Partially or indirectly considered — (1) An incomplete representation of the above, or (2) a non–physical (monetary) representation of infrastructure investments, or (3) considered indirectly as part of aggregate industrial output driven by GDP without a link to transport.
- Not considered — Neither of the above.

C.1.3 Vehicle components

- Considered — A detailed life–cycle representation of energetic and material inputs into vehicle production, explicitly distinguishing different vehicle/powertrain components, such as combustion engine, electric motor, fuel cell, battery (and type of battery), etc. Life stages considered pertain to production, use and end of life/recycling.

- Partially or indirectly considered — (1) An incomplete representation of the above, or (2) a non–physical (monetary) representation of vehicles and components, or (3) considered indirectly as part of aggregate industrial output driven by GDP without a link to transport.

- Not considered — Neither of the above.

C.1.4 Vehicle materials

- Considered — Different materials and their energy– and GHG intensities are explicitly considered during vehicle production, including recycled materials.

- Partially or indirectly considered — (1) An incomplete representation of the above, or (2) a non–physical (monetary) representation of vehicles and components, or (3) considered indirectly as part of aggregate industrial output driven by GDP without a link to transport.

- Not considered — Neither of the above.

C.1.5 Real–world driving

- Considered — (1) In the case of the US, EPA's adjusted fuel consumption values are used. In the case of other regions, (2) reasonable drive cycle correction factors from the literature are used in conjunction with official estimates, or (3) a realistic drive cycle is simulated. (4) Or for either region, statistical analysis of driver's self–reported fuel consumption is conducted. (5) LDV fuel consumption values are estimated from aggregated transport energy use statistics.

- Partially or indirectly considered — (1) Implausible correction factors are used. (2) Simulation of a more realistic yet not fully realistic drive cycle, such as the WLTP (Worldwide Harmonized Light Vehicles Test Procedure).

- Not considered — Fuel consumption values are based on official laboratory measurements.

C.1.6 Multi–fuel use

- Considered — (1) Plausible multi–fuel use (MFU) factors from the literature are used, or derived through (2) statistical analysis, e.g. of travel survey data, or (3) fuel choice modeling, such as logit. The most common multi–fuel vehicles (MFVs) such as plug–in hybrids, bi–fuel and flex–fuel vehicles are considered.

- Partially or indirectly considered — (1) MFU values are considered for some vehicle types but not for others, (2) implausible values are used, (3) a simplified approach is used assuming that for example ICEVs can use several fuels without any modifications (not explicitly considering MFVs).

- Not considered — Neither of the above.

C.1.7 EV–power system interaction

- Considered — Bilateral interactions between the EV fleet and the electric power system are considered, e.g. the influence of EVs on the amount, emissions intensity, costs etc. of electricity generation, as well as the influence of electricity generation on EV ownership costs, and energy chain emissions.

- Partially or indirectly considered — Only unilateral interactions between the EV fleet and the electric power system are considered, i.e. either the influence of EVs on the electric system or the influence of the electric system on EVs.

- Not considered — No connection between the EV fleet and the electric power system is considered.

C.1.8 Biofuel emissions

- Considered — A full life–cycle representation of energetic and material inputs into biofuel production including positive emissions from combustion and land use and land use change, as well as negative emissions, e.g. through feedstock carbon uptake, is achieved; either through (1) comprehensive land use change modeling, or (2) by using exogenous life–cycle factors and linking these to biofuel LDVs in an ad–hoc fashion.

- Partially or indirectly considered — (1) Biofuel emissions are included but not linked to the LDV life cycle, (2) implausible values are used, (3) certain life cycle stages are missing.

- Not considered — Neither of the above.

C.1.9 Crude oil grades

- Considered — A full life–cycle representation of energetic and material inputs into gasoline and diesel production, considering different crude oil grades.

- Partially or indirectly considered — (1) Different grades are included but their differences in carbon content are not considered in fuel production, (2) implausible values are used.

- Not considered — Neither of the above.

C.1.10 Methane leakage

- Considered — A full life–cycle representation of methane emissions from coal, oil, gas, electricity and hydrogen production, including methane leakage, flaring and venting. In the case of electricity from hydro power, this includes biogenic methane emissions.

- Partially or indirectly considered — (1) Incomplete representation of life–cycle methane emissions, e.g. methane leakages are included but not linked to fuel use in the transport sector, (2) implausible values are used.

- Not considered — Neither of the above.

C.1.11 Vehicle age

- Considered — Different vehicle age cohorts and their lifetimes are considered. Cohorts differ in terms of vehicle characteristics, such as fuel consumption, engine power, material mix, and/or curb weight etc. (Ideally, decreasing vehicle miles traveled as a function of increasing vehicle age is considered, too.)
- Partially or indirectly considered — Not applicable.
- Not considered — A vehicle vintage formulation is not used.

C.1.12 Travel demand

- Considered — Travel or vehicle demand is calculated endogenously in the model. For example, travel demand can be calculated as a function of projected fuel cost, personal income, vehicles per licensed driver, and employment rate, which can then be converted into vehicle demand as a function of travel demand and vehicle miles traveled per vehicle.
- Partially or indirectly considered — Travel or vehicle demand is exogenous.
- Not considered — Not applicable.

C.1.13 Vehicle mix

- Considered — The projected vehicle fleet mix is calculated endogenously, e.g. by employing a logit model or least–cost optimization. The vehicle mix changes over time as a function of changing vehicle characteristics, vehicle costs, policies and consumer preferences. A diverse set of powertrain technologies (and ideally vehicle sizes) are considered in the fleet mix.
- Partially or indirectly considered — Projected vehicle mix is (1) an exogenous variable, (2) is based on dated cost assumptions, (3) does not take into account the most important vehicle technologies such as ICEV, HEV, PHEV, BEV, HFCEV.
- Not considered — Not applicable.

C.2 Previous reviews related to transport and IEMs

Yeh et al.[257] provide a detailed review of GCAM, MESSAGE and two transport–sector models and compare modeling frameworks and outcomes in terms of CO_2 emissions. The authors suggest several model improvements, including harmonization of base–year data and key scenario parameters. Creutzig[258] reviews selected works of three different scientific communities, namely transport sector modelers, integrated assessment modelers and place–based modelers. He identifies differences in general approach, geographical scope, time frame and modeled mitigation measures and proposes stronger interaction of the different modeling communities. Edelenbosch[219] reports a divergence in modeling inputs to the LDV sector of several IEMs. Although not specific to transportation, three more reviews are worth mentioning: Debnath & Mourshed[95] highlight deficiencies in the description of the energy system in the context of developing countries among 34 energy planning models. Pauliuk et al.[19] find inadequacies in the modeling of material demand by industry, waste generation and recycling among five major integrated assessment models. Finally, Krey et al.[93] find large differences in techno–economic assumptions of the electricity sector among 16 popular integrated assessment models.

C.3 Previous works addressing life–cycle relationships in IEMs

Arvesen et al.[22] note that to date it is largely unexplored how life–cycle relationships may influence optimized national and global energy and climate change mitigation strategies. Exceptions include Daly et al.,[227] Scott et al.,[228] Pehl et al.,[171] and MacDowell and colleagues.[170] Daly et al. couple UK TIMES, a national energy optimization model, with a multiregional economic input–output model in order to analyze the importance of domestic and nondomestic indirect CO_2 emissions for the decarbonization of the UK energy system. Their results indicate that domestic indirect emissions have little significance, while nondomestic indirect emissions substantially increase mitigation cost. If all, direct and indirect, emissions were included in a decarbonization of UK's energy supply system, assuming absence of mitigation measures of other countries, marginal abatement cost of decarbonization were doubled. In a subsequent paper, the same authors suggest that the cost–optimal mitigation of emissions generated overseas would require stronger electrification and stronger use of nuclear energy .[228] Pehl et al. integrate LCA coefficients in the REMIND IAM in order to analyze to what extent the consideration of life–cycle GHG emissions leads to a more complete internalization of externalities. Their results suggest that the consideration of indirect emissions has only modest effects on the global cost–optimal mix of electricity generation technologies and electricity demand. However, in regions that have large capacities of technologies with a high share of indirect emissions, cost–optimal electricity mixes differ considerably when accounting for indirect emissions. Examples include Russia, Latin America, the Middle East & Northern Africa and the USA. McDowall et al. use a similar approach and integrate life cycle coefficients with a European TIMES energy system model. Another study worth mentioning is that by Boubault et al.[172] who address the role of raw material demand of low–carbon technologies by integrating LCA coefficients with the TIAM–FR global integrated model. Their focus is on resource efficiency, not on climate change mitigation however. No study has been prepared to date that analyzed the influence of comprehensive life–cycle relationships of LDVs on optimized national and global energy and climate change mitigation strategies.

C.4 Influence of selected factors

C.4.1 Multi–fuel use

Figure C.1 illustrates how the difference in a PHEV's utility factor (UF) can influence energy chain (well–to–wheel, WTW) emissions. Well–to–wheel describes the entire life cycle of an energy carrier from primary energy extraction to final use of the energy carrier. A low UF means that a small fraction of total travel is driven on electricity, whereas a high UF implies a high share of electric driven kilometers. The higher the UF, the more pronounced are differences in regional electric grid GHG intensity. Regions 1 through 26 are NPCC Upstate NY, WECC California, NPCC New England, NPCC NYC/Westchester, ASCC Miscellaneous, RFC East, SERC Virginia/Carolina, WECC Southwest, WECC Northwest, ASCC Alaska Grid, HICC Miscellaneous, SERC

Mississippi Valley, FRCC All, ERCOT All, SERC South, NPCC Long Island, SERC Tennessee Valley, MRO West, RFC West, SPP South, HICC Oahu, RFC Michigan, SPP North, MRO East, WECC Rockies, SERC Midwest. All data that was used to prepare Figure C.1 is contained in an Excel spreadsheet and can be requested from the author.

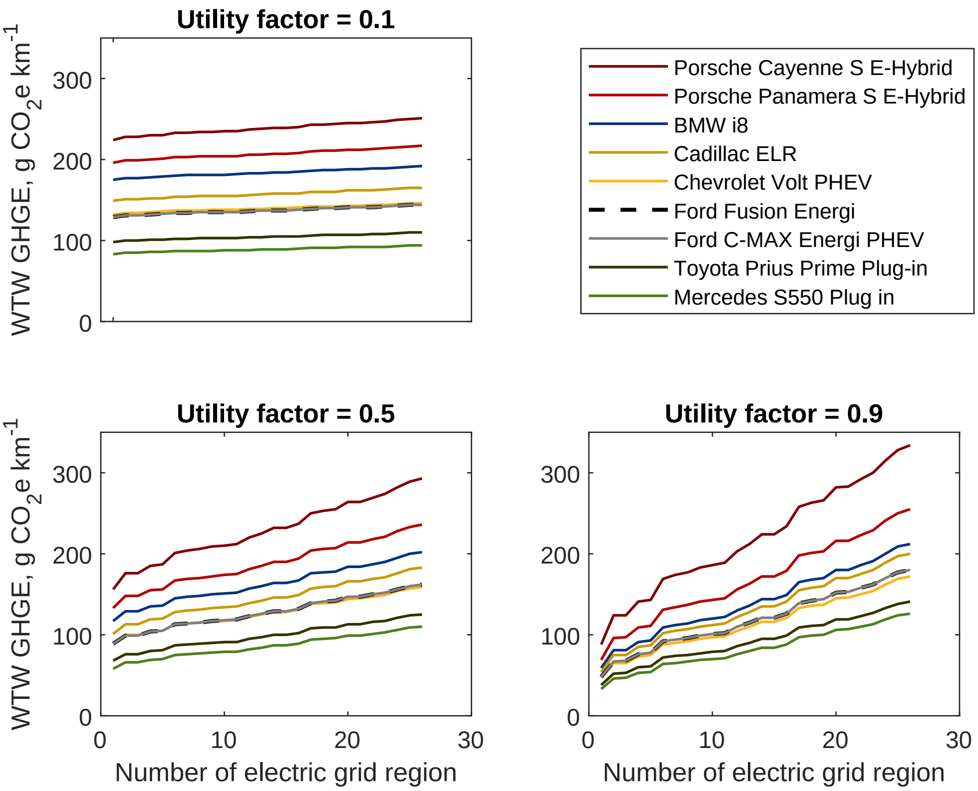

Figure C.1: Influence of the utility factor on energy chain (well–to–wheel, WTW) greenhouse gas emissions (GHGE) of plug–in hybrid electric vehicles. Electric grid regions are ordered by greenhouse–gas emissions intensity in ascending order.[259,260]

C.4.2 Biofuel emissions and crude oil grades

Figure C.2 shows the potential variation in the carbon intensity of gasoline, corn ethanol and different blends thereof. In general, corn ethanol and gasoline–ethanol blends can modestly lower GHG intensity (diamonds). However, under certain circumstances, they can also increase GHG intensity as indicated by the error bars. Different sources of variation have been considered, such as crude oil upstream and midstream emissions (15–129 g CO_2e kWh^{-1},[199] default value 24 g CO_2e kWh^{-1}),[201] gasoline chemical composition (C_4H_{10} to $C_{12}H_{26}$, default C_8H_{18}), gasoline lead content (lead/unlead),[261] biofuel feedstock carbon uptake (189–223 g CO_2e kWh^{-1}, default value 223 g CO_2e kWh^{-1})[12] and land use change emissions (0–374 g CO_2e kWh^{-1},[12] default value 26 g CO_2e kWh^{-1}).[90] Crude oil upstream and midstream GHG intensity causes the strongest variation in gasoline carbon intensity. Assumed land use change emissions have the strongest influence on biofuel carbon intensity.

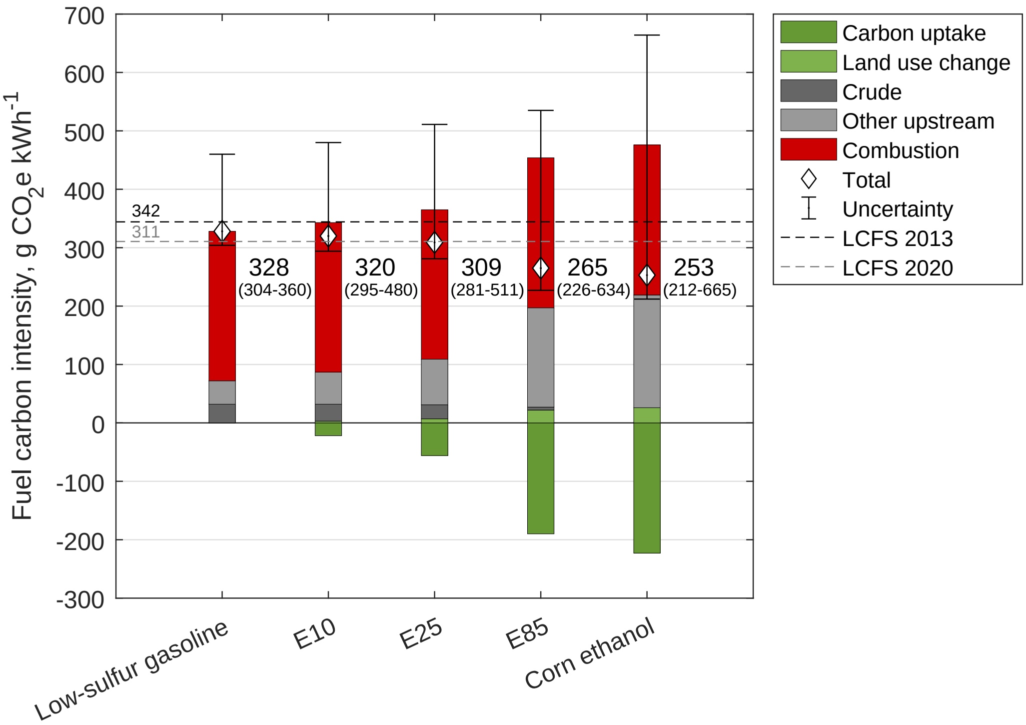

Figure C.2: Influence of different factors on upstream emissions of gasoline and ethanol fuel. E*xx* = corn ethanol–gasoline blend (*xx*% corn ethanol by volume). LCFS=California's low carbon fuel standard.[90, 196, 197, 199, 201, 261, 262]

C.4.3 Vehicle age

Figure C.3 shows total tailpipe CO_2 emissions of the US car fleet. The results are based on a vehicle vintage–stock model constructed with vehicle survival and vehicle travel as functions of vehicle age,[207] vehicle sales data,[263] and vehicle real–world fuel consumption estimates.[189] The general stock modeling method applied to vehicles is described by Fishman and colleagues.[264] Panel a) shows total emissions by year and by vintage (year of manufacture). Panel b) highlights the discrepancy between the vintage formulation (black line) compared to results that neglect the vintage formulation and thus assume that all vehicle kilometers are driven by new, more efficient vehicles (red line). The resulting difference in CO_2 is about 30% in 2015. These results highlight the existing inertia in the turnover of vehicles that can only be captured by a vintage formulation. Thus, the importance of employing vintage stock modeling in integrated models is demonstrated.

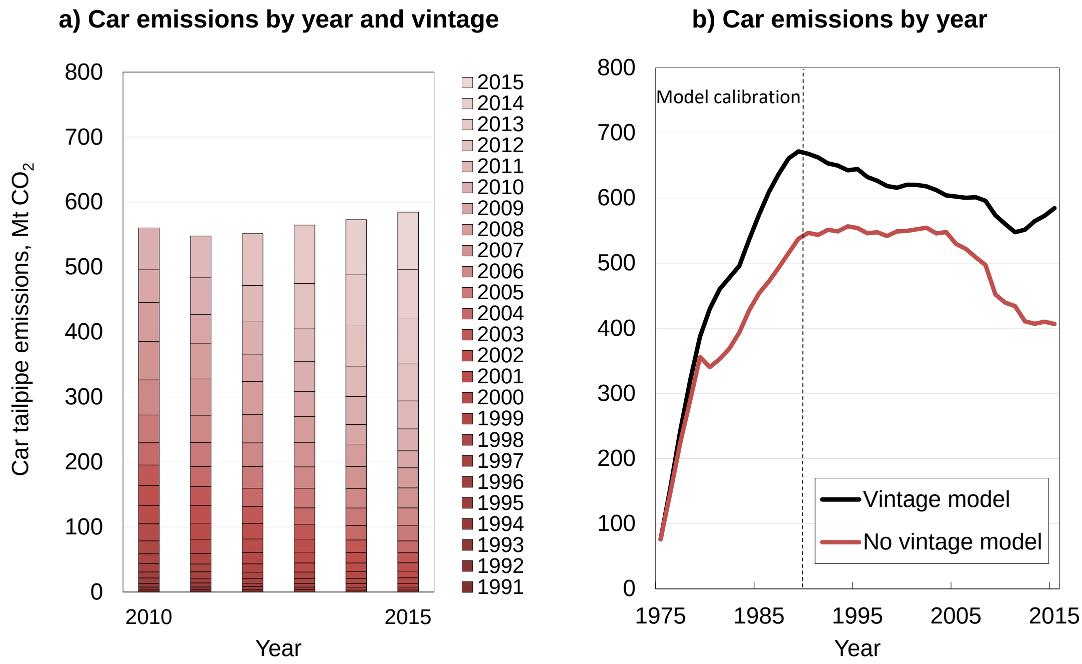

Figure C.3: Influence of vehicle age tracking on modelled fleet–wide CO_2 emissions: Car emissions by year and vintage (a). Car emissions by year (b).[189,207,263]

C.4.4 Vehicle mix

Figure C.4 shows how assumptions on EV battery costs can influence assumed future EV penetration. Panel a) illustrates a scenario of strong decline in lithium–ion battery costs, from about 320 USD kWh^{-1} in 2015 to about 130 USD kWh^{-1} in 2030 for BEVs, and from about 420 USD kWh^{-1} to about 200 USD kWh^{-1} for PHEVs.[73] In panel b), battery costs are assumed to remain at 2015 levels. Both scenarios assume cost reductions of other components consistent with previous work.[73,129] A simplified discrete choice model using a multinomial logit formulation based on Greene et al.[129,211] has been constructed to generate the technology shares. The model distinguishes small and large cars, and two points in time, 2015 and 2030. The small PHEV has a 60–mile all–electric range which is similar to the 2017 Chevrolet Volt, the large PHEV has a 20–mile all–electric range, similar to Ford's 2017 Fusion Energi. The small BEV has a 100–mile range, e.g. 2017 Nissan LEAF, the large BEV has a 200–mile range, e.g. 2017 Tesla Model S60. Assumptions on vehicle annual mileages (12,300 miles in the first year, then decreasing by 3% year^{-1}) and vehicle average lifetimes (10 years) are taken from the latest National Household Travel Survey.[206] The utility V of an agent is modeled as

$$V_{ijt} = \beta^P_{jt} \times P_{ijt} + \beta^R_{jt} \times R_{ijt} + \beta^F_{jt} \times F_{ijt} + \beta^M_{jt} \times M_{ijt} + \beta^A_{jt} \times A_{ijt} \qquad \text{(C.1)}$$

where P is the vehicle purchase price, R is the range, F is fuel cost, M is annual maintenance cost, and A is model availability. β is a weighting coefficient specific to each attribute.[211] Subscripts i, j, t denote technology (ICEV, BEV, PHEV), vehicle class (small/large car), and year (2015, 2030).

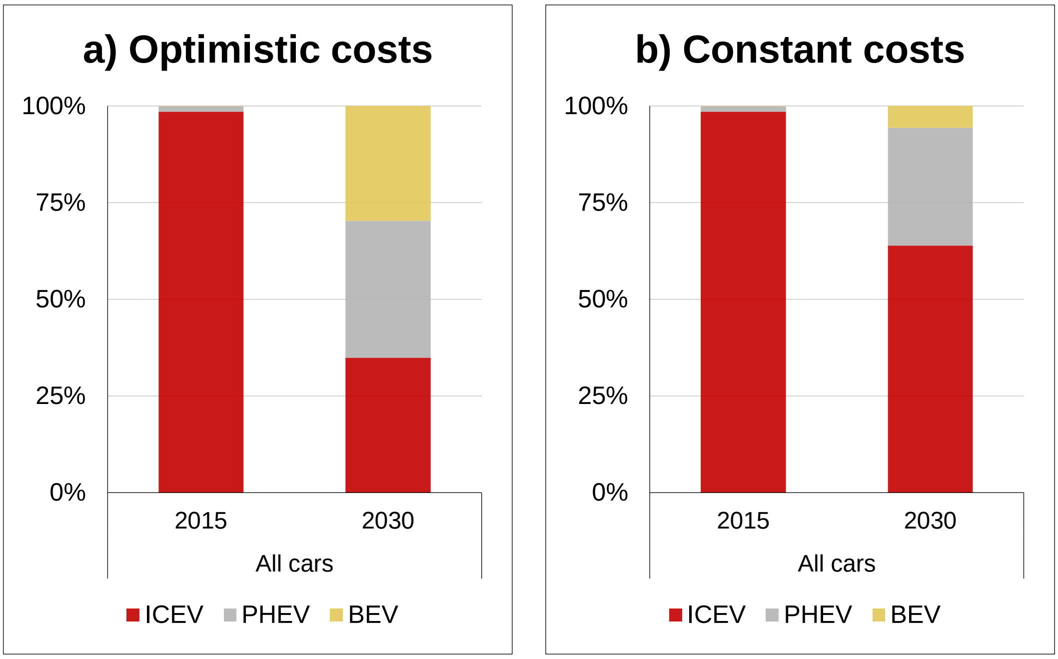

Figure C.4: Influence of assumed lithium–ion battery cost on new BEV and PHEV sales assuming optimistic costs (a) and constant costs (b). ICEV=internal combustion engine vehicle, PHEV=plug–in hybrid electric vehicle, BEV=battery electric vehicle.[73,129,206,211]

Table C.1: Search terms used to identify factors in each model.

Factor	**Keywords**
1) Road infrastructure	'Road infrastructure', road, highway, street, pavement, asphalt, cement, concrete, bitumen.
2) Ancillary infrastructure	Light, lighting, parking, 'parking lot', charg, 'charging infrastructure', 'fuel station', 'refuel infra', 'recharging infra', bridge, tunnel.
3) Vehicle components	'Vehicle component', component, battery, motor, engine, 'fuel cell', tank, 'hydrogen tank', 'hydrogen storage', 'vehicle body', body, 'body–in–white', glider, transmission.
4) Vehicle materials	'Vehicle material', material, metal, steel, aluminum, aluminium, rubber, plastic, lightweight, magnesium, composite, 'carbon fiber', 'carbon fibre', recycl, reuse, remanufactur.
5) Real–world energy use	Real–world, on–road, laboratory, 'fuel economy label', 'adjusted EPA', 'EPA adjusted', 'drive cycle', FTP, SC03, HWFET, US06, 5–cycle, WLTP, 'energy consumption', 'energy intensity', NEDC.
6) Multi–fuel use	Multi–fuel, 'utility factor', charge–depleting, charge–sustaining, 'electric driving', 'driving on electricity', 'gasoline driving', 'driving on gasoline', fraction, eVMT, displacement, displac, 'mileage share', 'VMT share', 'usage share', 'fuel share', 'dual fuel', bi–fuel, flex–fuel.
7) EV–power system interaction	'Marginal electricity', 'average electricity', 'marginal emissions factor', 'average emissions factor', dispatch, 'merit order', capacity, 'capacity expan', 'time slice', 'load curve', baseload, 'base load', peakload, 'peak load', 'load duration curve', 'load curve', 'load pattern', 'load band', 'vehicle–to–grid', 'power transfer'.
8) Biofuel emissions	Biofuel, 'land use', 'land use change', LUC, 'carbon uptake', feedstock, bioenergy, upstream, fertilizer.
9) Crude oil grades	'Oil type', 'crude oil', 'oil production', 'oil extraction', 'oil supply chain', unconventional, crude, reserve, 'petroleum slate', 'oil field', 'oil sand', 'shale oil', 'API gravity', 'heavy oil', 'heavy crude', 'light oil', 'light crude', 'sour crude', 'sweet crude', 'carbon content', 'carbon intensity'.
10) Methane leakage	'Methane leakage', 'biogenic methane', methane, leak, biogenic, CH_4, decay, pipeline, fugitive, vent, flaring, transmission, 'transmission loss', 'energy transport'.
11) Vehicle age	Vintage, stock 'vehicle age', 'car age', cohort, 'vehicle stock', 'stock model', age, surviv, turnover, scrapping, scrap, 'end of life'.
12) Travel demand	'Vehicle demand', 'travel demand', travel, demand, GDP, gross domestic product, price, 'fuel price', 'VMT demand'.
13) Vehicle mix	'Vehicle mix', 'discrete choice', logit, MNL, 'modal share', 'vehicle choice', 'consumer choice', least–cost.

C.5 Detailed evaluation results of the individual models

This section contains detailed descriptions of benchmarking results for individual models. Abbreviations used in the following tables include: BECCS=bioenergy with carbon capture and storage; BEV=battery electric vehicle; CCS=carbon capture and storage; CSP=concentrated solar power; FES=fuel economy standard HEV=hybrid electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; ICEV=internal combustion vehicle; IGCC=internal gasification combined cycle; LULUCF=land use, land–use change and forestry; MFV=multi–fuel vehicle; MSW=municipal solid waste; NGCC=natural gas combined cycle; PC=pulverized coal; PV=photovoltaics; PHEV=plug–in hybrid electric vehicle; RFS=renewable fuel standard. BEV/PHEV/HFCEV–x indicates all–electric range, e.g. PHEV–40 has a 40 mile all–electric range.

Table C.2: EPPA benchmarking results

Factors/items	**EPPA benchmarking results**
General items	
1) Model core and solver	General equilibrium model. Solution algorithm is recursive dynamic, i.e. it starts from a target emissions pathway, and solves recursively for the carbon price that would deliver the emissions target at each time step, and optimizes for the technology mix consistent with the resulting carbon price.[128, 265, 266]
2) Model extensions	EPPA is linked to the climate component of the MIT Integrated Global System Modeling (IGSM) framework and to a land use model. In Heywood et al.[37] EPPA receives inputs from the Autonomie vehicle drive cycle simulation tool and a vehicle–technological stock model.

Factors/items	EPPA benchmarking results
3) Future GDP	GDP is calculated endogenously as a function of factor productivity, such as labor, land and energy. Productivity growth rates are calibrated so that future GDP in a reference or baseline scenario is in line with other projections. Population forecasts are exogenous, based on UN projections.
4) Time horizon	2005–2100, 5–year steps.
5) Regions	17 regions, including USA, Japan, EU.
6) GHGs	All GHGs and other radiative agents. Data for GHGs (CO_2, CH_4, N_2O, HFCs, PFCs, SF_6) are based on the United States Environmental Protection Agency inventory data and projects.
7) Sectoral detail	The standard EPPA version distinguishes 13 sectors based on GTAP, which are then disaggregated into 40 sectors (energy–intensive industries, other industries, services, crops, livestock, forestry, food processing, coal production, oil production, refining, natural gas production, electricity (coal, natural gas, petroleum, nuclear, hydro, wind, solar, biomass, wind w/ gas backup, wind w/ biofuel backup, coal CCS, gas CCS, advanced nuclear, advanced gas), private transport (ICEV, PHEV, EV, CNGV), commercial transport, first–gen. biofuels (corn, sugarcane, sugarbeet, rapeseed, soybeen, wheat, palm oil), advanced biofuels, oil shale, synthetic gas from coal. In Heywood et al.[37] a version with 24 sectors, based on GTAP7, incl. agriculture, forestry, energy–intensive products, other industry, industrial transport, household transport, coal, crude oil, refined oil, and natural gas is used.
8) Transport sectors	Private transport and commercial transport. Private transport is disaggregated into ICEV, PHEV, EV, CNGV. Commercial transport is an aggregate that is inclusive of aviation, rail and marine transport. (“The model includes a technology–rich representation of the private passenger vehicle transport sector and its substitution with purchased modes of transportation, including aviation, rail, and marine transport, as well as road transport that is purchased by households as service”.[267])

Factors/items	EPPA benchmarking results
9) Electricity conversion technologies	14 (five traditional (coal, natural gas, oil, nuclear, hydro) and nine advanced electricity generation technologies: 1) wind, 2) solar, 3) bio–electricity, 4) wind with natural gas backup, 5) wind with biomass backup, 6) natural gas combined cycle (NGCC), 7) NGCC with carbon capture and sequestration (CCS), 8) coal with carbon capture and sequestration, and 9) advanced nuclear.)
10) LDV and fuel technologies	The standard EPPA model defines one vehicle class (mid–size sedans), four powertrain types (ICEV, BEV, PHEV, CNGV), and five fuels (electricity, gasoline, CNG, first generation biofuels (seven feedstocks), advanced biofuels). A version of EPPA, which has been used in Heywood et al.,[37] receives input data from a technological vehicle stock model, providing specific information on various powertrains (ICEV, HEV, FFV, Bi–fuel, PHEV–10, –30, CNG, BEV, HFCEV), fuels (XTL, E5–15, E85, CNG, electricity, hydrogen), and vehicle segments (subcompact, compact, midsize, large car; small, large SUV; small, large pickup; small, large van.). Other studies using EPPA may model different technologies, fuels and vehicle segments.
11) LDV life cycle stages	Well–to–wheel (energy chain) and vehicle manufacturing in an aggregate representation. Households purchase some outputs from the service sector and “other industries” (i.e. inclusive of auto manufacturing), so a fraction of the emissions attributable to these sectors can be assigned to households. In Heywood et al.[37], more detailed but generic vehicle production emissions are considered (25 g CO_2e km^{-1} for ICEVs, 43 g CO_2e $^{-1}$ for HFCEVs, none reported for BEVs, PHEVs, HEVs).
12) LDV cost	The standard EPPA model uses aggregated vehicle costs (e.g. PHEV costs are 30% higher than ICEV costs).[265] In Heywood et al.[37] costs are based on bottom–up cost estimates of specific components, such as batteries, fuel cells, engines etc. Costs of ICEV travel increase with increasing fuel cost and increasingly stricter fuel efficiency standards. Cost estimates for fuel cell vehicles seem to be on the optimistic side [37, Figure 6.12 therein], as these are based on figures based on a report by the National Academies of Sciences[129] who assume that fuel cells are fully learned. Heywood et al.[37] assumed 2014 energy prices of 3.04 USD gal^{-1} for E85, 3.34 USD gal^{-1} for gasoline, and 0.12 USD kWh^{-1} for electricity. Future fuel costs partially depend on gasoline tax assumptions.

Factors/items	EPPA benchmarking results
13) LDV efficiency	In the standard model version,[266,267] there is a substitution elasticity between fuel and powertrain (capital, i.e. output from 'other industries') inputs to the new–vehicle energy service. If constrained explicitly, or if the cost of fuel increases, households can increase the share of 'powertrain capital' and decrease the share of 'fuel' required to produce a given service output (i.e. same number of vehicle–miles). In Heywood et al.[37], powertrain efficiency is simulated using the Autonomie tool. Efficiency improvement opportunities include light–weighting, engine downsizing, and the addition of low rolling resistance tires, among others.
14) LDV policies / mitigation measures	Policies analyzed include carbon taxes, emission limits, tradeable permits, technology regulation,[265] FESs, RFSs, gas and diesel taxes,[37] and a combination of an FES and an economy–wide carbon cap.[268] Other mitigation strategies include lightweighting of vehicles (which can be interpreted as a consequence of stricter FESs).[37]
LDV life cycle factors	
1) Road infrastructure	CO_2 from cement production is included but not directly linked to road construction needs for vehicles. Monetary requirements and embodied emissions of road infrastructure construction are considered in the aggregate energy–intensive industry sector in the input–output representation of the model.
2) Ancillary infrastructure	Ancillary infrastructure is represented in a stylized fashion in the vehicle choice algorithm of the model.[37] Monetary requirements and embodied emissions of ancillary infrastructure construction are considered in the aggregate energy–intensive industry sector in the input–output representation of the model.
3) Vehicle components	Material and energy inputs into specific vehicle components are not treated explicitly. In Heywood et al.[37] vehicle body, drive type, engine, and efficiency features are considered, and so is the added weight from new features, which impacts fuel economy. EV battery capacities are taken into account. A 12 kWh EV battery roughly translates to 34 miles (55 km) electric driving range.

Factors/items	**EPPA benchmarking results**
4) Vehicle materials	The specific materials used in vehicles are within aggregate sectors through the use of input–output tables. In Heywood et al.[37] weight savings due to different materials are considered, and affect fuel economy.
5) Real–world energy use	In Heywood et al.[37] a uniform on–road/aggressiveness factor of 0.8 is considered across all technologies. On–road fuel economy is calculated by multiplying laboratory fuel economy values by the on–road factor. For PHEVs, adjustment factor is only applied to miles driven on gasoline. Paltsev et al.[267] apply ICCT's correction factors to estimate on–road fuel performance (of the EU vehicle fleet).
6) Multi–fuel use	The default version of EPPA assumes that PHEVs operate on electricity 60% and 40% on electricity.[265] In Heywood et al.[37] a "petroleum displacement" factor of 65% (constant over time) is assumed for PHEVs. Fuel use shares are not considered for other MFVs.
7) EV–power system interaction	It is assumed that EVs charge the average electricity mix. "We do not model hourly pricing or separately represent base load, peaking, and shoulder generation, nor do we represent regional differences in the electricity mix across the United States that could affect the marginal emissions rates for the PHEV fleet" [37, p. 257 therein].
8) Biofuel emissions	Land use change is included, distinguishing five different land use types: crop, pasture, managed forest, forest and natural grass. Biofuel technologies include ethanol from corn, sugarcane, sugar beet and wheat; and diesel from palm fruit, soybeans and rapeseed/canola, and cellulosic. CO_2 emissions from deforestation and biomass burning and CH_4 from deforestation burning are included. Land use change emissions are assumed negligible in Heywood et al.[37]: "These numbers are based on the assumption that the land use changes in producing these substantial volumes of biomass–based ethanol do not result in significant CO_2 emissions from this land use change. This assumption is increasingly viewed as unrealistic. Thus these biofuels benefits could well be overestimated."

Factors/items	EPPA benchmarking results
9) Crude oil grade	Different crude oil grades and their differences in carbon content are not considered in the EPPA standard version. In Heywood et al.[37] a world average crude oil is assumed to consist of 82% conventional crude, 13% Canadian tar sand, and 5% Venezuelan heavy and sour crude. Tar sand gasoline cars have a higher well–to–wheel GHG balance than conventional gasoline cars.
10) Methane leakage	Methane from coal seams, petroleum production, natural gas transmission and distribution losses and other sources is included.[265] Biogenic methane release from hydro power is not mentioned.
11) Vehicle age	A simplified vintage stock model is used. Two vintages, new (0–5 years) and used (older than 5 years), are distinguished.
12) Travel demand	Travel demand is a function of income growth.
13) Vehicle mix	Consumer vehicle choice is calculated endogenously. Technology growth follows Bass diffusion curves and can be restricted by maximum growth rates. A time lag in technology deployment is considered as well. HFCEV shares are based on optimistic fuel cell system costs [37, Figure 6.12 therein] (based on figures from NAS[129] who assume that fuel cells are fully learned).

Table C.3: GCAM benchmarking results

Factors/items	GCAM benchmarking results
General items	
1) Model core and solver	GCAM is an integrated model of the energy, land, agricultural, water, and climate systems that calculates equilibria between supply and demand globally and regionally for a number of modeled commodities in 32 global regions. The solution is a partial equilibrium as not all markets are represented in the solution (as would be the case in a general equilibrium). The solution algorithm is recursive dynamic, i.e. agents do not have any foresight about the future when making a decision today.
2) Model extensions	GCAM is linked to a reduced–form climate model.
3) Future GDP	Future GDP and population are exogenous to the model.
4) Time horizon	2010–2100, 5–year time steps.
5) Regions	32 geopolitical regions; there are 384 land use regions for the agricultural, land use, and hydrological systems, which are constructed from the intersection between the geopolitical regions and 235 global hydrologic basins.
6) GHGs	All GHGs and other radiative forcing agents, including CO_2, CH_4, N_2O and SO_2.
7) Sectoral detail	Three end–use sectors (transport, buildings, industry), agriculture, land use, water. The buildings sector is divided into residential and commercial.

Factors/items	GCAM benchmarking results
8) Transport sectors	Transport is divided into two fundamental demand types (freight and passenger), each of which is supplied with a range of modes and vehicle technologies. Passenger transport is provided by LDVs, two–wheelers, three–wheelers, bus, passenger rail, high speed rail, aviation (short & medium distance, long distance), and non–motorized modes. Freight shipping is provided by freight truck, freight rail, and water–borne shipping (domestic, international). The demands are driven by exogenous population and GDP assumptions, the services are represented in physical units (passenger–km and tonne–km, respectively), and the allocation of service and energy to modes and specific vehicle technologies is driven by costs, which include value of time, capital and non–fuel operating costs, and fuel costs.
9) Electricity conversion technologies	Biomass (conventioal, IGCC, con. CCUS, IGCC CCUS), coal (PC, PC CCUS, IGCC, IGCC CCUS), gas (CC, steam/CT, CC CCUS). refined liquids (steam/CT, CC, CC CCUS), nuclear (gen II LWR, gen III), CSP, CSP w/ storage, PV, PV w/ storage, wind, wind w/ storage, rooftop PV, geothermal.
10) LDV technologies	The range of vehicle size classes are region–specific; the USA has four LDV segments (compact car, midsize car, large car, light truck and SUV). All LDV size classes have five technologies represented (ICEV gasoline, CNG, HEV, BEV, HFCEV). No PHEVs considered.

Factors/items	GCAM benchmarking results
11) LDV life cycle stages	Well–to–wheel (energy chain). LDV manufacturing is included in industrial sector and not linked to LDV activity. LDV distribution is included in freight sector and not linked to LDV activity. LDV fuel consumption and transformation–related energy use (for refining, electricity generation, hydrogen) are explicitly included. Fuel consumption for fuel distribution is explicitly included for electricity and natural gas, whereas energy used for distributing liquid fuels is accounted for in the freight sector. Vehicle end–of–life is included in the freight and industrial sectors and not linked to LDV activity. "The full fuel cycle of each fuel is represented, from primary energy production and transformation to delivery to the transportation sector. This includes biomass from an agriculture and land use model. No other upstream inputs to the sector are considered (e.g. vehicle manufacturing, roads). Transportation in GCAM does not include pipeline energy use, or infrastructural energy used (e.g. airport operations, highway construction and maintenance)."[257]
12) LDV cost	LDV capital costs of ICE and hybrid–electric vehicles are based on current market data; values in OECD regions are held constant, while costs in developing countries are assumed to increase over time as more features are added. BEV costs are determined by subtracting the engine cost of the corresponding ICEV, and adding in the cost of the electric motor and batteries. Initial battery cost are 1,000 USD kWh^{-1} in 2005 and fall to 137 USD kWh^{-1} by 2095. In more progressive scenarios, costs decline faster. Fuel cell costs are quite optimistic based on a report by NAS.[129] Further cost components are fuel cost, maintenance cost, fuel taxes, infrastructure costs. The latter is either reflected as road toll or fuel tax. In GCAM–USA[155] current and future energy prices are largely based on EIA's Annual Energy Outlook 2016.
13) LDV efficiency	Efficiency increases are exogenous within each modeled vehicle technology; the rates of improvement are faster in the near–term than the long term (about 0.75% $year^{-1}$ to 2035, and about 0.1% $year^{-1}$ after 2050), and can differ by scenario or by study.[269]

Factors/items	GCAM benchmarking results
14) LDV climate policies / mitigation measures	Fuel economy standard, road toll, fuel tax, and carbon tax may be explicitly considered.
LDV life cycle factors	
1) Road infrastructure	Not included in the transportation sector. Construction energy use is in the industrial sector, in which cement production–related energy and emissions are explicitly modeled.
2) Ancillary infrastructure	Costs of fuel stations (around 2 ct. vkm^{-1}) is included. Material or energy inputs into ancillary infrastructure are not explicitly considered.
3) Vehicle components	Mass of different components, such as engine, motor and battery, and vehicle curb weight are considered. Different vehicle characteristics, such as battery capacity and engine displacement are considered. BEV and HFCEV battery energy densities are taken into account (4.76 kg kWh^{-1}), and remain constant over the modeling time horizon (2005–2095). HEV battery energy density is assumed constant at 16.7 kg kWh^{-1}. No material needs are considered.
4) Vehicle materials	Steel production is included in the model but not linked to vehicle production.
5) Real–world energy use	Assumed fuel consumption of 2005 ICEVs (liquid fuels) ranges from 2.91 to 4.0 MJ vkm^{-1} (81–111 kWh vkm^{-1}), depending on size. EPA's adjusted fleet average value of 90 kWh vkm^{-1} is well within that range.
6) Multi–fuel use	MFVs are not considered.
7) EV–power system interaction	Electric vehicles are assumed to be charged by the average electricity mix. A dispatch or merit–order model is not included in GCAM.
8) Biofuel emissions	Bioenergy production is modeled in the agriculture and land use module.[151] Increased demand of biofuels reduces oil demand through a link between the energy and the agriculture sector.

Factors/items	GCAM benchmarking results
9) Crude oil grade	Crude oil and unconventional oil are considered but their carbon content is not distinguished, nor linked to fuel production for use in vehicles. In addition, "the difference in carbon content of crude oil and refined fuels is assumed to be negligible".[50]
10) Methane leakage	Upstream CO_2 and CH_4 incl. fugitive CH_4 emissions from natural gas, oil, and coal production are considered. Activities in the transportation sector indirectly drive these emissions due to their effect on fuel demands. Biogenic methane release from hydro power is not considered.
11) Vehicle age	Vintage tracking is implemented.
12) Travel demand	Transport demand is a function of per–capita GDP, the total service price aggregated across all transport sectors, population and income and price elasticities. LDV travel is projected to grow by an average of 1% per year from 2017 to 2040.
13) Vehicle mix	Endogenously determined using a calibrated logit formulation. PHEVs are not considered. HFCEV shares are based on optimistic fuel cell system costs from NAS[129] who assume that fuel cells are fully learned. The range of vehicle size classes are region–specific; the USA has four LDV segments (compact car, midsize car, large car, light truck and SUV).

Table C.4: NEMS benchmarking results

Factors/items	NEMS benchmarking results
General items	
1) Model core and solver	General equilibrium. The Integrating Module uses the Gauss–Seidel algorithm for solving a set of linear equations simultaneously.
2) Model extensions	NEMS' Macroeconomic Activity module uses the following models from IHS Markit: Macroeconomic Model of the U.S. Economy, National Industrial Output Model, and the National Employment by Industry Model, as well as EIA's model of the regional economies. NEMS does not integrate a climate module.
3) Future GDP	Calculated within IHS' Macroeconomic Model of the U.S. Economy. (The Macro module is usually deactivated unless used for the Annual Energy Outlook). National population by age cohort and GDP of major trading partners are exogenous inputs to this model.
4) Time horizon	Through 2050, annual steps.
5) Regions	Regional detail can differ across different modules. The Macroeconomic module distinguishes 9 US Census Divisions. Emissions and mitigation costs are calculated for these nine regions. Within the International Energy Market module the US is set within the global energy market (one global region). The Electricity Market Module distinguishes 15 US electricity supply regions.
6) GHGs	CO_2, complete GHG coverage for fuels under the Renewable Fuel Standard.
7) Sectoral detail	Sectoral detail differs across different modules. The Industrial Output Model is a 2007 input–output model of the US economy distinguishing 73 sectors, including four non–manufacturing industries, five mining industries, four construction sectors, 14 services, and the remainder being manufacturing industries. The construction sector distinguishes general construction, construction of buildings, heavy and civil engineering construction and specialty trade contractors.
8) Transport sectors	LDVs, aviation, freight (trucking, shipping, rail) and others (mass transit, recreational boating, military).

Factors/items	NEMS benchmarking results
9) Electricity conversion technologies	Coal, natural gas and petroleum technologies, wind, geothermal, solar photovoltaic, solar thermal, landfill gas, biomass, hydropower, conventional nuclear, advanced nuclear light water reactor, several environmental control technologies such as carbon capture, scrubbers, filters, and nitrogen oxides reduction.
10) LDV technologies	Six car sizes, six light truck sizes, 86 conventional fuel–saving technologies for light–duty vehicles; gasoline, diesel, and fourteen alternative fuel vehicle types: flex–fuel methanol, flex–fuel ethanol, dedicated ethanol, dedicated CNG, dedicated LPG, CNG/LNG bi–fuel, LPG bi–fuel, dedicated electric, diesel/electric hybrid, plug–in gasoline/electric hybrid, gasoline/electric hybrid, methanol fuel cell, hydrogen fuel cell, and gasoline fuel cell. Fuels include different types of gasoline (conventional (oxygenated and non–oxygenated), reformulated, and California reformulated gasoline), distillates (kerosene, heating oil, low sulfur (LSD) and ultra–low–sulfur (ULSD) highway diesel, distillate fuel oil, and distillate fuel from various non–crude feedstocks (coal, biomass, natural gas) via the Fischer–Tropsch process (BTL, CTL, GTL)), alternative fuels (Biofuels (including ethanol, biodiesel (methyl–ester), renewable diesel, biomass–to–liquids (BTL)], coal–to–liquids (CTL), gas–to–liquids (GTL), liquefied petroleum gas (LPG)).
11) LDV life cycle stages	Well–to–wheel (energy chain).
12) LDV cost	Vehicle costs are included. Dated EV battery costs assumed. Motor gasoline prices increase from 2.59 USD gal^{-1} up to 3.66 USD gal^{-1} between 208 and 2050 in the reference case, and up to 5.57 USD gal^{-1} in the high oil price scenario.
13) LDV efficiency	Efficiency improvement factors exist for different efficiency improvement technologies, e.g. material substitution, drag reduction, 5–speed automatic transmission, continuous variable transmission (CVT), automated manual transmission, VVL–6 cylinder, camless valve actuation 6 cylinder, electric power steering, 42V–launch assist and regenerative braking.

Factors/items	NEMS benchmarking results
14) LDV policies / mitigation measures	“The transportation module can evaluate a range of policy issues, including fuel taxes and subsidies; fuel economy performance by market class; fuel economy standards for light, medium, and heavy–duty vehicles; vehicle pricing by market class; demand for vehicle performance within market classes; fleet vehicle sales by technology type; alternative–fuel vehicle sales share; the California Low–Emission Vehicle Program; changes in vehicle–miles traveled (VMT); and various other policies and developments related to transportation energy use and greenhouse gas emissions”,[270] R&D policy (optimistic technology scenario).
LDV life cycle factors	
1) Road infrastructure	Through input–output tables, monetary inputs into the transport equipment sector is represented in an aggregated way. Process emissions of clinker production at cement manufacturers are considered. Cement production is driven by the level of construction activity, which is projected by the MAM (Macroeconomic Activity Module) and transferred to the IDM (Industrial Demand Module) as an input.
2) Ancillary infrastructure	Total number of refueling stations needed is calculated, including gasoline, diesel, ethanol, methanol, CNG/LNG, LPG, electricity, and hydrogen stations/chargers. Costs for station infrastructure is considered. Through input–output tables, monetary inputs into the transport equipment sector is represented in an aggregated way.
3) Vehicle components	Battery costs and capacities are included but no material requirements. Fixed battery energy densities (inversed) are assumed, e.g. 0.000842 kwh per vehicle pound for PHEV–10, or 0.00344 kWh per vehicle pound for PHEV–40.
4) Vehicle materials	Through input–output tables, material inputs into the transport equipment sector is represented in an aggregated way, in monetary units. Material substitution is further represented in a highly stylized fashion as a fuel efficiency improvement factor.
5) Real–world energy use	Fleet–wide fuel consumption values are based on official values provided by the NHTSA and do not correspond with EPA’s adjusted values.

Factors/items	NEMS benchmarking results
6) Multi–fuel use	An alternative fuel choice logit model based on fuel price and fuel availability is used to calculate fuel shares for MFVs, including PHEVs, bi–fuel and flex–fuel vehicles. Utility factors for PHEVs are 0.21 for PHEV–10 and 0.58 for PHEV–40.
7) EV–power system interaction	Dispatch modeling allows for marginal and average cost pricing. Dispatch is determined for representative hours (three seasons by three times of day). Average electricity emissions are linked to the vehicle life cycle.
8) Biofuel emissions	Life–cycle carbon emission intensities are included for 24 different fuels, including different types of biofuels. Upstream emissions include indirect land use change. Carbon intensities for biofuels are based on life–cycle factors by the California Air Resources Board.
9) Crude oil grade	Five different crude oil grades are distinguished, according to their API gravity and sulfur content. Differences in upstream emissions of different crude oil grades are not linked to fuel production.
10) Methane leakage	Methane emissions are not included.
11) Vehicle age	Twenty vintages are distinguished within a vintage stock model. Age–dependent driving schedules (vehicles tend to be driven less with increasing age) are considered. An MPG degradation factor is considered.
12) Travel demand	Vehicle sales are calculated endogenously in MAM (Macroeconomic Activity Module) as a function of energy product prices, population, GDP and personal income. Vehicles sales are converted to vehicle travel demand by applying exogenous assumptions of annual vehicle mileages by technology and vintage. It is not considered that EVs may lead to higher vehicle ownership rates per household.

Factors/items	NEMS benchmarking results
13) Vehicle mix	Discrete choice model simulates consumer choice. Manufacturer technology choice is considered as well and takes into account requirements of CAFE and potential regulatory cost of failing to meet CAFE. Nine manufacturer groups are considered. Dated EV battery costs assumed. Six car sizes, six light truck sizes.

Table C.5: IMACLIM–R benchmarking results

Factors/items	**IMACLIM–R benchmarking results**
General items	
1) Model core and solver	General equilibrium, annual recursive-dynamic iteration (simulation), i.e. no inter-temporal optimization.[153,271,272]
2) Model extensions	A climate and a land use module are integrated in IMACLIM-R. The representation of LDVs is based on EIA's SMP model.[273]
3) Future GDP	Population and GDP drivers (active population and labour productivity) are exogenous. GDP itself is endogenous.[274]
4) Time horizon	2001–2050 (or 2100), yearly time steps.
5) Regions	12 (USA, Canada, Europe, OECD Pacific, Commonwealth of Independent States, China, India, Brazil, Middle East, Africa, Rest of Latin America, Rest of Asia). Regions are connected through trade of goods, capital and emissions permits.
6) GHGs	CO_2 from fossil fuel combustion and industry. Non-CO_2 forcing agents are not explicitly tracked but represented in the climate module by an exogenous forcing factor.
7) Sectoral detail	Five energy sectors (oil extraction, gas extraction, coal extraction, refinery, power generation), four transport sectors, construction, agriculture, energy intensive industry, services and light industry.
8) Transport sectors	Three transport sectors (air, maritime and terrestrial) and four modes for passenger mobility (private vehicles, non-motorized, public transport and air). Private vehicles, and non-motorized transport are not productive sectors per se, they are "self-produced" services by households for own use.
9) Electricity conversion technologies	26 power plant technologies (15 conventional including coal, gas, oil, nuclear, hydro and 11 renewables, including biomass, wind, PV, CCS, BECCS). Characteristics of technologies are calibrated on the POLES model.

Factors/items	**IMACLIM–R benchmarking results**
10) LDV technologies	Initially, the model included only HEVs and ICEVs (standard and improved).[153] Technological detail has been improved in McCollum et al.:[214] ICEV (gasoline, diesel, biofuel, synthetic fossil fuel), HEV (gasoline, diesel, biofuel, synthetic fossil fuel), PHEV-20 (gasoline, diesel, biofuel, synthetic fossil fuel), BEV-150. Other studies using IMACLIM-R may model different technologies.
11) LDV life cycle stages	Direct tailpipe CO_2 emissions only .[214] "As a CGE model all GHG-emitting and energy producing/consuming sectors are included. This implies that indirect energy use and emissions from fuel production and vehicle manufacture are included, but in the energy transformation and industry sectors".[219]
12) LDV cost	Purchase costs, fixed and variable maintenance cost are included. All cost data is calibrated with IEA data and evolve over time. Purchase costs reduce through learning-by-doing.
13) LDV efficiency	"Hybrid vehicle technology is assumed to improve so as to make possible consumption levels in the order of 1.5 litres per 100 kilometres. This figure can also be understood as being an average of electrical vehicles and rechargeable hybrid vehicles".[153] In addition, efficiency of the LDV fleet may improve as a result of technology shifts towards more efficient technologies.
14) LDV policies / mitigation measures	Carbon/energy tax, permit trading, specific technology subsidies, regulations, investments into public transport infrastructure.
LDV life cycle factors	
1) Road infrastructure	CO_2 emissions from the industry sector are included. Industrial demand of cement and metals is included but not linked to road construction. Costs of road infrastructure and public transport infrastructure are included to estimate the demand for transport and how infrastructure capacity evolves over time. Infrastructure congestion is also considered.[220,275]

Factors/items	**IMACLIM–R benchmarking results**
2) Ancillary infrastructure	Ancillary infrastructure such as electric chargers, fuel stations, parking infrastructure may be indirectly considered in overall demand but it is not specifically treated in terms of material and energy requirements. Infrastructure availability and costs are part of the discrete choice formulation in McCollum et al.[214]
3) Vehicle components	Specific vehicle components, such as batteries or fuel cells are not considered.
4) Vehicle materials	Industrial demand for metals (and cement) is included but not linked to vehicle production.
5) Real-world energy use	Considered, based on IEA's SMP model which takes an on-road efficiency "gap" factor into account, e.g. 22% for North America.
6) Multi-fuel use	"In IMACLIM-R, ethanol and biodiesel are assumed to be directly usable in internal combustion engines (i.e., no engine modification is necessary), by mixing with oil-based fuels (petrol and diesel, respectively) according to set proportions".[153] Fuel shares are not specified. It is unknown how utility factors for PHEVs are treated.
7) EV–power system interaction	Power plant technologies compete either for base load or peak load generation, following a load curve. Average electricity emission rates are calculated and linked to EV charging.
8) Biofuel emissions	CO_2 emissions from land use change included in overall solution but not linked to the fuel life cycle.
9) Crude oil grade	Six different grades of oil reserves are distinguished according to the cost of exploration. The carbon intensity of different crude oil grades is not defined. The carbon content of gasoline therefore does not vary depending on the crude oil source.
10) Methane leakage	No CH_4 emissions considered, thus CH_4 leakage from coal and gas production and distribution or biogenic CH_4 release from hydro power is not considered.
11) Vehicle age	Considered based on stock-vintage representation of vehicles.

Factors/items	IMACLIM–R benchmarking results
12) Travel demand	“The mobility demand and modal split result endogenously from household’s utility maximization under constraints of revenues and time spent in transport. Each mode is characterized by a price and a speed. The price of car mobility depends on fuel prices and the cost of car ownership, while other modes by the intermediate consumption shares and prices within the general equilibrium framework. When infrastructure use reaches congestion, the marginal speed of the mode decreases, which limits its use”.[219]
13) Vehicle mix	Calculated endogenously based on a logit discrete choice model. HFCEVs are not considered as a competing technology.

Table C.6: GEM–E3 benchmarking results

Factors/items	GEM–E3 benchmarking results
General items	
1) Model core and solver	General equilibrium, recursive-dynamic (simulation) solved with mixed non-linear complementarity.
2) Model extensions	In GEM-E3T, the GEM-E3 general equilibrium model is linked the PRIMES-TREMOVE economic-engineering model of passenger and freight transport, which is part of the energy system model PRIMES. PRIMES also includes a biomass supply module. Tailpipe emission factors are taken from the COPERT model.
3) Future GDP	Calculated endogenously as a function of technological progress, population, labor productivity improvements, degree of market competitiveness, and other assumptions.
4) Time horizon	Up to 2050, 5-year steps.
5) Regions	38 (28 EU Member states, USA, Japan, Canada, Brazil, China, India, Oceania, Russia, rest of Annex I, rest of world). Regions are linked through endogenous bilateral trade based on the Armington assumption that imported and domestically produced goods are imperfect substitutes.
6) GHGs	Kyoto gases (CO_2 from energy and industrial processes, CH_4, N_2O, F-gases).
7) Sectoral detail	GEM-E3T distinguishes 30 sectors, including agriculture, oil seeds, coal, crude oil, oil refining, gas, electricity supply, ferrous metals, non-ferrous metals, chemicals, paper, non-metallic minerals, electric goods, transport equipment excl. EVs, EVs, other equipment, consumer goods, construction, transport (air, road-freight, road-passenger, rail-freight, rail-passenger, water-freight, water-passenger), market services, non-market services, ethanol, biodiesel.

Factors/items	GEM–E3 benchmarking results
8) Transport sectors	Transport equipment excl. EVs, manufacturing of EVs, air, road-freight, road-passenger, rail-freight, rail-passenger, water-freight, water-passenger. PRIMES-TREMOVE provides more granular data on several transport segments, such as cars (small, medium large), motorcycles, mopeds, buses, heavy trucks, airplanes, rail, inland navigation etc.
9) Electricity conversion technologies	10 (coal, oil, gas, nuclear, biomass, hydro, wind, PV, CCS coal, CCS gas).
10) LDV technologies	McCollum et al.[214] model ICEV (gasoline, diesel, biofuel), HEV (gasoline, diesel, biofuel), PHEV-40 (gasoline, diesel, biofuel), BEV-250. Siskos et al.[276] also include HFCEVs, flex-fuel vehicles, as well as LPG and LNG ICEVs but use the PRIMES-TREMOVE model as a stand-alone tool without linking it to GEM-E3. PRIMES-TREMOVE also includes different segments such as small, medium and larger passenger cars and light trucks. The core version of GEM-E3T includes conventional vehicles (using gasoline, diesel of biofuels), plug-in hybrids (using electricity, petroleum products or biofuels) and battery electric vehicles.
11) LDV life cycle stages	Well-to-wheel (energy chain). “[T]he model relates the operation of the transport means to sectors producing the energy commodities, including alternative fuels, such as electricity and biofuels”.[214] “[L]ife cycle evaluations of energy supply, resources, prices, costs-investment and emissions” are part of the PRIMES model.[277]
12) LDV cost	Costs include purchasing cost, running costs (including fuel purchase cost) and cost factors reflecting uncertainty, technology maturity and the availability of recharging or refueling infrastructure. “The techno-economic parameters are exogenously assumed and change over time.”[219] Cost of EV batteries fall as a function of production volume (endogenous learning by doing) and as a function of cumulative expenditure for R&D in batteries (endogenous learning by research).[278]

Factors/items	GEM–E3 benchmarking results
13) LDV efficiency	Fuel consumption of vehicles is calculated in COPERT as a function of speed, trip length, occupancy factor and load factor. Different passenger car types with different energy efficiencies compete against each other based on a Weibull function function driven by relative costs of competing options.
14) LDV policies / mitigation measures	Energy efficiency standards (applied on a tank-to-wheel basis), CO_2 standards (tank-to-wheel basis), carbon tax (exogenous tax), emissions cap (endogenous tax), emission allowances, emission reduction target, emissions trading, fuel tax, technology subsidies.
LDV life cycle factors	
1) Road infrastructure	CO_2 from cement, chemicals and nonmetallic minerals production is included[279] and is linked to aggregate construction sector through input-output tables. The construction sector is linked to the transport sectors but does not distinguish different road types or ancillary infrastructures, such as parking infrastructure. Subsidies and expenditures for public infrastructure are also considered.
2) Ancillary infrastructure	Refueling and recharging infrastructure costs and availability are included in the vehicle discrete choice formulation of PRIMES-TREMOVE (and can also be included in the vehicle choice formulation of GEM-E3T).
3) Vehicle components	Costs of vehicles and selected components (like batteries) are considered. "Manufacturing of vehicles distinguishes production of conventional vehicles and electric vehicles, so as to capture price differentials of car types and the impacts of global competition in the manufacturing of new car types. The sector producing electric vehicles has endogenous learning functions reflecting the possibility of cost reduction, mainly for batteries, as a function of production volume."[159] Within the PRIMES–TREMOVE transport model[280], battery energy density is assumed to improve over time.
4) Vehicle materials	Ferrous metal production is included[279] and linked to aggregate transport equipment sectors via input-output tables.
5) Real-world energy use	PRIMES-TREMOVE uses COPERT correction factors. "Electricity consumption for plug-in hybrids and pure electric vehicles is being calculated using suggested efficiency figures from IEA and Argonne National Laboratory from the U.S. DOE."[277]

Factors/items	GEM–E3 benchmarking results
6) Multi-fuel use	Siskos et al.[276] mention: "The CO_2 emissions from PHEVs depend on the rate of use of their electric motor or the fraction of the trip that is powered by electricity" and quote a study by Samaras and Meisterling[281] who use utility factors to determine the fuel share for PHEVs. This is applied in PRIMES-TREMOVE as a stand-alone tool. The GEM-E3T model uses the bottom-up information from PRIMES-TREMOVE to estimate average rates of use of alternative fuels in plug-in hybrids (electricity, biofuels and oil products); these are then used as constant factors in GE modeling.
7) EV–power system interaction	EV charging is based on the average electricity mix. A power plant dispatch model for deriving marginal electricity emission rates is included in the full-scale PRIMES model and can derive the marginal electricity mix used for battery recharging.
8) Biofuel emissions	N_2O emissions from agriculture are considered and production of biogasoline and biodiesel uses feedstock from the agricultural sectors. COPERT accounts for LULUC emissions and assigns emissions to forestry sector. The PRIMES-Biomass Supply Model is linked to the transport model and evaluates biomass life-cycle emissions.
9) Crude oil grade	Different types of crude oil and the differences in carbon content are not differentiated. The model distinguishes between different types of refined oil products used in transport (diesel, gasoline, kerosene, LPG and others).
10) Methane leakage	Methane from gas and and coal mining, and oil exploration are considered[279] but not linked to the fuel life cycle. Biogenic methane from hydro power is not considered either.
11) Vehicle age	Vehicle stock model included.
12) Travel demand	PRIMES-TREMOVE projects passenger transport activity and fuel use endogenously as a function of GDP, income, energy prices and modal shifts (behavior). These projections are reproduced by GEM-E3T in the Baseline scenario projection.

Factors/items	GEM–E3 benchmarking results
13) Vehicle mix	Calculated in PRIMES-TREMOVE using a discrete choice model (Weibull distribution) and reproduced in GEM-E3 (also using a Weibull function). Cost of EV batteries fall as a function of production volume (endogenous learning by doing) and as a function of cumulative expenditure for R&D in batteries (endogenous learning by research).[278] PRIMES-TREMOVE also includes different segments such as small, medium and larger passenger cars and light trucks.

Table C.7: AIM/CGE benchmarking results

Factors/items	AIM/CGE benchmarking results
General items	
1) Model core and solver	General equilibrium, mixed complementarity, recursive dynamic.
2) Model extensions	AIM-CGE can be linked to the bottom-up technology-rich global model AIM/Enduse, the AIM/Transport model, which has a detailed transport sector representation, the land allocation model AIM/PLUM, and the MAGICC reduced form climate model.
3) Future GDP	Future population and GDP are exogenous.
4) Time horizon	2005–2100, with one-year intervals.
5) Regions	17 (Japan, China, India, Southeast Asia, Rest of Asia, Oceania, EU25, Rest of Europe, Former Soviet Union, Turkey, Canada, US, Brazil, Rest of South America, Middle East, North Africa, Rest of Africa).
6) GHGs	All major GHGs and other climate forcers.
7) Sectoral detail	End-use sectors include industry, transport, commercial, residential, non-energy use and other sectors (residential and commercial are sometimes aggregated). Industry is broken down into iron and steel, chemicals, non-metallic minerals, food processing, pulp and paper, construction, etc. Agriculture is broken down into rice, wheat, forestry, sugar crops etc.
8) Transport sectors	Passenger cars, small and large trucks, passenger bus, ships, aircraft and rail. Rail, navigation, and aviation have freight and passenger services.

Factors/items	AIM/CGE benchmarking results
9) Electricity conversion technologies	Coal (PCC, SC-PCC, USC-PCC, AUSC-PCC, IGCC, SC-PCC CCS, USC-PCC CCS, AUSC-PCC CCS, IGCC CCS), oil CC, gas (CC, ACC level 1–2, ACC CCS), hydro, geothermal, CCS, nuclear, wind (level 1–3), wind with storage (level 1–3), solar PV (level 1–4), PV with storage (level 1–4), waste biomass, advanced biomass (IGCC, IGCC CCS). Various hydrogen pathways are included as well.
10) LDV technologies	ICEV gasoline/diesel (including many efficiency technologies, e.g. weight reduction, engine friction reduction, aerodynamic drag reduction, rolling resistance reduction, brake drag reduction, continuously variable transmission (CVT), variable valve life and time (VVLT) and cylinder reactivation, direct injection), HEV gasoline/diesel, PHEV gasoline/diesel, BEV, HFCEV, biofuels.
11) LDV life cycle stages	Well-to-wheel (energy chain). "Indirect energy use is treated in energy transformation sector".[219]
12) LDV cost	LDV costs are derived from AIM/Enduse.[42] The default assumption is 0.5% annual improvement in future costs.[282]
13) LDV efficiency	Energy efficiency of transport technologies are derived from AIM/Enduse.[42] In Mittal et al., the base year energy efficiency for US cars is 2.58 MJ pkm^{-1}.[283] Efficiency improvement factors are exogenous and a result of light-weighting and other efficiency measures (relative efficiency improvement per year assumed). Depending on scenario, Zhang et al.[284] assume ICEV efficiency improvements to range between 30% by 2100 and 50% by 2050.
14) LDV policies / mitigation measures	Carbon tax, emissions constraint with carbon tax.
LDV life cycle factors	
1) Road infrastructure	It is possible to represent transport infrastructure and congestion (as a function of travel time) in AIM/Transport.[51] Process emissions from cement production are included but not linked to vehicle infrastructure production.

Factors/items	AIM/CGE benchmarking results
2) Ancillary infrastructure	Ancillary infrastructure such as electric chargers, fuel stations or parking infrastructure are not explicitly treated. Process emissions from cement and metal production are included but not linked to vehicle infrastructure production.
3) Vehicle components	Specifications of various vehicle components are not provided, e.g. capacity of batteries, or power of fuel cell system.
4) Vehicle materials	Steel production sector is included but not linked to vehicle cycle [282, p. 318 therein]. Efficiency improvements are assumed as a result of light-weighting but upstream emissions of materials are not considered.
5) Real-world energy use	Assumed US car fuel consumption values are higher than EPA's adjusted values. Assumptions: 2005 US car energy use is 2.58 MJ pkm^{-1} / 4.13 MJ vkm^{-1} (vehicle occupancy: 1.6 passengers) = 114.6 kWh vkm^{-1}. Compare with EPA's adjusted fuel economy for an average 2005 car (non-SUV): 23.5 MPG (89 kWh vkm^{-1}).[189]
6) Multi-fuel use	Fuel shares of multi-fuel vehicles are not mentioned.
7) EV–power system interaction	Average electric power plant emissions are linked to EV charging. No power plant dispatch model is employed.
8) Biofuel emissions	"Bioenergy supply is assumed to cause no major land use change or additional CO_2 emission in any of the scenarios in this study."[42] "AIM/Transport estimates relatively higher shares of biomass and electricity than other models. Due to the differences in energy intensity and fuel structure, AIM/Transport projects a lower GHG emission trajectory."[51]
9) Crude oil grade	Different types of crude oil, e.g. conventional/unconventional, and their different carbon content, are not distinguished.
10) Methane leakage	Fugitive emissions from fuel production are considered: "Coal mining (e.g., degasification for natural gas pipeline injection, degasification for electricity, ventilation for electricity, ventilation oxidizer for heat), natural gas production and distribution (e.g., use of instrument air, use of low bleed pneumatic devices), crude oil production (e.g., flaring in place of venting, direct use of CH_4, reinjection of CH_4)."[42] Biogenic methane from hydro power is not considered.

Factors/items	AIM/CGE benchmarking results
11) Vehicle age	The stock of new and old devices is considered (“Capital vintage is taken into account and the old and new capitals are aggregated by the CES function”).[285]
12) Travel demand	Passenger transport is determined as a function of GDP, generalized travel cost and population.
13) Vehicle mix	Calculated endogenously using a multinomial logit type equation. Simplified cost assumptions: the default assumption is 0.5% annual improvement in future costs[282]

Table C.8: MESSAGE benchmarking results

Factors/items	MESSAGE benchmarking results
General items	
1) Model core and solver	Partial equilibrium soft-linked to general equilibrium, inter-temporal optimization (linear programming) to assess the least-cost investment and operation plan consistent with a climate target. Linear program optimization is used for the energy systems and land-use modules, non-linear program optimization for the macro-economic module. MESSAGE can be run both with perfect foresight and myopically.
2) Model extensions	MESSAGE-Transport is a version of the mainline MESSAGE that includes a vehicle choice model. Other models that link to MESSAGE include the MAGICC climate model, the MACRO aggregated macro-economic model, the GLOBIOM land use model and the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model.
3) Future GDP	Exogenous, based on Shared Socio-Economic Pathways database. MACRO adjusts GDP and consumption based on service demand price changes, syste-mwide investments, and other inputs from MESSAGE.
4) Time horizon	1990 through 2100, in 10-year steps.
5) Regions	11 global regions (North America, Western Europe, Pacific OECD, Central and Eastern Europe, Former Soviet Union, Centrally Planned Asia and China, South Asia, Other Pacific Asia, Middle East and North Africa, Latin America and the Caribbean, Sub-Saharan Africa). Regions are linked through imports and exports.
6) GHGs	All GHGs and other radiative forcing agents.

Factors/items	MESSAGE benchmarking results
7) Sectoral detail	MACRO represents one uniform macro-economic sector. Specific modules within the overall integrated framework model the agriculture sector (GLOBIOM), and the energy supply and conversion sector, including energy conversion, and energy demand for transport (MESSAGE-Transport), industry and households. Industry is broken down into thermal and electric demand of total industry, non-energy use, and cement process emissions. Industry is broken down into thermal and electric demand of total industry, non-energy use, cement process emissions. Residential is broken down into thermal and electric demands. In MESSAGE-Transport, the more detailed sectoral representation of transport is broken down into numerous modes, see below.
8) Transport sectors	MESSAGE-Transport distinguishes LDVs, two-wheelers, freight trucks, passenger aviation, buses, passenger rail, and a residual category covering freight aviation, freight rail and domestic shipping.
9) Electricity conversion technologies	Super-/sub-critical PC with/without desulphurization/denox., IGCC, IGCC CCS, heavy fuel oil, light fuel oil, oil combined cycle, gas steam, gas combustion, gas combined cycle, nuclear light water reactor Gen II / III+, nuclear high temp., nuclear fast breeder, biomass steam, biomass IGCC, biomass IGCC CCS, large hydro, small hydro, solar PV, CSP, geothermal, wind (on- and offshore). A total of more than 100 conversion and end-use technologies are explicitly considered.
10) LDV technologies	MESSAGE-Transport distinguishes ICEV (gasoline, diesel / low, high, medium efficiency), ICEV (natural gas, biofuel, synthetic fossil fuel), HEV (gasoline, diesel, natural gas, biofuel, synthetic fossil fuel), PHEV-40 (gasoline, diesel), BEV-100, HFCEV.[214]
11) LDV life cycle stages	Well-to-wheel (energy chain). "All GHG-emitting and energy producing/consuming sectors are included. This implies that indirect (i.e., lifecycle) energy use and emissions from fuel production and vehicle manufacture are included, but the latter (vehicle manufacture) is not represented by a direct/endogenous linkage, rather only through the assumed future energy demands in the industrial sector."[257]

Factors/items	MESSAGE benchmarking results
12) LDV cost	Capital cost, fuel cost and operation & maintenance cost included. Fuel costs include potential fuel taxes. Future fuel costs are "[e]ndogenously determined by supply sector part of model where fuel costs are determined by an exogenous sets of supply curves and the prices are set when supply and demand are in equilibrium".[257] "The technoeconomic parameters for each technology are exogenously assumed and change over time.'[168] Costs of vehicle batteries or other specific components are not treated explicitly.
13) LDV efficiency	Three different efficiency levels are assumed for ICEVs. Apart from that, efficiency improvements only occur through switching to more efficient technologies.
14) LDV policies / mitigation measures	Economy- and sector-wide GHG and energy pricing, GHG emissions cap, fuel subsidies and taxes (and other monetary policies can be modeled), vehicle sales mandates.
LDV life cycle factors	
1) Road infrastructure	CO_2 emissions from cement production are included but not linked to road construction. Apart from that "energy transport and distribution infrastructure is included in MESSAGE at a level relevant to represent the associated costs as well as transmission and distribution losses".[219]
2) Ancillary infrastructure	Highly stylized representation. Fuel availability is part of the vehicle choice model in MESSAGE-Transport. "Within individual model regions the capital stock of transmission and distribution infrastructure and its turnover is modeled for the following set of energy carriers: electricity, district heat, natural gas, hydrogen"[271]
3) Vehicle components	Not explicitly represented.
4) Vehicle materials	Process emissions of producing steel and other vehicle-relevant materials are not explicitly represented, neither linked to vehicle production.

Factors/items	MESSAGE benchmarking results
5) Real-world energy use	In McCollum et al.,[214] the average ICEV fuel economy is assumed to be 30 MPG (0.698 kWh km^{-1}, assuming gasoline fuel). Compare with EPA's adjusted fuel economy for an average 2005 car (non-SUV): 23.5 MPG (0.89 kWh km^{-1}).
6) Multi-fuel use	Not considered.
7) EV–power system interaction	In the standard version of MESSAGE, "[e]lectricity is considered as annual average load; there are no time-slices or load-curves".[271] In the ADVANCE project, several features have been added to account for power sector dynamics, for example: "Thermoelectric technologies are represented in two modes of operation, baseload and flexible, to better account for the cost, efficiency, and availability penalties associated with flexible operation."[286] Share-dependent flexibility and capacity constraints partially reproduce the shape of a load duration curve.
8) Biofuel emissions	In Yeh et al.[257] it is stated that "[b]iomass is currently assumed to be carbon neutral. Feedstock production incurs no negative emissions, and biofuels combustion incurs no positive emissions. Only second-generation biofuels are assumed to be available".[257] In McCollum et al.[214] biofuel upstream emissions have been updated and assumed to be 0, 15, 50 g CO_2 MJ^{-1} (optimistic, central, pessimistic). "[C]arbon sequestration and emissions associated with biomass growth and land use changes are included in the agriculture and land use sectors"[257] (within GLOBIOM). GLOBIOM can be used to calculate complete biofuel life-cycle emissions when agriculture and energy sectors are linked.[151] However, GLOBIOM is currently not linked to MESSAGE-Transport. (According to private communication with the MESSAGE team linking of MESSAGE-Transport and GLOBIOM is anticipated for Spring 2019.)
9) Crude oil grade	The varying carbon content of processing different fuel grades (conventional vs. unconventional) is considered in the model, and therefore well-to-wheel carbon intensity may change over time or may differ by region at a given point in time.
10) Methane leakage	CO_2 from gas flaring is included. CH_4 sources include production and transport of coal, natural gas, and oil, including pipeline leakages. Biogenic CH_4 release from hydro power is not considered.

Factors/items	**MESSAGE benchmarking results**
11) Vehicle age	Included through a vintage model.
12) Travel demand	In MESSAGE-Transport "[f]uture demand for passenger travel in the various modes is projected on a passenger-kilometer (pkm) basis as a function of per-capita GDP, with gradual regional convergence".[214] "Total passenger transport demand (aggregate of all modes) moves toward a saturation point (at the highest incomes reached in the very long term) of 150,000 pkm year^{-1}."[257] In the conventional MESSAGE version, a simplified "scenario generator" approach is used in which energy service demands are provided exogenously.
13) Vehicle mix	LDV technology mix and mode choice develop endogenously through the MESSAGE-Transport discrete choice model. "Passenger mode choices are responsive to service prices and travel-money and travel-time constraints (via a soft-linked logit-based model)."[168]

Table C.9: WITCH benchmarking results

Factors/items	WITCH benchmarking results
General items	
1) Model core and solver	General equilibrium, inter-temporal optimization (non-linear and game-theoretic).
2) Model extensions	WITCH is linked to the GLOBIOM land use-forestry-bioenergy model (partial equilibrium) and the MAGICC climate model. Some parameters and assumptions regarding the transport sector are sourced from IEA SMP (the predecessor of IEA's Mobility Model, MoMo). These include vehicle fuel efficiency, and vehicle forecasts based on GDP and population.
3) Future GDP	GDP and population forecasts are exogenous. GDP forecasts are based on projections made by the OECD. Population forecasts follow the SSP2 "middle of the road" scenario, based on the projections developed at IIASA for the SSP database.
4) Time horizon	2005–2100, 5-year steps.
5) Regions	13 global regions.
6) GHGs	Kyoto gases (CO_2, CH_4, N_2O, short-lived and long-lived F-gases).
7) Sectoral detail	One economic production sector that uses capital, labor and energy services; one electricity sector with 13 technologies; one transport sector with two explicit modes; one aggregated non-electric sector (incl. industry, services, residential); one land use sector.
8) Transport sectors	LDVs and road freight are explicitly modeled, while other transport modes are modeled indirectly in the aggregated non-electric sector.
9) Electricity conversion technologies	13 electric technologies: PC, IGCC CCS, NGCC, NGCC CCS, wind onshore, wind offshore, solar PV, CSP, nuclear, advanced nuclear, bio, BECCS, hydro; six non-electric technologies: biomass, oil, gas, coal, traditional biofuels, advanced biofuels.

Factors/items	**WITCH benchmarking results**
10) LDV technologies	ICEV (gasoline, diesel, biofuel), HEV (gasoline diesel, biofuel), PHEV-40 (gasoline, diesel, biofuel), BEV-250.[214] Other studies using WITCH may have modeled different technologies.
11) LDV life cycle stages	Well-to-wheel (without biofuel upstream emissions). "Aspects such as infrastructure and the vehicle manufacturing are incorporated in the overall GDP and representation of final goods."[219]
12) LDV cost	"A Leontief production function combines the operation and maintenance (O&M) costs, fuel cost, carbon cost and investment cost associated with each vehicle type. These parameters have unique values for each vehicle type."[152] Vehicle and fuel costs differ across time and regions. ICEV production costs are held constant at 2005 levels. EV battery costs decrease endogenously at a 14.4% learning rate (learning by researching). 2010 lithium-ion battery costs are 550 USD kWh^{-1}, which is a quite optimistic value. Costs fall to 380 USD kWh^{-1} and 166 USD kWh^{-1} by 2020 and 2050. In a rapid battery cost improvement scenario, costs fall down to 51 USD kWh^{-1} by 2100.[152] Carrara et al.[287] focused on the heavy duty sector and assumed less optimistic battery costs following a 12.5% learning rate.
13) LDV efficiency	Exogenous improvements assumed.
14) LDV policies / mitigation measures	Carbon tax, global carbon cap (450 or 535 ppm CO_2e by 2100), R&D (rapidly falling EV battery costs), energy taxes and subsidies (e.g. on gasoline and diesel in the transport sector, as well as gas and electricity in the stationary sector). (Biofuel levels are assumed to meet the renewable energy targets set in the US and the EU).
LDV life cycle factors	
1) Road infrastructure	Indirectly considered in overall GDP and representation of final goods. Production of cement and other inputs into infrastructure construction are not explicitly modeled.
2) Ancillary infrastructure	Fuel infrastructure availability and costs are considered in the vehicle choice algorithm in McCollum et al.[214]

Factors/items	WITCH benchmarking results
3) Vehicle components	Only EV battery capacity is specified.
4) Vehicle materials	Vehicle manufacturing indirectly incorporated in overall GDP and representation of final goods. Production of steel and other inputs into vehicle production are not explicitly modeled.
5) Real-world energy use	Based on IEA SMP model which includes on-road efficiency gap factor (22% in North America in 2000). Uniform factor assumed for all technologies.
6) Multi-fuel use	Biofuel use in MFVs is limited to a maximum of 50% by 2020, then linearly increasing to 100% by 2100. PHEV utility factors are not mentioned.
7) EV–power system interaction	Flexibility and capacity constraints with fixed parameters create demand for peak-load technologies and allow for output reduction.[286] Average emission factors are calculated and linked to EV charging.
8) Biofuel emissions	CO_2 and CH_4 from deforestation and afforestation, and CH_4 and N_2O from agriculture are accounted for based on GLOBIOM. GLOBIOM can be used to calculate complete biofuel life-cycle emissions when linking the agriculture and energy sectors.[151] "Land use emissions are accounted for within WITCH, as are the emissions from the use of bio-energy as biofuel or when co-fired with gas/coal with or without CCS."[152] Biofuel can be sourced either from traditional or advanced sources and are constrained to a maximum of an E50 fuel mixture with oil-based fuels.
9) Crude oil grade	Eight different oil grades are considered, and differentiated by extraction CO_2 emissions and costs Lower cost resources are exploited first. Carbon content of different grades is not considered and not linked to vehicle life cycle.
10) Methane leakage	Emissions associated with coal and gas extraction are not considered. Hydro power is treated as carbon-free.
11) Vehicle age	Vehicle aging is considered through a vintage stock model that is part of IEA SMP model.

Factors/items	WITCH benchmarking results
12) Travel demand	Vehicle demand is calculated as a function of population and GDP projections, following IEA SMP modeling assumptions. Vehicle demand is multiplied by constant annual travel demand to calculate total transport demand (in vehicle kilometers). Vehicle kilometers are are multiplied by a load factor to calculate person kilometers.
13) Vehicle mix	Least-cost minimization (life cycle costs (fixed operation and maintenance costs, fuel and investment costs)). Technology restrictions can be imposed following an S-shaped diffusion path. EV battery costs decrease endogenously at a 14.4% learning rate (learning by researching). HFCEVs are not considered.

Table C.10: REMIND benchmarking results

Factors/items	REMIND benchmarking results
General items	
1) Model core and solver	General equilibrium, intertemporal optimization with perfect foresight (the macro-economic core is a Ramsey-type optimal growth model in which inter-temporal welfare is maximized).
2) Model extensions	The macro-economic module is linked to an energy systems module. Land-use and agricultural emissions and bioenergy supply are derived from the land-use and agricultural model MAgPIE. A reduced-form climate model MAGICC6 is used to convert emissions into atmospheric composition, radiative forcing and climate change.
3) Future GDP	Baseline population and GDP are inputs based on the Shared Socio-economic Pathway (SSP) scenarios. REMIND's default population projections (both total population as well as working age population) are based on IIASA (and the GDP scenarios from the OECD). GDP in climate policy scenarios changes endogenously, as investments change in reaction to carbon prices/mitigation policies.
4) Time horizon	REMIND spans the years 2005–2100. 5-year steps for 2005–2060, 10-year steps for 2060–2100.
5) Regions	The world is divided into 11 regions (US, China, India, Japan, Russia, EU, Latin America, sub-Saharan Africa w/o South Africa, Middle East / North Africa / Central Asia, other Asia, Rest of world). The regions are linked via resource trade.
6) GHGs	All Kyoto gases and other radiative agents. Non-CO_2 GHG emissions are determined by applying marginal abatement costs curves relative to baseline emission levels that depend on activity variables or by assuming exogenous scenarios.

Factors/items	REMIND benchmarking results
7) Sectoral detail	Three end-use sectors are considered, namely residential/commercial, industry and transport, which are part of a CES (constant elasticity of substitution) function. The buildings and industry sectors are users of electric and non-electric (gases, solids, liquids, hydrogen, heat) energy sources.
8) Transport sectors	"For passenger transport, we consider LDV (powered by liquids, electricity or hydrogen), Aviation and Bus (aggregated, only powered by liquids) and Electric Trains (only powered by electricity). For freight transport, there is only one generic mode based on liquid fuels."[271]
9) Electricity conversion technologies	A total of 50 energy conversion and end-use technologies are available. Around 20 electricity generation technologies are available, including coal (conventional, CHP, ICG CC, oxyfuel), oil (diesel or turbine), gas (CHP, turbine, CC), nuclear (light water reactor), solar (PV, CSP), wind, hydro, geothermal (hot dry rock), biomass (CHP, IGCC).
10) LDV technologies	ICEV, BEV, HFCEV.
11) LDV life cycle stages	Well-to-wheel (complete energy chain). The transport sector uses electricity, liquid fuels, and hydrogen. "Input of final energy in different forms is required together with investments and operation and maintenance payments into the distribution infrastructure as well as into the vehicle stock. Material needs and embodied energy are not considered."[219] Vehicle production and infrastructure construction are not explicitly linked to/part of the vehicle life cycle.
12) LDV cost	Investment costs, O&M costs, and fixed costs change over time in response to an endogenous learning curve. Costs of ICEVs remain constant, BEVs and HFCEVs follow a 10% learning rate. Base year investment cost of an ICEV, a BEV and an HFCEV are: 11,000 USD, 26,000 USD and 32,000 USD. BEV and HFCEV floor cost are 15,000 USD. Fixed O&M cost are assumed to be 10% of investment cost. Fuel costs are fully endogenized.

Factors/items	**REMIND benchmarking results**
13) LDV efficiency	Simple efficiency factor for BEVs (3) and HFCEVs (2.5) relative to ICEVs (1) are used. "[T]he model can endogenously improve end-use efficiency by investing in more efficient technologies for the conversion of final energies into energy services."[271]
14) LDV policies / mitigation measures	Fuel taxes and subsidies, carbon cap, carbon tax, resource constraints.
LDV life cycle factors	
1) Road infrastructure	Investments are considered for energy distribution infrastructure, not for transport infrastructure. CO_2 from cement production is included, but not explicitly linked to road infrastructure construction. "[O]peration and maintenance payments into the distribution infrastructure (infrastructure capacity grows linearly with distributed final energy)" is considered.[271]
2) Ancillary infrastructure	Investments are considered for energy distribution infrastructure, not for ancillary transport infrastructure. Material and energy needs of ancillary infrastructure are not explicitly considered either.
3) Vehicle components	Specific vehicle components such as batteries (and their characteristics, costs, material and energy needs) are not explicitly considered.
4) Vehicle materials	Steel emissions are considered but not explicitly linked to vehicle production. ("Emissions of the three largest industry sub-sectors (cement, chemicals and steel production) can partially be abated by the use of CCS. [...] [E]missions of the sub-sectors are calculated based on region-specific sub-sector shares in the use of CO_2-emitting final energy carriers."[271])
5) Real-world energy use	2005 vehicle energy efficiencies are calibrated against IEA energy balances, and therefore account for the gap between real-world efficiencies and labeled efficiencies in 2005. (IEA energy balances do not distinguish LDVs from other road transport modes.) The model does not account for changes of the increasing gap since then.
6) Multi-fuel use	Multi-fuel vehicles (MFVs) are not considered.

Factors/items	REMIND benchmarking results
7) EV–power system interaction	The power sector in REMIND captures the effects of adding wind and solar power to the power sector on a) capacity adequacy, b) dispatch, c) storage and d) curtailment. Region-specific load duration curves with four load bands are considered.[286] Average electricity emission factors are calculated and linked to EV charging.
8) Biofuel emissions	Three different feedstocks are considered but the main source of bioenergy supply is second generation biomass and ligno-cellulosic and forestry residues, whereas first-generation bioenergy is assumed to phase out in the standard scenario. GHG emissions from agriculture, forestry and land use are supplied by MAgPIE. LULUC emissions (CO_2, CH_4 and N_2O) from biomass production and negative CO_2 emissions from bioenergy with CCS (BECCS) are considered and accounted for when using biomass to produce transportation fuels.
9) Crude oil grade	Three fossil resources are considered, oil, coal, gas, which are characterized by extraction cost curves (marginal cost of extraction per unit of energy is a function of cumulative extraction). REMIND prescribes decline rates for the extraction of coal, oil, and gas. The carbon intensity of different crude oil grades is not considered. Thus, variations in the carbon content of crude oil grades are not captured in/linked to the production of gasoline.
10) Methane leakage	CH_4 from waste, land use change and fossil fuel extraction are considered as MAC curves. Upstream CH_4 from coal and gas production and biogenic CH_4 from hydropower emissions have recently been added.[171] These emissions are linked to transport demand.
11) Vehicle age	Considered through full vintage tracking for all technologies. Vehicle lifetime is 13 years.
12) Travel demand	"Mobility from the different modes is an input to a CES function, the output of which is combined with stationary energy in a CES function to generate a generalized energy good, which is combined with labor and capital in the main production function for GDP."[219]

Factors/items	REMIND benchmarking results
13) Vehicle mix	"The distribution of vehicles inside the LDV mode follows cost optimization (perfect linear substitutability)."[271] Costs of ICEVs remain constant, BEVs and HFCEVs follow a 10% learning rate. HEVs and PHEVs are not considered. The share of BEVs is restricted to 70%, HFCEVs to 90%. (Modal shift is possible too.)

Table C.11: IMAGE benchmarking results

Factors/items	IMAGE benchmarking results
General items	
1) Model core and solver	IMAGE is a partial equilibrium model that calculates equilibria between energy supply and certain energy demand sectors (as opposed to all energy demand sectors in a general equilibrium model). The solution algorithm is recursive dynamic (simulation), i.e. agents do not have any foresight about the future when making a decision today.
2) Model extensions	Several models are integrated with IMAGE, e.g. the TRAVEL discrete choice model (part of the TIMER energy supply and demand model), the MAGNET agro-economic general equilibrium model, the MAGICC 6.0 reduced-form climate model, the plant growth, carbon and water cycle model LPJmL, the GLOBIO land use model, FAIR (climate policy), GLOFRIS (flood risks) and GISMO (human development).
3) Future GDP	The baseline relies on exogenous income and population projections from the OECD. The current main branch uses the SSP GDP and population projections, with SSP2 being the 'middle of the' road baseline.
4) Time horizon	2005–2100. 1970–2005 data is used for model calibration.
5) Regions	TAVEL and IMAGE cover 26 regions (Canada, USA, Mexico, Rest Central America, Brazil, Rest South America, Northern Africa, Western Africa, Eastern Africa, South Africa, OECD Europe, Eastern Europe, Turkey, Ukraine, Asia-Stan, Russia, Middle East, India, Korea, China, South East Asia, Indonesia, Japan, Oceania, Rest of South Asia, Rest of South Africa).
6) GHGs	All GHGs and other radiative agents.

Factors/items	**IMAGE benchmarking results**
7) Sectoral detail	Transport, forestry, livestock, households, manufacturing, electricity, hydrogen, industry (includes heavy industry submodule with two sectors, steel and cement), services. All energy demand sectors are represented but with varying detail (e.g. more detail in the cement and steel sector). “The economy is represented separately in different model components, notably in the agriculture and energy models with monetary feedback not well represented in the energy model.”[288]
8) Transport sectors	Seven passenger transport modes (foot, bicycle, bus, rail, car, high-speed train, airplane) and six freight transport modes (national and international shipping, air transport, medium trucks, heavy trucks and rail).
9) Electricity conversion technologies	20 different power plant types using fossil fuels (oil, coal, natural gas) and bioenergy including CC, CHP, and CCS options; wind and solar; hydro; nuclear. (11 hydrogen production pathways are included too.)
10) LDV technologies	ICEV (gasoline, diesel / conventional, efficient), ICEV (biofuel, hydrogen), HEV (gasoline, diesel, biofuel), PHEV-10 / -30 (gasoline, diesel, biofuel), BEV-90 / -150, HFCEV.[214] Edelenbosch et al.[137] assume a 45 kWh battery capacity of BEVs on average, with a sensitivity range of 30–90 kWh. Battery energy density is not explicitly considered. Other studies using IMAGE may model different technologies.
11) LDV life cycle stages	Well-to-wheel (energy chain). The transport module is fully incorporated within IMAGE which means that all upstream fuel emissions are accounted for. However they will be allocated to the upstream sectors in the reporting (e.g. biofuel upstream emissions will be accounted for in the agriculture sector). Note that Girod et al.[167] assume that hydrogen and electricity upstream emissions are negligible. In addition, assumed biofuel upstream emissions are quite optimistic. Therefore, Girod et al. achieve a well-to-wheel representation only for gasoline and biofuel used in vehicles. Deetman et al.[150] consider upstream electricity emissions but use TIMER as a stand-alone tool without a link to IMAGE. Other studies using IMAGE and TIMER may make different assumptions.

Factors/items	IMAGE benchmarking results
12) LDV cost	In Edelenbosch et al.[137] baseline EV battery costs are in line with Nykvist et al.[215] but costs can vary by scenario. For example, the "market leader" scenario assumes battery costs to fall to 150 USD kWh^{-1} by 2025. Other studies may follow different cost trajectories.[289] Electricity and fuel costs develop endogenously over time.
13) LDV efficiency	"Different vehicle types with different energy efficiencies compete against each other (based on the multinomial logit), which allows for a change of energy efficiency of the mode."[219] Further exogenous energy efficiency improvements are possible. Mode shift is possible too.
14) LDV policies / mitigation measures	Carbon tax (rising up to 249 USD t^{-1} in 2050,[137]) carbon storage price, EV subsidies, biofuel mandates and obligations, taxes on energy use, climate target (defined in terms of concentration level, radiative forcing, temperature increase, or cumulative emissions), efficiency standard (e.g. in transport, heavy industry, households), implementation of sustainability criteria in biofuel production.
LDV life cycle factors	
1) Road infrastructure	Cement and steel cycles are included. Cement process CO_2 emissions are included but not linked to road infrastructure production. Cost estimates are considered for energy supply infrastructure (e.g. pipelines), but not for road infrastructure.
2) Ancillary infrastructure	Fuel station and electric charger availability is part of the discrete choice formulation in McCollum et al.[214]
3) Vehicle components	Costs and capacity of EV batteries are considered.[137] Specifications on battery energy densities have not been identified.
4) Vehicle materials	Steel cycle is included, including CO_2 emissions, but not linked to vehicle production. Embodied emissions of vehicles are included in the industry sector.

Factors/items	**IMAGE benchmarking results**
5) Real-world energy use	Girod et al.[167] use ICEV and HFCEV energy efficiencies reported by Ogden and colleagues.[290] Ogden et al. assume an ICEV fuel economy of 27 MPG. This value is slightly higher than the fleet average 2004 real-world fuel economy of 23 MPG.[189] PHEV and BEV fuel efficiencies are based on Kromer and Heywood,[291] who adjust for aggressive driving using EPA's US06 drive cycle. ("The reason that US06 is deemed more appropriate is that the standard FTP and HWFET adjustments (0.9 and 0.78), which are used to reflect "real-world" conditions, do not reflect the fact that marginal power in a blended mode plug-in hybrid come from the engine. The fixed multipliers correct for real-world driving conditions by scaling the average fuel consumption, which includes both highly efficient electric operation and peaking engine power. The aggressiveness of the US06 avoids this problem.")
6) Multi-fuel use	Generally, each vehicle is assumed to use one fuel [288, p. 80 therein]. Girod et al.[167] assume that PHEVs use half electricity, half gasoline. Other studies using IMAGE may make different assumptions.
7) EV–power system interaction	TIMER energy model distinguishes between baseload and peakload electricity generation and calculates demand on the basis of a monthly load duration curve with 156 time slices. Technology dispatch occurs according to merit order.[286] This potentially enables calculation of marginal emission factors, however average emission factors have so far been used. Girod et al.[167] assume that electricity upstream emissions are negligible. Other studies using IMAGE may make different assumptions.
8) Biofuel emissions	LUC emissions from clearing forests, indirect fertilizer N_2O emissions, carbon uptake and release of plants included, and linked to fuel life cycle. (Girod et al.[167] linked exogenous biofuel upstream emission factors to available LDV technologies in an ad-hoc fashion. With 30 g CO_2e MJ^{-1} (108 g CO_2e kWh^{-1}), these are quite optimistic and much lower than current first generation biofuels, cf. Figure C.2.)
9) Crude oil grade	12 resource categories for oil exist, including unconventional resources. Carbon content of crude oil grades vary, which is taken into account in gasoline production.

Factors/items	IMAGE benchmarking results
10) Methane leakage	Several methane sources are included. Gas fueled cars are linked to gas production. Methane emissions during energy transport are considered (indirectly considering pipeline leakage). Methane emissions during power production are considered, but biogenic methane release from hydro power is not explicitly described in Stehfest et al.[288]
11) Vehicle age	Vintage structure of the vehicle stock is implemented (15 years lifetime for cars).
12) Travel demand	Determined endogenously as a function of GDP, population, fuel price, non-energy prices, vehicle load factor, mode preferences, energy efficiency, mode speed, service demand per mode, on the basis of travel money budget (TMB) and travel time budget (TTB) formulation.
13) Vehicle mix	Discrete choice (logit). In Edelenbosch et al.[137] baseline EV battery costs are in line with Nykvist et al.[215] but costs can vary by scenario.

Table C.12: DNE21+ benchmarking results

Factors/items	**DNE21+ benchmarking results**
General items	
1) Model core and solver	Partial equilibrium, intertemporal optimization with perfect foresight (linear programming). Total discounted energy systems cost is minimized.
2) Model extensions	DNE21+ assess energy-related CO_2 emissions. A simple climate model based on MAGICC is integrated with DNE21+. Within the RITE GHG Assessment Model framework, DNE21+ is linked to a non-energy CO_2 module and a non-CO_2 GHG module. "Land use model assesses land area for food, energy crops and afforestation. Crop productivity is based on GAEZ model."[271]
3) Future GDP	Population scenarios are based on UN estimates. Two GDP scenarios are developed. "In Scenario A, the current developed countries slow down the GDP per capita growth until 2100 and the growth rate converges to 0.5% per year in 2100. Developing countries continue to grow steadily. The current emerging economies and least developed countries have the per capita GDP growth rates of around 1% per year and around 2% per year in 2100, respectively. The global average growth rate from 2000 to 2100 is 1.5% per year. In Scenario B, the current developed countries continue to increase GDP per capita by 1.0% per year in 2100. Developing countries continue to grow rapidly. The current emerging economies and least developed countries grow at the rate of around 2% per year and around 3% per year even in 2100, respectively. The global average growth rate from 2000 to 2100 is 2.1% per year."[271]
4) Time horizon	2005–2050. The period 2005–2030 is solved in 5-year steps. The period 2030–2050 is solved in 10-year steps. "2005 represents the period from 2003 to 2007, 2010 represents the period from 2008 to 2012, 2015 represents the period from 2013 to 2017 and so on."[271]

Factors/items	DNE21+ benchmarking results
5) Regions	77 including USA, Canada, EU-15, EU-12, Other Western Europe, Japan, Oceania, China, Korea, India, Other Asia, Middle East & North Africa, Turkey, Africa, Mexico, Brazil, Other Latin America, Russia, Other FUSSR. Regions are linked to each other by interregional trading of seven items: coal, crude oil, synthetic oil, methane, methanol, hydrogen and CO_2.
6) GHGs	All GHGs and other radiative agents.
7) Sectoral detail	Four end-use sectors (transport, residential and commercial, industrial, other). Indusry is divided into iron & steel, cement, paper & pulp, chemical (ethylene, propylene, ammonia), aluminum, fuels & electricity. Transport sectors see below.
8) Transport sectors	Passenger cars (small, large), trucks (small large), buses.
9) Electricity conversion technologies	Coal (sub-critical, critical, super critical, IGCC, IGFC), IGCC/IGFC with CCS, oil (diesel, sub-critical, critical, CHP), gas (steam turbine, combined cycle, combined cycle with high temperature, CHP, oxy-blown combined cycle with CCS), biomass (steam turbine, combined cycle), nuclear (conventional, advanced), hydrogenm, electricity storage (pumping-up, battery for PV and wind). 200–300 conversion and end-use technologies are modeled in total.
10) LDV technologies	Gasoline and ethanol (ethanol content $<20\%$): ICEV (high, low efficiency), HEV, PHEV; Gasoline and ethanol (ethanol content $\leq 20\%$): ICEV, HEV, PHEV; Diesel and biodiesel (biodiesel content $<20\%$): ICEV (high, low efficiency), HEV, PHEV; Diesel biodiesel (biodieseel content $\leq 20\%$): ICEV, HEV, PHEV; CNG: HEV, ICEV; BEV; HFCEV. Two segments, small and large.
11) LDV life cycle stages	Well-to-wheel (energy chain). "Indirect energy use is not included. For example, emissions from car manufacturing process is classified into the industrial sector."[219]
12) LDV cost	ICEV costs are constant over entire time horizon. BEVs start out at about 85,000 USD and drop to about 23,000 USD. HFCEVs start at 134,000 and drop to 24,000 USD. Li-ion batteries start at 1,667 USD kWh^{-1} and fall down to 181 USD kWh^{-1}.

Factors/items	DNE21+ benchmarking results
13) LDV efficiency	Two efficiency levels exist for ICEVs. No efficiency improvements of power trains. Mode efficiency improvements only through technology choice/switching.
14) LDV policies / mitigation measures	"[C]arbon pricing, emission cap and trade system, carbon tax, preferred tax on specific energy sources, fuel subsidies, fuel standards and energy standards. In general, these policies are implemented via constraints or a price mark-up on energy sources."[271]
LDV life cycle factors	
1) Road infrastructure	Cement production is modeled including process emissions but not linked to infrastructure production.
2) Ancillary infrastructure	Not considered.
3) Vehicle components	Battery costs are taken into account.
4) Vehicle materials	Steel, aluminum, and chemical products (e.g. ethylene and propylene) are modeled (including process emissions) and availability of steel scrap is considered but not linked to vehicle production.
5) Real-world energy use	Fuel consumption for a small ICEV in 2010 ranges from 4.4 to 8.0 l 100 km^{-1} (39–71 kWh km^{-1}). Large ICEV ranges from 12.1 to 12.7 l 100 km^{-1} (108–113 kWh km^{-1}). (Fuel efficiencies are not adjusted by region.) EPA's adjusted values for a small ICEV car is 79 kWh km^{-1}, kWh km^{-1} for a large ICEV car 86 kWh km^{-1} (data provided by Aaron Hula at EPA).
6) Multi-fuel use	Not considered.
7) EV–power system interaction	Within the RITE GHG Assessment Model framework " [e]lectricity demand is modeled so that demand-supply balance is ensured; four kinds of time periods are set based on annual load duration curves, and electricity supply follows varying loads. This enables appropriate evaluation of electricity system corresponding to the characteristics of individual power generation technologies such as the base power source, the peak power source et cetera".[292] Average electricity emission factors are linked to EV charging.

Factors/items	**DNE21+ benchmarking results**
8) Biofuel emissions	"CO_2 fixation through afforestation and the use of bioenergy technologies are also explicitly modeled by estimating the potential productivity of land areas via a food supply and demand and land-use model".[293] "N_2O emissions are considered in 6 sectors: agriculture, oil, natural gas, residential and transportation, energy intensive industries, and other industrial sectors."[292]
9) Crude oil grade	Conventional and unconventional oil is considered.
10) Methane leakage	CH_4 from oil, coal and natural gas sectors is included and several methane mitigation options are implemented including flaring and coal mining methane capture. Biogenic methane from hydro power is not considered.
11) Vehicle age	Not considered (no vehicle vintage formulation is used).
12) Travel demand	"The transportation service is assumed to be exogenous according to region and the five categories, and the scenario is fixed for all the scenarios analyzed in this study. Therefore, the impacts of climate change mitigation on the level of road transport service cannot be evaluated endogenously in this analysis."[293]
13) Vehicle mix	Technological options are endogenously determined through least-cost optimization. Li-ion batteries start at 1,667 USD kWh^{-1} and fall down to 181 USD kWh^{-1}.

Table C.13: TIAM–UCL benchmarking results

Factors/items	**TIAM–UCL benchmarking results**
General items	
1) Model core and solver	Partial equilibrium, inter-temporal optimization (linear programming).
2) Model extensions	TIAM-UCL uses an integrated climate module. TIAM-UCL can be coupled to BUEGO (Bottom up Economic and Geological Oil field production model).[294]
3) Future GDP	GDP and population are exogenous, provided by the GEM-E3 model or by accepted external sources.
4) Time horizon	2005–2100, 5-year steps. (2010–2035, 5-year steps in BUEGO.)
5) Regions	16 (Africa, Australia, New Zealand, Canada, Central and South America, China, Eastern Europe, Former Soviet Union, India, Japan, Mexico, Middle-East, Other Developing Asia, So-Korea, USA, Western Europe w/o UK, UK). The world regions are linked through trade in fossil fuels, biomass and emissions via the trade module.
6) GHGs	CO_2, CH_4, N_2O.
7) Sectoral detail	Three end use sectors (transport, buildings, industry), upstream and power sector and 43 energy service demands (14 transport, 10 residential, 10 industry energy service demands). Industrial production is subdivided into chemical industry, iron & steel and non-ferrous metals, pulp & paper and non-metallic minerals, and other industries. See transport sectors below.
8) Transport sectors	Domestic aviation, international aviation, bus, commercial trucks, 3-wheelers, 2-wheelers, heavy trucks, medium trucks, LDVs, auto, rail freight, rail passengers, domestic navigation, international navigation, non-energy.

Factors/items	TIAM–UCL benchmarking results
9) Electricity conversion technologies	Coal (atmospheric FI bed, air blown IGCC, oxygen blown IGCC, pressurized FI bed, PC), natural gas (steam, fuel cells), dual gas/oil (gas-oil combined cycle, advanced gas-oil turbine, oil steam), nuclear (advanced, fusion, advanced LWR, advanced PBMR), hydro (impoundment, run-of river), biomass (crop direct combustion, crop gasification, waste biogas, MSW direct combustion, solid biomass direct combustion, solid biomass gasification, solid biomass direct combustion), geothermal (3 types), PV (14 types), solar thermal, wind (4 types), heat (6 types), 11 sequestration technologies, 10 storage technologies.
10) LDV technologies	ICEV (gasoline, diesel, synthetic fossil fuel, natural gas, LPG, ethanol), HEV (gasoline, diesel, biofuel, synthetic fossil fuel), PHEV-10 (gasoline, diesel, biofuel, synthetic fossil fuel), BEV-100, HFCEV, HFCEV-10.[214] Note that technologies may be altered in other works.
11) LDV life cycle stages	Well-to-wheel (energy chain). All primary energy sources (oil, gas, coal, nuclear, biomass, renewables) are modeled, from resource extraction through to conversion, infrastructure requirements, and end-use. “The fuel mix is determined endogenously. Indirect fuel use from manufacturing, upstream energy and emissions are calculated but not tied to transport.”[219]
12) LDV cost	Investment cost, operation and maintenance cost considered. In the standard version, costs are not component-specific, and learning is not endogenized. The version used by Anandarajah et al.,[295] used endogenous technology learning with initial fuel cell system costs of 883 USD kW^{-1} in 2010 and long-term floor cost of 27 USD kW^{-1}. Batteries initially cost 756 USD kWh^{-1} in 2010 and decrease to 151 USD kWh^{-1}. Energy prices are calculated endogenously.
13) LDV efficiency	“Efficiency and cost of these technologies improve over the period with vintages,”[296] i.e. more efficient technologies become available over time.
14) LDV policies / mitigation measures	Carbon tax, cap and trade, global and regional carbon caps, technology subsidy, efficiency requirement.

Factors/items	TIAM–UCL benchmarking results
LDV life cycle factors	
1) Road infrastructure	Physical output of iron and steel, non-ferrous metals, non-metallic materials and others is represented in TIAM-UCL, but not linked to vehicle cycle. Fuel infrastructure availability is considered in the vehicle choice formulation by McCollum and colleagues.[214]
2) Ancillary infrastructure	Hydrogen and electricity supply infrastructure is modeled in great detail[295] but physical requirements are not considered.
3) Vehicle components	Typically, vehicles are represented in an aggregated form. In a version of TIAM-UCL, several components are modeled in terms of costs (USD), power (kW) and capacity (kWh).[213, 295] Battery energy densities are not specified. No materialistic representation. Components are scaled to match the size and performance of average European vehicles.
4) Vehicle materials	Physical output of iron and steel, non-ferrous metals, non-metallic materials and others is represented in TIAM-UCL, but not linked to vehicle cycle. Both, demand for vehicles and materials is independently determined by population and GDP.
5) Real-world energy use	Generally, base-year energy consumption of road transport and other modes is calibrated against IEA's extended regional energy balances (which do not distinguish LDVs from other road transport modes or different vehicle technologies). In Anandarajah et al.[295] a uniform gap of 15% between the New European Drive Cycle and real-world fuel consumption is assumed although this factor has been found to be higher and to differ by technology.[73] More recent versions may make different assumptions.
6) Multi-fuel use	In McDowall et al.,[213] the PHEV utility factor is assumed to be 0.5. Other MFVs are not considered. More recent versions may make different assumptions.
7) EV–power system interaction	The model employs additional (marginal) electricity technologies as electricity demand grows with increasing EV deployment. Changes in overall power sector emissions associated with EV charging therefore reflect the marginal technologies. EV charging is based on the average electricity mix.

Factors/items	**TIAM–UCL benchmarking results**
8) Biofuel emissions	Energy and net CO_2 emissions from direct land use are accounted for in the agriculture sector. Net CO_2 emissions consider afforestation, deforestation and forest degradation. N_2O emissions in the industry and agriculture sectors are included as well. Emissions are not linked to the fuel life cycle since agricultural emissions are independent from biofuel production in the energy sector.
9) Crude oil grades	Different oil grades, such as light oil, heavy oil, shale, synthetic oil sands, ultra heavy oil sands and differences in their costs, carbon intensities and energy requirements are considered. The model can choose upstream oil sources with lower emissions for gasoline production.
10) Methane leakage	Methane emissions from oil, coal, gas reserves, extraction, and gas transmission including leakage.[297] These emissions are linked to the fuel life cycle. 50 mitigation technologies exist including flaring, venting and investments in reducing methane emissions. Biogenic methane emissions from hydro power are not mentioned. Included are non-energy methane emissions from landfills, manure, biomass burning, rice cultivation, enteric fermentation and wastewater (accounted for in the residential and agricultural sectors).
11) Vehicle age	Addressed by using a vintage model.
12) Travel demand	Endogenously determined as a function of per capita GDP. Demand growth is subject to demand elasticity for different services, between different regions and over time.
13) Vehicle mix	Least-cost minimization (full life cycle cost). The version used in Anandarajah et al.[295], used endogenous technology learning with initial fuel cell system costs of 883 USD kW^{-1} in 2010 and long-term floor cost of 27 USD kW^{-1}. Batteries initially cost 756 USD kWh^{-1} in 2010 and decrease to 151 USD kWh^{-1}. (BEV market share can be constrained, representing the inability of meeting consumer energy demand, e.g. range limitations). (The split between rail and road modes is set exogenously.)

Table C.14: POLES benchmarking results

Factors/items	POELS benchmarking results
General items	
1) Model core and solver	Partial equilibrium, recursive dynamic (simulation). Myopic anticipation of future costs.
2) Model extensions	Additional modules allow covering GHG emissions from industrial sources; agriculture and land-use emissions are derived from linkages with specialized models. POLES can be linked to the GLOBIOM global land-use model, the MAGICC reduced-form climate model, the GAINS air pollutants model (including pollutants from road transport and other transport modes), and the EUCAD power plant dispatch model.
3) Future GDP	Per capita GDP and population are exogenous. Frequently, POLES is soft-linked with the general equilibrium model GEM-E3 to assess policy costs on GDP.[298] “An on-going work will allow to connect POLES to the macro-econometric model MAGE (CEPII institute / JRC) through an energy factor in the production function that will link dynamically GDP, energy intensity and energy prices.”[271]
4) Time horizon	Usually 1990–2050, in annual time steps. For the ADVANCE project, the time horizon has been extended to 2100.
5) Regions	45 individual countries (28 EU Member States, Norway, Switzerland, Iceland, Turkey, Russia, Ukraine, Canada, USA, Mexico, Brazil, Japan, South Korea, China, India, Indonesia, Egypt, South Africa) and 12 residual regions. Additional individual countries are present in more recent versions of the model (Australia, New Zealand, Argentina, Chile, Iran, Saudi Arabia, Thailand, Malaysia, Vietnam). Oil and gas production is described for 88 producing countries. Coal production distinguishes 74 producers, including an infra-national disaggregation for large producers (USA, China, Australia, India). Producing regions and consuming regions are linked through energy markets.

Factors/items	POLES benchmarking results
6) GHGs	Kyoto gases from fossil fuel combustion and industry (CO_2, CH_4, N_2O, SF_6, HFCs, PFCs). Other emissions (agriculture, land use) come from a soft linkage with the GLOBIOM/G4M model.
7) Sectoral detail	Agriculture, industry, services, residential, transport. Industry is divided into iron & steel, chemicals, non-metallic minerals (cement, lime, glass, ceramics and other), other (other manufacturing, mining and construction).
8) Transport sectors	Passenger cars, motorbikes, buses, passenger rail, aviation (national, international), heavy freight trucks, light freight trucks, freight rail, waterways freight shipping, international maritime freight shipping.
9) Electricity conversion technologies	Coal (pressurized supercritical, IGCC, lignite, conventional), nuclear (conventional, 4^{th} generation), gas (conventional, turbine, combined cycle, fuel cell, CHP), oil (conv., oil-fired gas turbine), hydro (large dams, large run-of-river, large pumped storage, small, tidal & wave), geothermal, biomass (conv., gasification), wind (onshore, offshore, three different resource quality areas each), PV (centralized, decentralized), CSP (with/without storage), hydrogen fuel cell. Several CCS technologies are available for power generation using coal, gas, and biomass and for hydrogen production.
10) LDV technologies	Six LDV engine technologies and fuels consumed: ICEV (oil products, biofuels), BEV (electricity), PHEV (oil products, biofuels, electricity), HFCEV (hydrogen), gas fuel cell (gas), natural gas combustion (compressed natural gas; can be synthetic methane).
11) LDV life cycle stages	Well-to-wheel (complete energy chain). Biofuel upstream emissions are considered but combustion of biofuels is assumed carbon neutral.
12) LDV cost	Total cost includes fixed cost (investment, life-time, user discount rate) and variable cost (consumption per km, fuel price). Fuel prices include fuel taxes which include carbon prices, and develop endogenously. Cost of batteries and fuel cells are considered.[299]
13) LDV efficiency	Fuel efficiency evolves with a price effect.

Factors/items	POLES benchmarking results
14) LDV policies / mitigation measures	Carbon tax, cap-and-trade, carbon pricing, CO_2 budget, environmental damage tax on non-conventional fuels production, phase-out of fossil fuel subsidies, introduction of renewable fuels subsidy, modal shift, fuel efficiency standard, acceleration of the penetration emerging vehicle technologies (which can be interpreted as a result of R&D policy).
LDV life cycle factors	
1) Road infrastructure	Non-metallic minerals (incl. cement) production is considered. "CO_2 is emitted when carbonates contained in the raw material are thermally decomposed in the process."[154] CO_2 emissions are not linked to road infrastructure construction.
2) Ancillary infrastructure	Availability of refueling stations is considered in the multinomial logit function of vehicle choice. "An additional maturity factor accelerates or decelerates the adoption of new technologies, reflecting the development of new infrastructure and consumer preference."[154] Material and energy needs of ancillary infrastructure are not explicitly considered.
3) Vehicle components	Only costs are considered (e.g. for batteries and fuel cells). Component specifications, material and energy needs are not explicitly considered.
4) Vehicle materials	CO_2 from iron and steel production is considered but not linked to vehicle manufacturing. Demand of steel is represented in physical quantities (metric tons). Availability of recycled steel is considered as well.
5) Real-world energy use	Not considered.
6) Multi-fuel use	Considered indirectly by defining a maximum blending constraint for biofuels, which increases for new sales over time.
7) EV–power system interaction	Electricity dispatch model EUCAD is used based on six representative days with hourly resolution for all regions. Average emission factors are assumed for EV charging.

Factors/items	POLES benchmarking results
8) Biofuel upstream	Four biomass-to-liquids technologies are described by cost, efficiency and type of feedstock. "[T]he combustion of liquid biofuels is considered to be carbon neutral (CO_2 is only emitted due to the energy use in their production process, which is captured endogenously); however, an emission factor can be used for the calculation of vehicle emission standards. [...] GHG emissions from agriculture and land-use are derived from a soft linkage with the GLOBIOM model. [...] The surface of forests evolves to account for the expansion of the agriculture surface."[154] Net sinks in LULUCF are considered as well.
9) Crude oil grade	POLES describes explicitly the costs, direct energy use, and the corresponding emissions, of the extraction process of conventional on- and offshore oil, tight oil, tar sands, extra heavy oil, and oil shale. CO_2 pricing can affect the production of different grades, such as lowering tar sand production. "Crude oil production is transformed into oil products (one energy carrier represented in the model) with a refineries efficiency."[271] The carbon content of different grades is captured in the life-cycle emissions of gasoline production.
10) Methane leakage	CH_4 emitted by the fossil fuel sector accounts for processes in the oil industry (exploration, production and refining, venting and flaring), upstream processes of natural gas production, transmission and distribution in the natural gas sector, underground mining and surface coal mining. CH_4 and N_2O as by-products of incomplete combustion processes are accounted for in the electricity and industrial sectors, the residential and service sectors, the transport sector. Biogenic methane release from hydro power is not considered.
11) Vehicle age	Vehicle vintages are considered.
12) Travel demand	Calculated endogenously as a function of cost of transport relative to income. Capped by saturation effects, e.g. maximum number of vehicles per capita. "The average mileage per vehicle is driven by the equipment rate (more vehicles translates into lower usage per vehicle) and average fuel price (decrease of use with higher prices)."[271]

Factors/items	POLES benchmarking results
13) Vehicle mix	“The competition across vehicle types (6 types of vehicles in cars and trucks: conventional ICE, electric, plugin hybrid, H_2 fuel cell, H_2 thermal, gas) uses a multinomial logit function that depends on the total cost for the user, considering fixed cost (investment, life-time, user discount rate) and variable cost (consumption per km, fuel price), and is constrained by infrastructure developments for refueling stations.”[271] HEVs are not considered.

Table C.15: ETP–TIMES benchmarking results

Factors/items	**ETP–TIMES benchmarking results**
General items	
1) Model core and solver	Partial equilibrium, optimization (linear programming).
2) Model extensions	The ETP-TIMES energy supply model includes an energy conversion module and is soft-linked to end-use sector models for industry, transport (MoMo mobilty model),[300] and households. No climate module is integrated in ETP-TIMES.
3) Future GDP	GDP and population estimates are exogenous.[301,302]
4) Time horizon	Through 2060, 5-year steps.
5) Regions	27 world regions.
6) GHGs	CO_2, other energy chain emissions, such as N_2O and CH_4, are based on the work by Edwards and colleagues.[71]
7) Sectoral detail	One energy conversion sector (with around 550 technologies) and three end-use sectors: industry , buildings, transport. The "industrial sector includes International Standard Industrial Classification (ISIC) Divisions 7, 8, 10-18, 20-32 and 41-43, and Group 099, covering mining and quarrying (excluding mining and extraction of fuels), construction, and manufacturing. Petrochemical feedstock use and blast furnace and coke oven energy use are also included within the boundaries of industry".[47] The buildings sector is split into residential and non-residential buildings. The transport sector covers seven transport modes, and several technologies (see below).
8) Transport sectors	MoMo considers rail, shipping, air, 2-and 3-wheelers, LDVs, road freight, buses.
9) Electricity conversion technologies	Coal, oil, natural gas, nuclear, biomass, hydro, wind, solar, geothermal, ocean. 550 conversion and end-use technologies in total.

Factors/items	**ETP–TIMES benchmarking results**
10) LDV technologies	ICEVs (gasoline, diesel, CNG and LNG), HEVs, PHEVs, BEVs, HFCEVs. Fuels include "gasoline and diesel, biofuels (ethanol and biodiesel via various production pathways) and synthetic alternatives to liquid fuels (coal-to-liquid and gas-to-liquid); gaseous fuels, including natural gas (CNG and liquefied petroleum gas) and hydrogen via various production pathways; and electricity (with emissions according to the average national generation mix as modeled by the ETP-TIMES model in the relevant scenario)".[47]
11) LDV life cycle stages	Well-to-wheel (fuel production, use) based on Edwards et al.[71] and vehicle manufacturing based on MoMo.
12) LDV cost	Assumptions on 2015 battery costs are quite optimistic compared to Nykvist et al.:[215] 270 USD kWh^{-1} for a PHEV and 210 USD kWh^{-1} for a BEV. In B2DS (Beyond 2°C scenario), battery costs are assumed to fall strongly through 2060, down to 100 USD kWh^{-1} for PHEVs and 80 USD kWh^{-1} for BEVs. A learning rate of 20% is assumed. Fossil fuel prices are assumed to increase. Future fuel costs partially depend on assumptions on fuel and carbon taxes: "In 2060, the CO2 price is assumed to reach USD 540/tCO_2. The oil price assumptions (in 2015 constant USD) used for this assessment are USD 50 per barrel (bbl) in 2015, USD 140/bbl in the RTS and USD 75/bbl in the B2DS. Fuel taxes reflect the assumptions outlined in this chapter."[47]
13) LDV efficiency	Efficiency measures include aerodynamic improvement, low rolling resistance tires, lightweighting, transmission and drivetrain efficiency improvements, engine efficiency, hybridization. Based on several literature sources.
14) LDV policies / mitigation measures	In B2DS, gasoline taxes are assumed to increase from 11% to more than 200% in the US, reflecting a rising carbon price. By 2060, cost of ICEVs increases by almost 40% as a result. Introduction of a carbon tax that takes into account life-cycle performance of energy carriers increases over time and reaches 540 USD t^{-1}. Further measures that are mentioned but whose effects are not quantified: Introduction of feebates, congestion charging, parking fees.
LDV life cycle factors	

Factors/items	ETP–TIMES benchmarking results
1) Road infrastructure	Cement production is included in ETP-TIMES. Investment costs for roads are considered. Infrastructure cost estimates include capital costs, operations and maintenance, and reconstruction costs. No linking of material needs for infrastructure development, such as cement, to vehicle cycle.
2) Ancillary infrastructure	No physical description. Costs of electric home chargers are included in EV powertrain costs, costs of public chargers are included in electricity costs (roughly 5 ct kWh^{-1}).
3) Vehicle components	Considered in terms of costs, unclear whether specific material needs are considered at component-specific level. "Cost functions define various vehicle configurations, including vehicle component efficiency upgrades (e.g. improved tyres or airconditioning controls), material substitution and vehicle downsizing, conventional spark and compression ignition engine improvements, conventional and plug-in hybrid powertrain configurations, batteries, electric motors, and fuel cells. These configurations are added to a basic glider cost."[47]
4) Vehicle materials	Primary material needs for vehicles are included in MoMo, based on GREET. (Steel, iron and aluminum production sectors are also included in ETP-TIMES.)
5) Real-world energy use	A gap-factor is added to official laboratory consumption estimates, based on MoMo.
6) Multi-fuel use	For PHEVs: In the B2DS (beyond 2 degrees), electric driving shares are assumed to increase to 50% by 2020 and to 80% by 2030. For other MFVs a simplified approach is used, allocating fuel shares to ICE vehicles. This reflects an assumption that high shares of alternative fuels are only achieved in case of fuel blending or wide adoption of MFVs (currently a reality only in Brazil).
7) EV–power system interaction	Linear dispatch model is used. Average emission rates are linked to electric vehicle charging.

Factors/items	ETP–TIMES benchmarking results
8) Biofuel upstream	Direct land use change GHG emissions are considered, based on the work by Edwards and colleagues.[71] "Well-to-tank emissions for fossil fuel-derived fuels and biofuels are largely based on data from the Joint Research Centre, EUCAR and CONCAWE and do not include indirect land-use change factors."[47]
9) Crude oil grade	Considered based on ref.[71], who differentiate specific GHG emissions for oil grades of different world regions.
10) Methane leakage	Considered are GHG emissions from venting, flaring and fugitive losses, based on the work by Edwards and colleagues.[71] Due to leakage issues, CNG and LNG vehicles are not considered in the assessment. Biogenic methane from hydro power is not considered.
11) Vehicle age	Implemented through a stock vintage model (except for multi-fuel vehicles).
12) Travel demand	Exogenous.
13) Vehicle mix	Defined exogenously. (Modal share is determined exogenously as well.)

C.6 LDV climate change mitigation options in IEMs

In the main text we provide examples on how future improvements to IEMs could enhance the potential of IEMs for effective policy formulation at the nexus of transport, energy and climate at national and supra–national level. Here we provide a more comprehensive list for several prominent policies tested in IEMs and potential implications of considering life–cycle factors.

Table C.16: Fuel economy standard (FES).

Policy description: Prescribes fuel efficiency and GHG targets to be met by the average new vehicle fleet, whereby BEVs, HFCEVs, and PHEVs count as zero emission vehicles and receive multiplier credits. The sole focus on reducing TTW emission intensity can lead to an increase in WTT and vehicle production emissions. Absolute travel demand is not regulated. Used vehicles are not addressed. **Applied in:** EPPA,[37] NEMS,[149] IMAGE,[150] POLES.[154] **Influential factors:** Factors 2–10, 12, 13. **Potential implications of considering factors:** FES may shift vehicle mix (factor 13) towards HEVs and AFVs. Emissions of the vehicle mix in turn are influenced by various factors (2–10, 12). As a result, uncertainties in overall life–cycle GHG emission reductions exist and emission shifts between different life–cycle phases cannot be evaluated. For example, if based on real–world emissions (factor 5, considered in EPPA but not in NEMS), embodied emissions from vehicle production have lower relative weight. (Current regulation does not take real–world energy use into account, whereas some models do in their policy analysis, e.g. EPPA.) EPPA considers improved fuel economy due to lightweight materials, but not the additional energy inputs into material and components production. Therefore supply chain GHG emissions may be underestimated. Further, GHG savings due to stronger use of recycled materials vs. virgin materials cannot be evaluated. (Current regulation does not take embodied emissions into account, whereas some models do, e.g. IMAGE considers all energy chain emissions, EPPA considers emissions in vehicle production as well.) A shift to AFVs can also increase total vehicle ownership (factor 12).

Table C.17: Renewable fuels standard (RFS).

Policy description: Mandates the ratio of biofuels in gasoline. **Applied in:** EPPA,[37] GCAM,[151] IMAGE,[288] WITCH.[152] **Influential factors:** Factors 6, 8, 9, 10. **Potential implications of considering factors:** RFS can reduce the carbon intensity of driving ICEVs, HEVs, and PHEVs through higher biofuel ratios in gasoline, but can increase biofuel upstream emissions. Due to a shift in the ratio of biofuels and gasoline, multi–fuel use is influential too, as well as factors related to gasoline production, such as crude oil grades and methane leakage.

Table C.18: Energy efficiency standard.

Policy description: Different designs are possible, (1) a TTW efficiency standard that takes into account the direct energy use during driving, or (2) a WTW efficiency standard that takes into account all energy use of the entire energy chain. The sole focus on reducing TTW efficiency can lead to an increase in embodied energy/emissions in the WTT and vehicle production phase. A WTW based efficiency standard would internalize the former. Absolute travel demand is not regulated. Used vehicles are not addressed. **Applied in:** GEM–E3 (TTW).[277] **Influential factors:** Factors 2–6 (2–10), 12, 13. **Potential implications of considering factors:** Efficiency standards will shift vehicle mix (factor 13) towards high– efficiency vehicles (either based on on TTW or WTW), thereby reducing driving energy, but potentially increasing energy use during energy conversion (TTW) and vehicle production (TTW, WTW). Energy implications of shifts in the vehicle mix are influenced by factors 2–6, (TTW), respectively 2–10 (WTW). A shift to low–energy vehicles can also increase total vehicle ownership (factor 12).

Table C.19: Low–carbon fuel standard (LCFS).

Policy description: Requires fuel suppliers to reduce the life–cycle emissions of their fuels relative to gasoline and diesel and can be fulfilled by any energy source replacing gasoline. The baseline value for gasoline is 347 g CO_2e kWh^{-1} in 2016 and reduces to 319 g CO_2e kWh^{-1} from 2020 onwards. **Applied in:** None identified. **Influential factors:** Factors 6–10. **Potential implications of considering factors:** LCFS can lower the carbon intensity of driving of any powertrain, as well as energy upstream emissions of any fuel. Energy chain factors of all energy sources are potentially influential. Due to a shift in the energy carrier mix, multi–fuel use is an influential factor too.

Table C.20: EV technology mandates.

Policy description: Vehicle manufacturers have to fulfill minimum EV sales requirements as a percentage of overall sales. **Applied in:** NEMS,[149] MESSAGE.[257] **Influential factors:** Factors 2–10, 12. **Potential implications of considering factors:** Increases the share of EVs and therewith alters the overall vehicle mix. Emissions of the vehicle mix in turn are influenced by various factors (2–10, 12). See above for details.

Table C.21: Government R&D policy.

Policy description: Government invests into R&D activities for certain lower–carbon technologies with the aim of reducing their costs and increasing their sales. **Applied in:** GCAM–USA,[155] NEMS,[149] WITCH,[152] POLES.[154] **Influential factors:** Factors 2–10, 12. **Potential implications of considering factors:** Increases the share of EVs and therewith alters the overall vehicle mix (12). Emissions of the vehicle mix in turn are influenced by various factors (2–10). See above for details.

Table C.22: Energy tax/subsidy.

Policy description: Government can tax or subsidize certain fuels in order to influence their costs and thus sales volume. **Applied in:** EPPA,[37] NEMS,[270] IMACLIM–R,[153,219] GEM–E3,[279] MESSAGE,[214,219] REMIND,[271] IMAGE,[288] POLES,[219] ETP–TIMES.[47] **Influential factors:** Factors 2–10, 12, 13. **Potential implications of considering factors:** Fuel taxes can increase the prices for certain fuels and therefore lower driving demand (factor 13) or force technology switching, thereby influencing the technology mix (factor 12). Emissions of the vehicle mix in turn are influenced by various factors (2–10). See above for details.

Table C.23: Carbon tax.

Policy description: Prices the carbon content of energy carriers, such as gasoline, biofuels, natural gas or coal, in the form of a tax. **Applied in:** EPPA,[37] GCAM,[50,97,219] IMACLIM–R,[219] GEM–E3,[279] WITCH,[97,287] REMIND,[97,271] IMAGE,[167,219] DNE21+,[219,303] TIAM–UCL,[219] POLES,[219] ETP–TIMES,[47] AIM/CGE,[219] MESSAGE.[219] **Influential factors:** Factors 5–10. **Potential implications of considering factors:** Can potentially reduce all energy chain emissions (factors 5–10). A carbon tax is often implemented as a mark up on the prices of sold fuels, thus implicitly taxing the actual real–world fuel consumption of the transport sector. Most IEMs however model the effects of carbon taxes based on official vehicle energy consumption, while few account for real–world vehicle operation. Additionally, some modelers may apply taxes to direct tailpipe emissions only, while others may apply taxes to emissions of the entire energy chain.

D Appendix to Chapter 5

D.1 Specific vehicle life–cycle emissions

Specific life–cycle emissions in g CO_2/km include all life stages including the entire vehicle supply chain (considering material production, vehicle assembly, recycling of materials, reuse of components, and material substitution through lightweighting), as well as the entire energy chain (production and use of energy carriers). A detailed description of the specific production processes can be found elsewhere[18,68] and all assumed data points can be requested from the author as a spreadsheet file. Here we calibrate these processes to the US case as described in Section 5.7 in the main text.

It can be seen from Figure D.1 that fossil–fueled vehicles remain at more or less steady specific emissions after 2025, which is the last year of the CAFE requirement in Yale–NEMS. Specific emissions of BEVs, and of PHEVs to some extent, continue to fall due to decarbonization of the electric grid. In a side case we assume that hydrogen production transitions from the currently assumed steam methane reforming (SMR) pathway to an illustrative net–zero emissions pathway. Net–zero could be achieved by a hydrogen production mix consisting primarily of hydrogen from biomethane with carbon capture and storage, representing a carbon sink with about – 36 g CO_2e/kWh,[304] and a small remainder, around 7–8%, of hydrogen from SMR, emitting around 450 g CO_2e/kWh.[71]

Figure D.2 provides a breakdown of specific emissions by life–cycle stage. Compared to previous work[8,9,18] emissions embodied in vehicle production are relatively small when normalized by vehicle kilometers travelled (Figure D.2d and e). This is mostly due to the relatively high average lifetime mileage of US light vehicles of around 270,000 km[207] which is reflected in Yale–NEMS. Previous work has often assumed kilometers travelled in the range of 150,000–180,000 over the lifetime of a vehicle.[8,9,18]

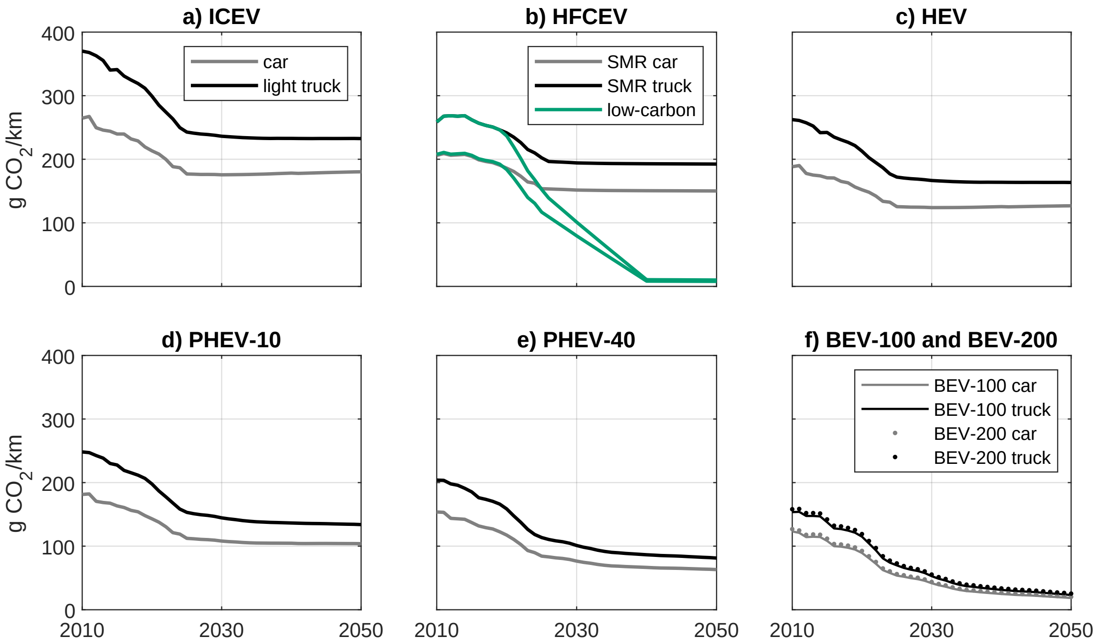

Figure D.1: Specific life–cycle emissions of modelled powertrains in all scenarios. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –100=100 miles of electric range; SMR=steam–methane reforming. The underlying data used to compile this figure can be found in Supplementary Table 20.

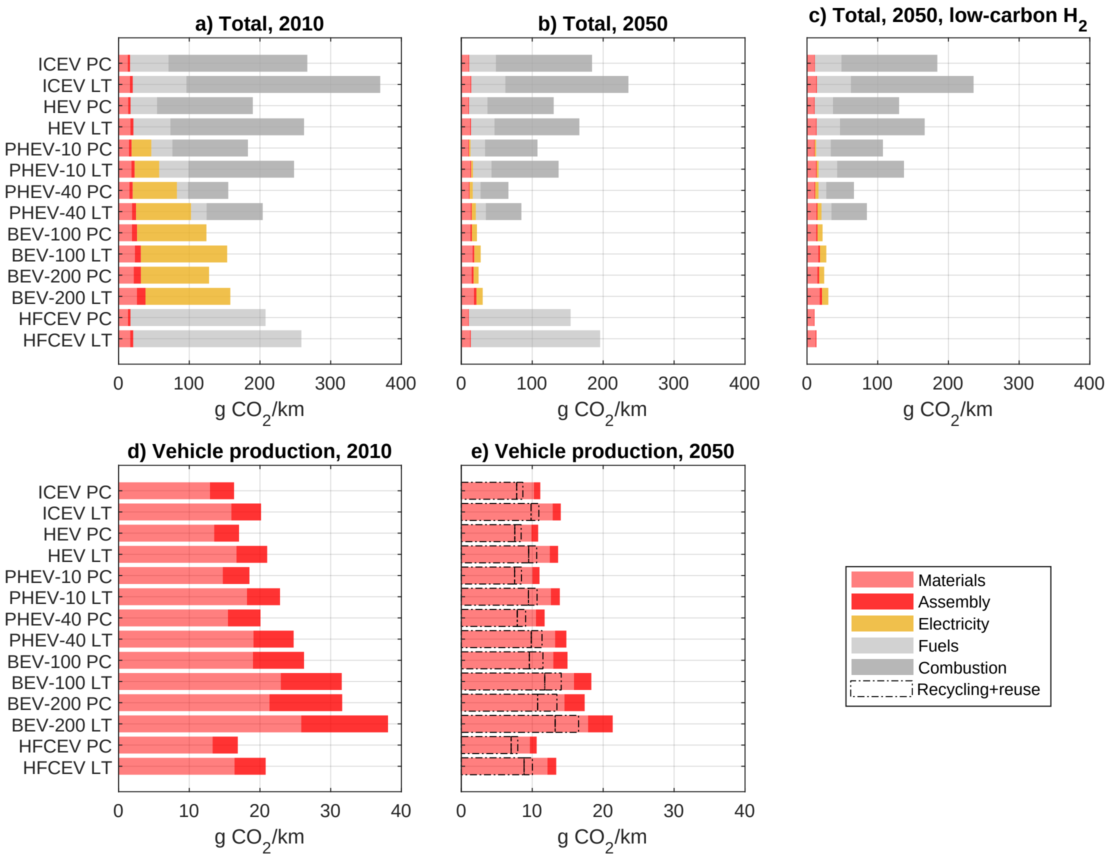

Figure D.2: Specific life–cycle emissions broken down by life–cycle stage in 2010 and 2050. ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –100=100 miles of electric range; H_2 = hydrogen. The underlying data used to compile this figure can be found in Supplementary Table 20.

D.2 Potential emission reductions due to reuse and recycling

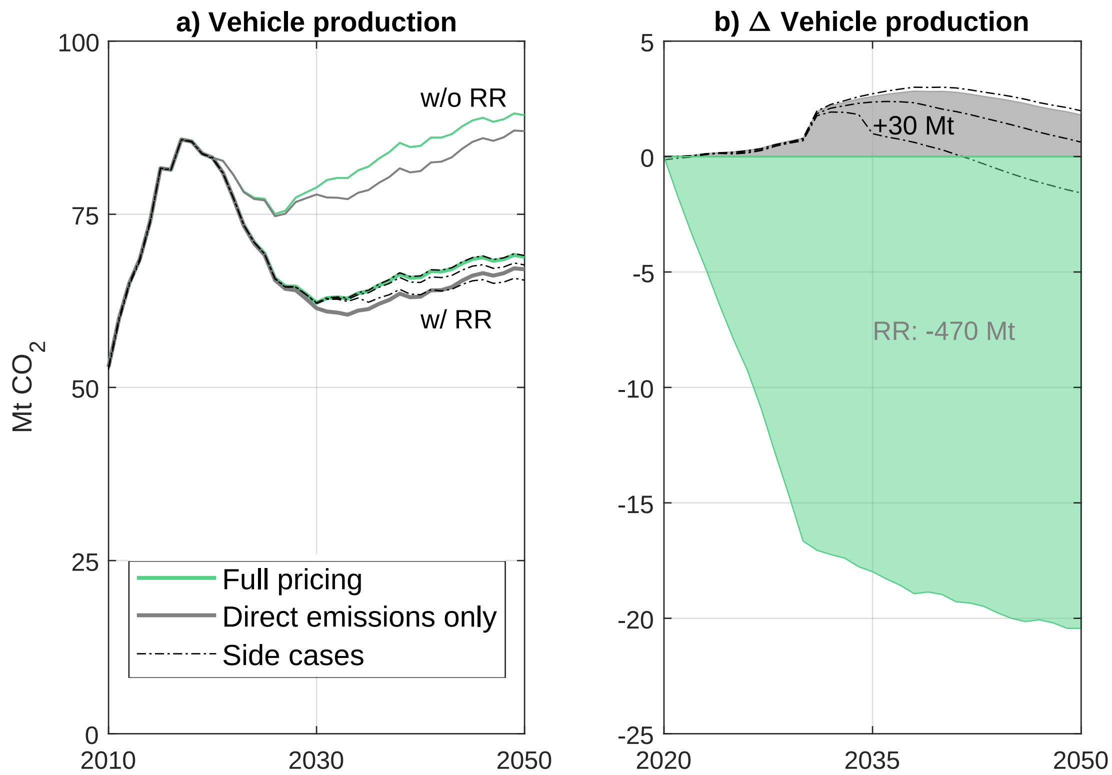

Figure D.3: Life–cycle CO_2 emissions of producing the stock of US light vehicles, under full pricing and direct–emissions–only pricing, with and without reuse and recycling (RR) (a). The grey shaded area shows the difference in emissions between full and direct–emissions–only pricing. The light green shaded area illustrates the emission reduction potential from RR (b). Dotted lines illustrate results from side cases.

D.3 Technology costs and vehicle choice

Production costs of various powertrains (ICEV, BEV, ...) are calculated using a detailed bottom–up cost model.[73] For this work the model has been extended to 2050 and battery prices reach floor costs of about 83 USD/kWh within the modeling time horizon. This cost development is within the range of previous estimates.[137] Following that, vehicle purchase prices are calculated endogenously in Yale–NEMS (Figure D.4). All cost figures take into account potential feebates as shown in Figure D.5. While no feebate is implemented under direct–emissions–only pricing (colored bars in Figure D.4), the full–pricing cases consider feebates on vehicle production (see also Figure D.5a) and on energy supply and use (Figure D.5b/d), while the well–to–wheel (WTW) pricing cases only consider feebates on energy supply and use (Figure D.5b/d). In scenario 'WTW pricing / low–c H_2 / low–\$ HFCEV' it is assumed that HFCEVs become cost–competitive with BEVs by 2035. The resulting optimal vehicle choice for each scenario can be seen in Figure D.6 (for the side cases) and in Figure 5.1 in the main text (for the main cases).

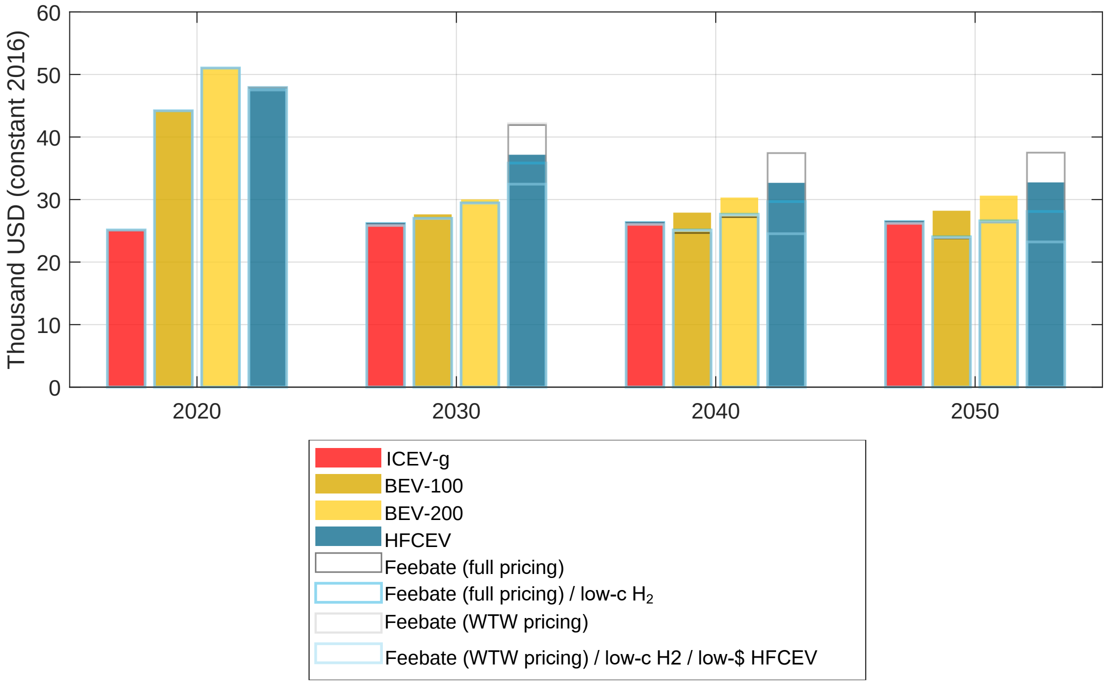

Figure D.4: Purchase price development of selected powertrains in the midsize car segment. Default figures (colored bars) show prices in the absence of feebates. WTW=well–to–wheel; low–c H_2=low–carbon hydrogen; low–\$=low–cost; ICEV=internal combustion engine vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –g=gasoline; –100=100 miles of electric range. The underlying data used to compile this figure can be found in Supplementary Table 13.

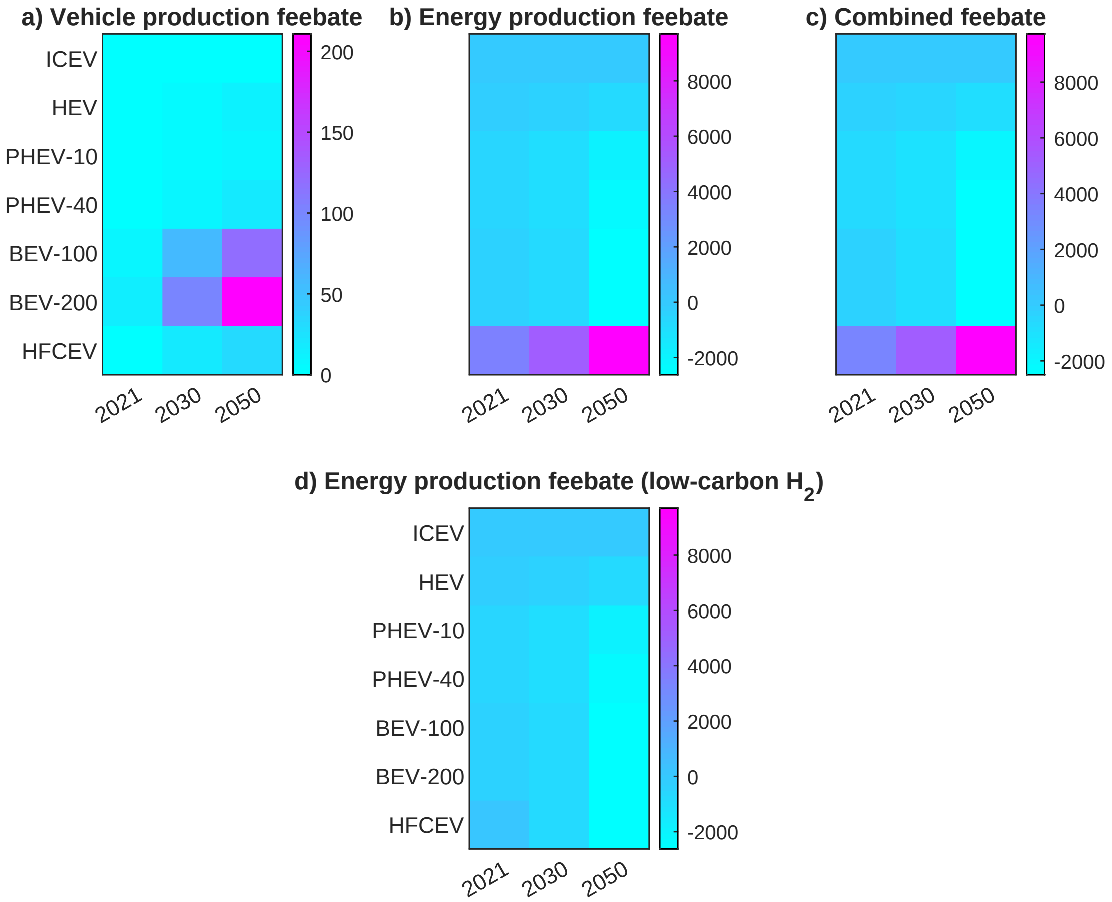

Figure D.5: Feebate (in USD/vehicle) on vehicle production (a), energy carrier production (b), total (c), and on energy carrier production assuming low–carbon hydrogen (d). ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle. –100=100 miles of electric range; H_2=hydrogen. The underlying data used to compile this figure can be found in Supplementary Table 10.

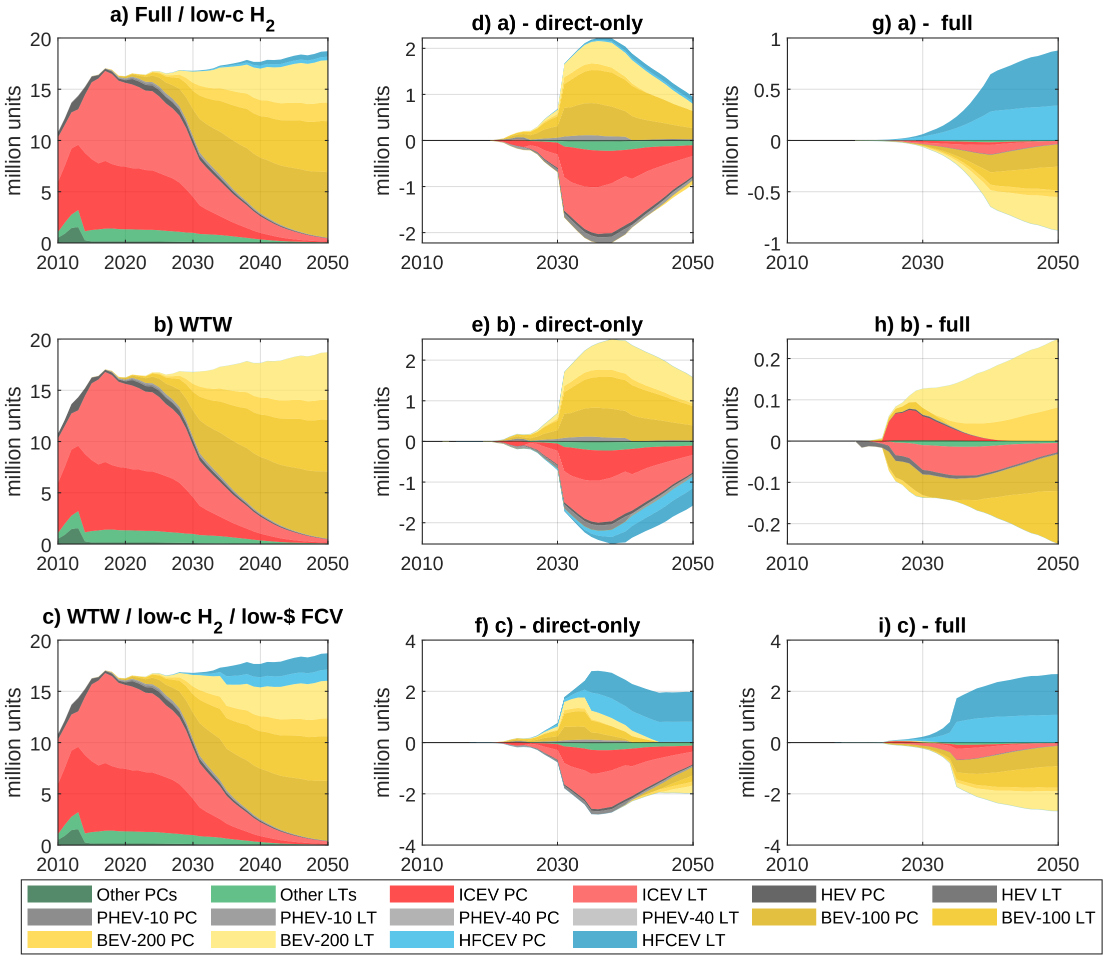

Figure D.6: Optimal vehicle choice in the side cases under full pricing (a), and well–to–wheel (WTW) pricing (b, c). A transition to low–carbon hydrogen is assumed in a) and c). Further cost reductions of HFCEVs are assumed in c). Differences between the side cases and scenario one in the main text (direct–emissions–only pricing) (d–f) and scenario two in the main text (full–emissions pricing) (g–i). low–c H_2=low–carbon hydrogen; low–$ FCV=low–cost fuel cell vehicle; ICEV=internal combustion engine vehicle; HEV=hybrid electric vehicle; PHEV=plug–in hybrid electric vehicle; BEV=battery electric vehicle; HFCEV=hydrogen fuel cell electric vehicle; –100=100 miles of electric range; PC=passenger car; LT=light truck. The underlying data used to compile this figure can be found in Supplementary Table 19.

D.4 Electricity supply

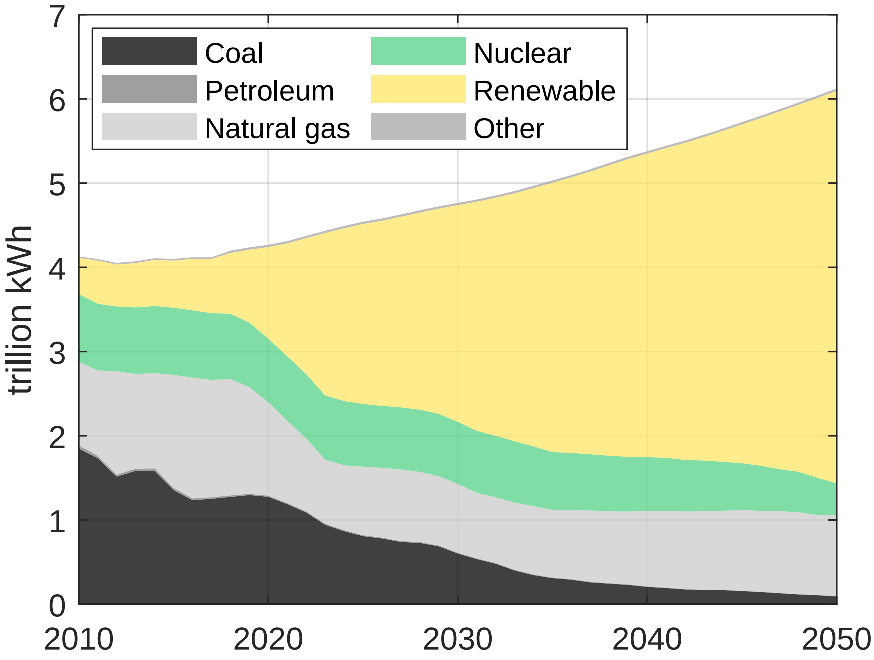

Figure D.7: Total electricity generated by utility companies, residential and commercial buildings in all scenarios. The underlying data used to compile this figure can be found in Supplementary Table 18.

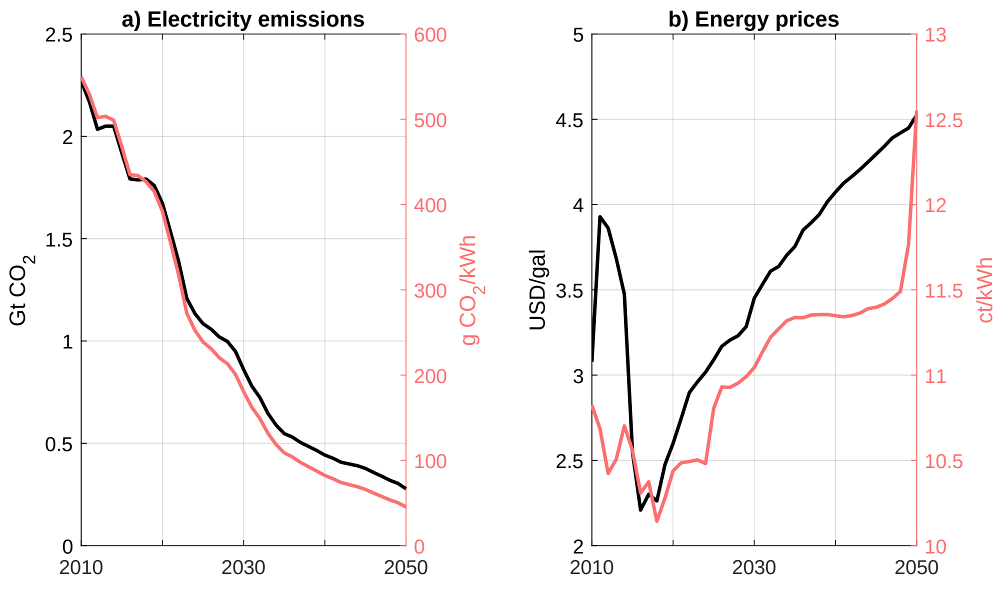

Figure D.8: CO_2 emissions and emissions intensity from total electricity generated by utility companies, residential and commercial buildings in all scenarios (a) and development of gasoline prices and electricity prices in all scenarios (b). The underlying data used to compile this figure can be found in Supplementary Table 18.

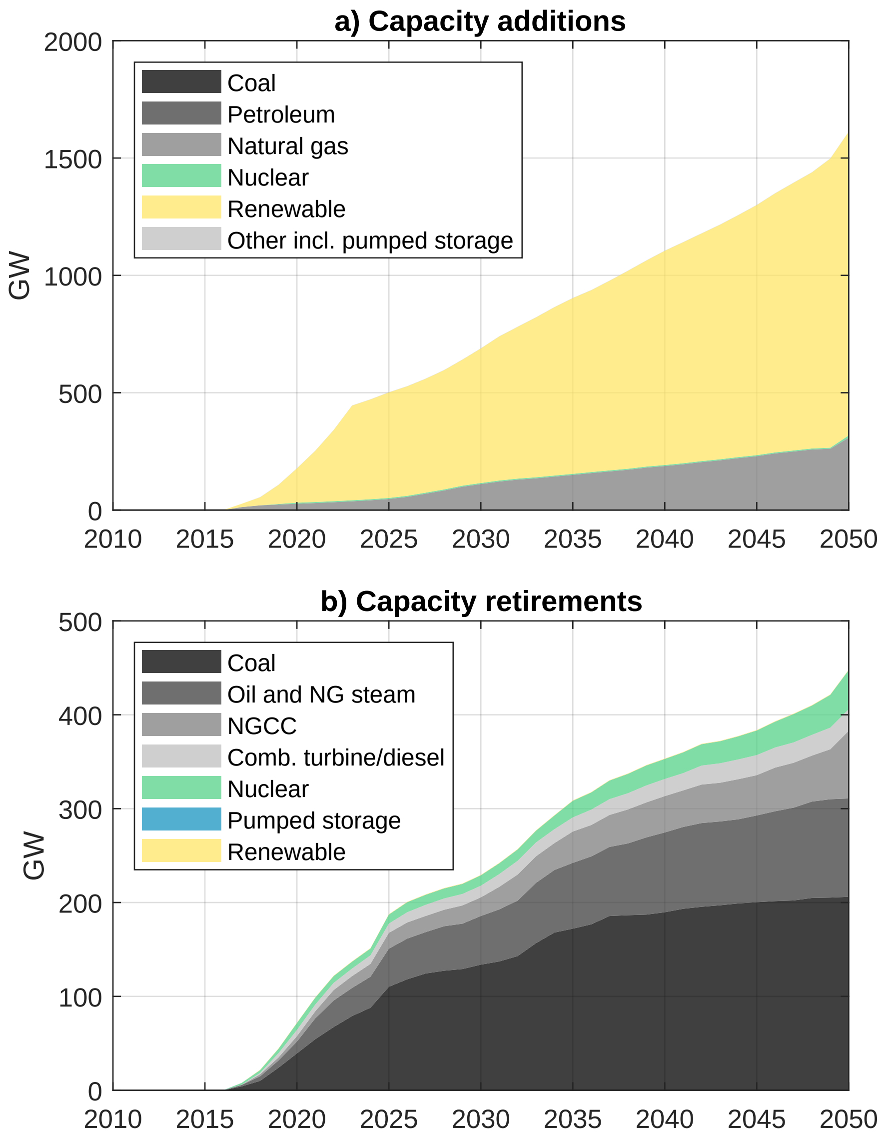

Figure D.9: Total power plant capacity additions by utility companies, residential and commercial buildings (a) and power plant capacity retirements by utility companies in all scenarios (b). NGCC=natural gas combined cycle. The underlying data used to compile this figure can be found in Supplementary Table 18.

D.5 Vehicle fleet characteristics

While slight differences in average vehicle weight and the degree of lightweighting can be observed between the different accounting approaches, the curves are generally quite flat after 2025 in either scenario (Figure D.10a and b). This flattening can be explained by the fact that CAFE standards exist only through 2025. Due to the implementation of a feebate, a rebate is provided to BEVs, which is why average vehicle prices remain relatively constant after 2030 (Section D.3). Conversely, vehicle prices grow considerably without a feebate system in place. Average vehicle prices are also slightly higher with higher shares of HFCEVs except in the side case in which HFCEVs reach cost parity with BEVs (Supplementary Table 13). Figures D.10d and f exhibit potential adverse side–effects of the feebate system. The lower prices seem to induce slightly lower sales shares of cars, giving rise to light trucks, while travel demand is showing marginally stronger growth but the differences may be too small to be of significance. The side cases exhibit some variation in these outcomes (see thin green lines in Figures D.10a–f).

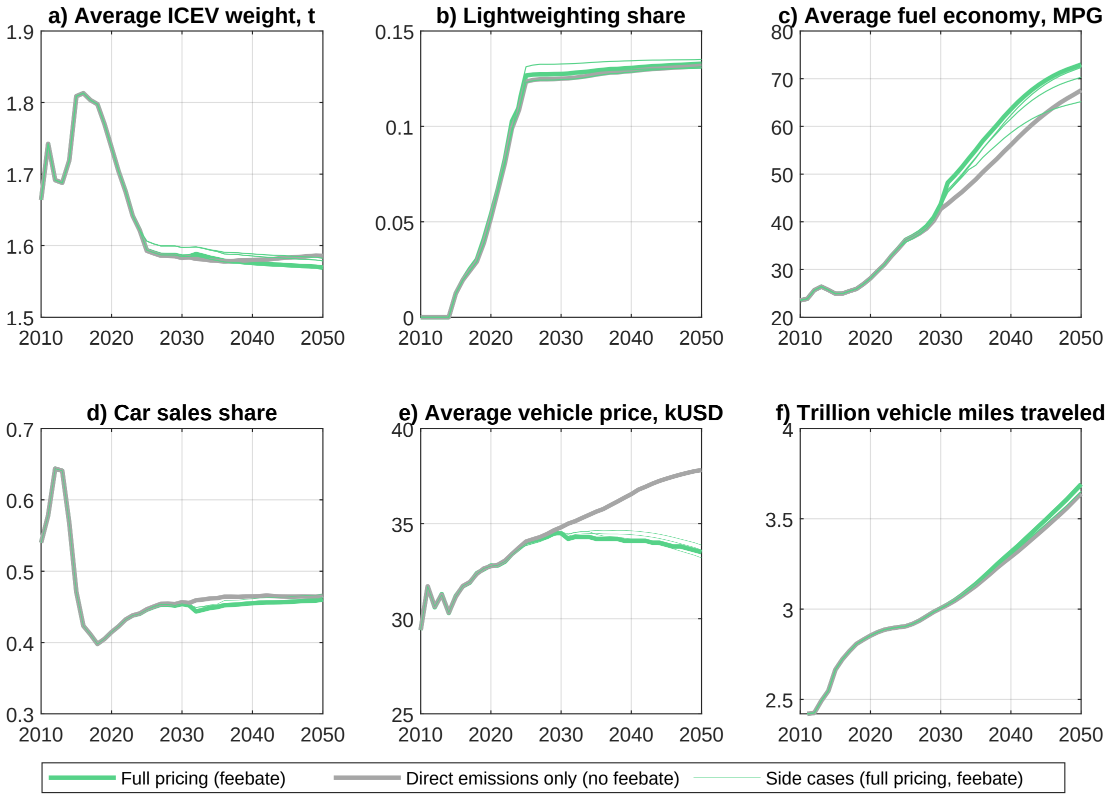

Figure D.10: Characteristics of the US light vehicle fleet under full pricing and direct–emissions–only pricing. The thin green lines show the range of results from the side cases. ICEV=internal combustion engine vehicle; MPG=miles per gallon; kUSD=thousand US dollars.

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