Supplementary Information

Interaction of consumer preferences and climate policies in the global transition to low-carbon vehicles

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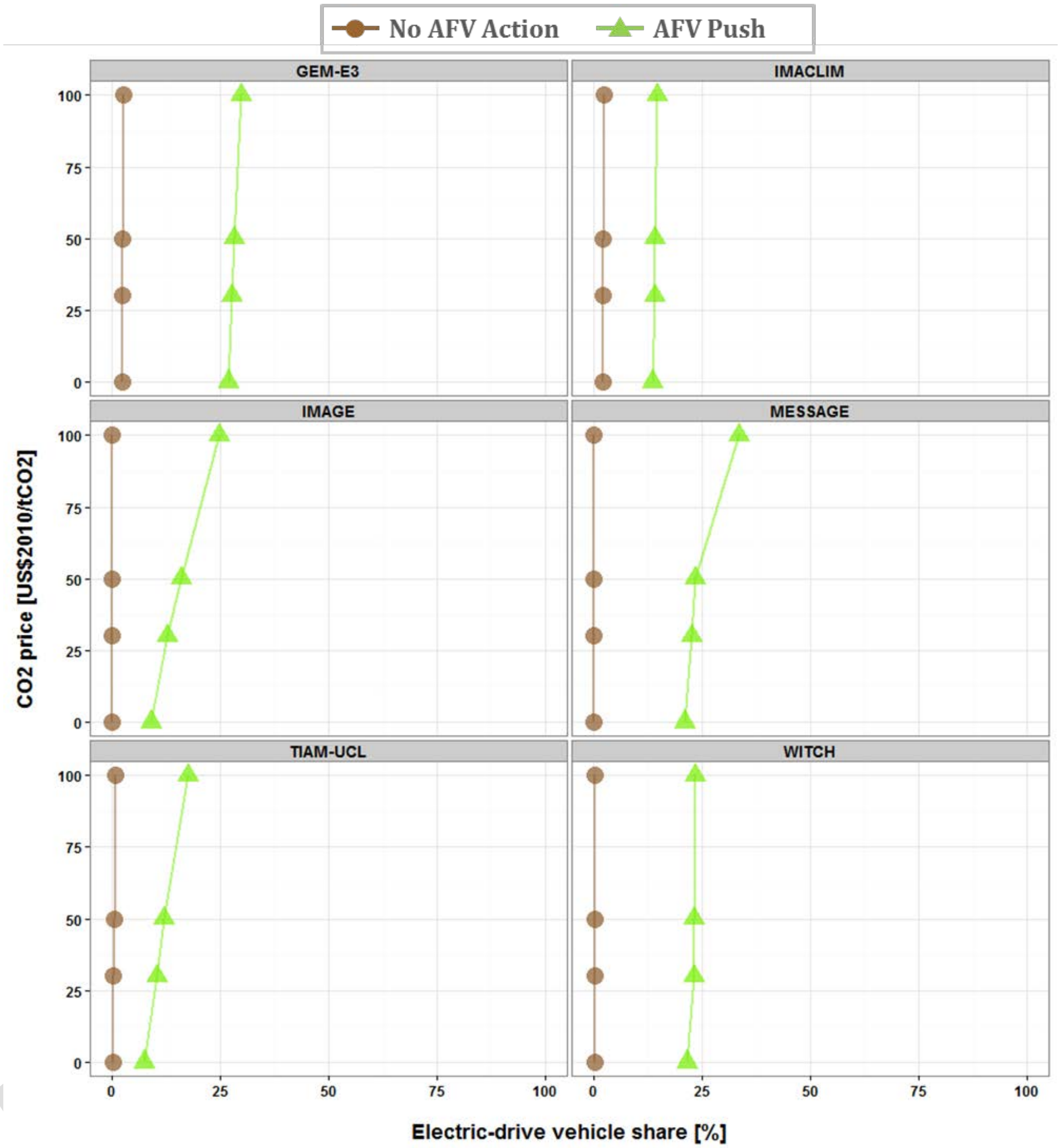
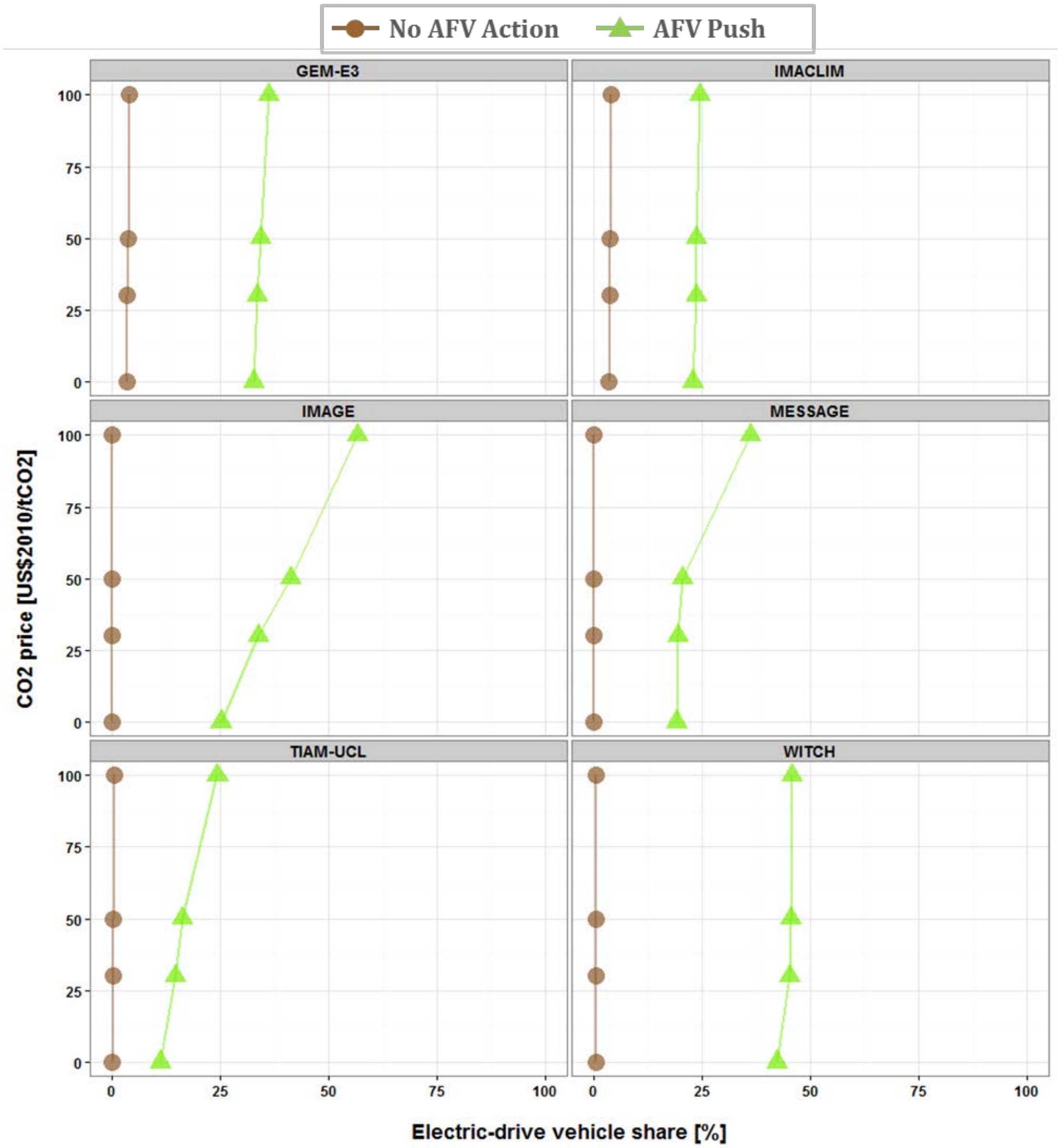
Supplementary Table 1. CO_2 emissions (direct + indirect) from the global light-duty vehicle fleet in the counterfactual 'No AFV Action (+ 0 US$/t$CO_2$)' scenario, across six integrated assessment models. Emissions are cumulative (2010-50) and in units of Gigatonnes. For calculating the upstream (indirect) component of emissions, average fuel-specific carbon intensities are in most cases assumed exogenously[1-5]. In the central case values shown here, these are the following: +20 gCO_2/MJ for gasoline/diesel, +15 gCO_2/MJ for biofuels, +20 gCO_2/MJ for natural gas, +100 gCO_2/MJ for hydrogen, and +50 gCO_2/MJ for fossil synfuels. Only for electricity were model-specific carbon intensities estimated and applied. Comprehensive lifecycle assessments based on model results were not conducted for the other fuels, due to insufficient information; hence the exogenous assumptions.

Supplementary Figures



Supplementary Figure 1. Shares of electric-drive vehicles (EDVs = PHEVs, BEVs, and FCVs) in 2050, assuming strong behavior-influencing measures ('AFV Push'; green curve with triangles) or no such measures ('No AFV Action'; brown curve with circles), across six global integrated assessment models. Global economy-wide carbon pricing starts immediately after 2020 and is then held constant to 2050 (at a level of 30, 50, or 100 US$/t$CO_2$). Global results shown here.



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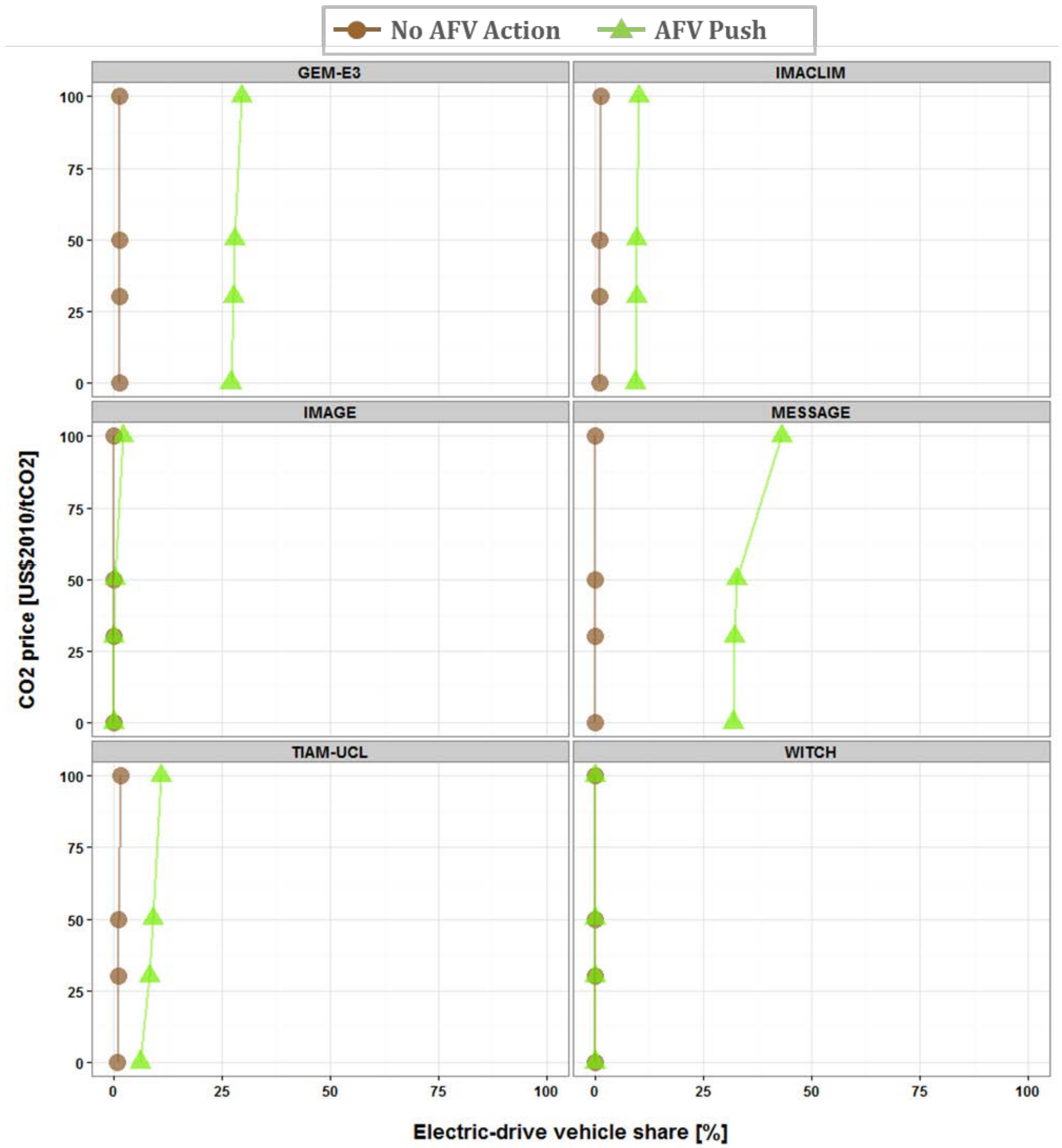

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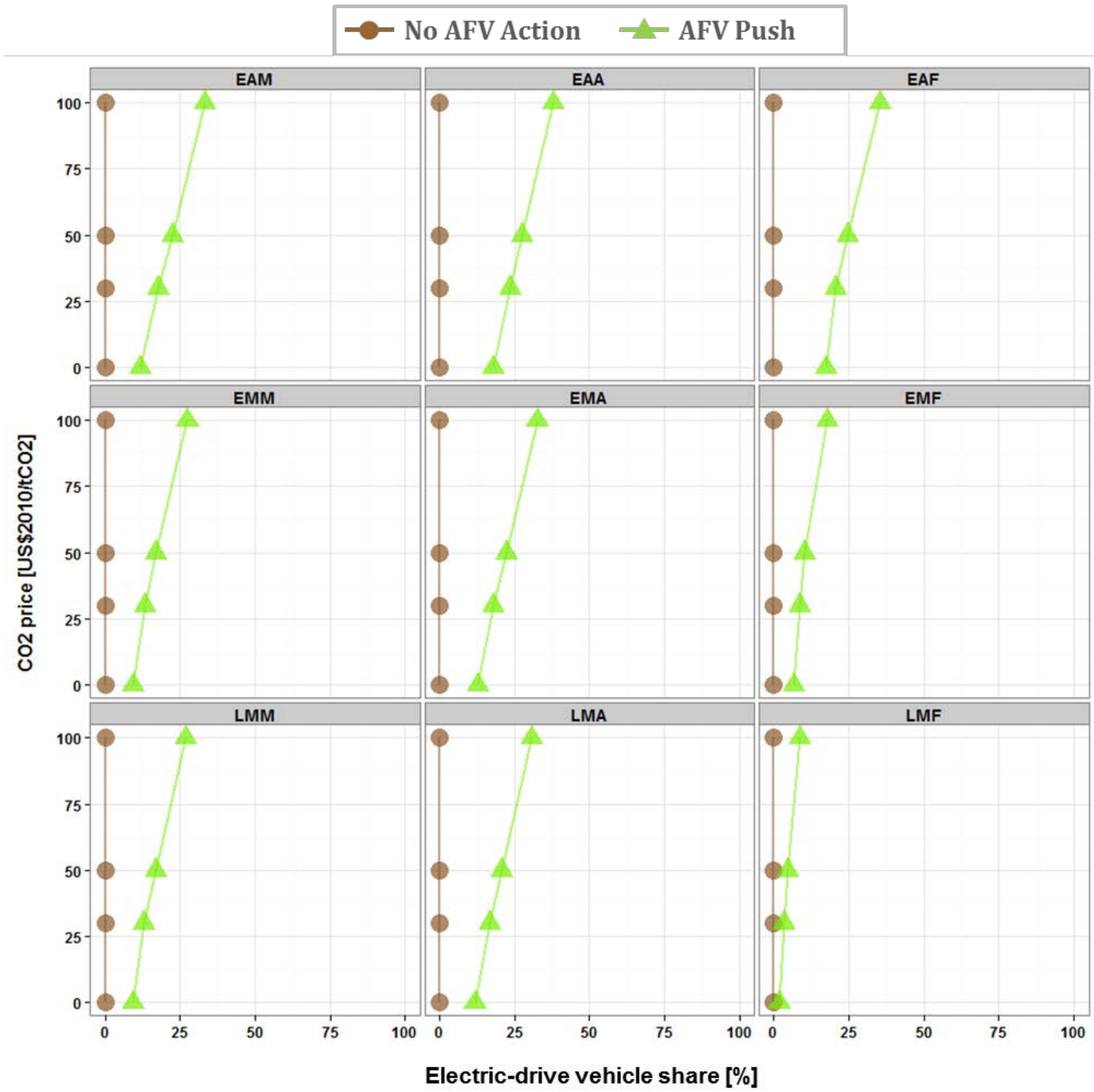

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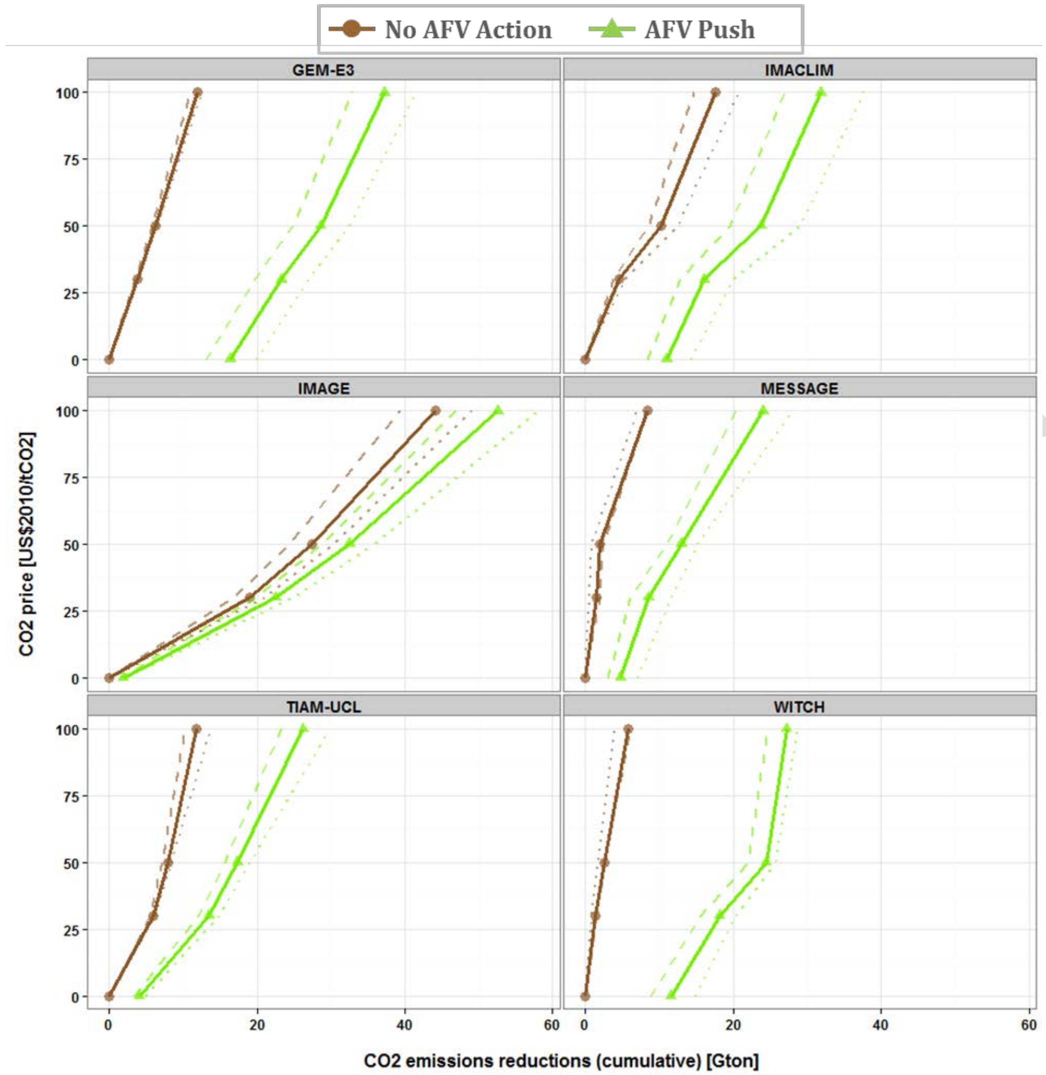

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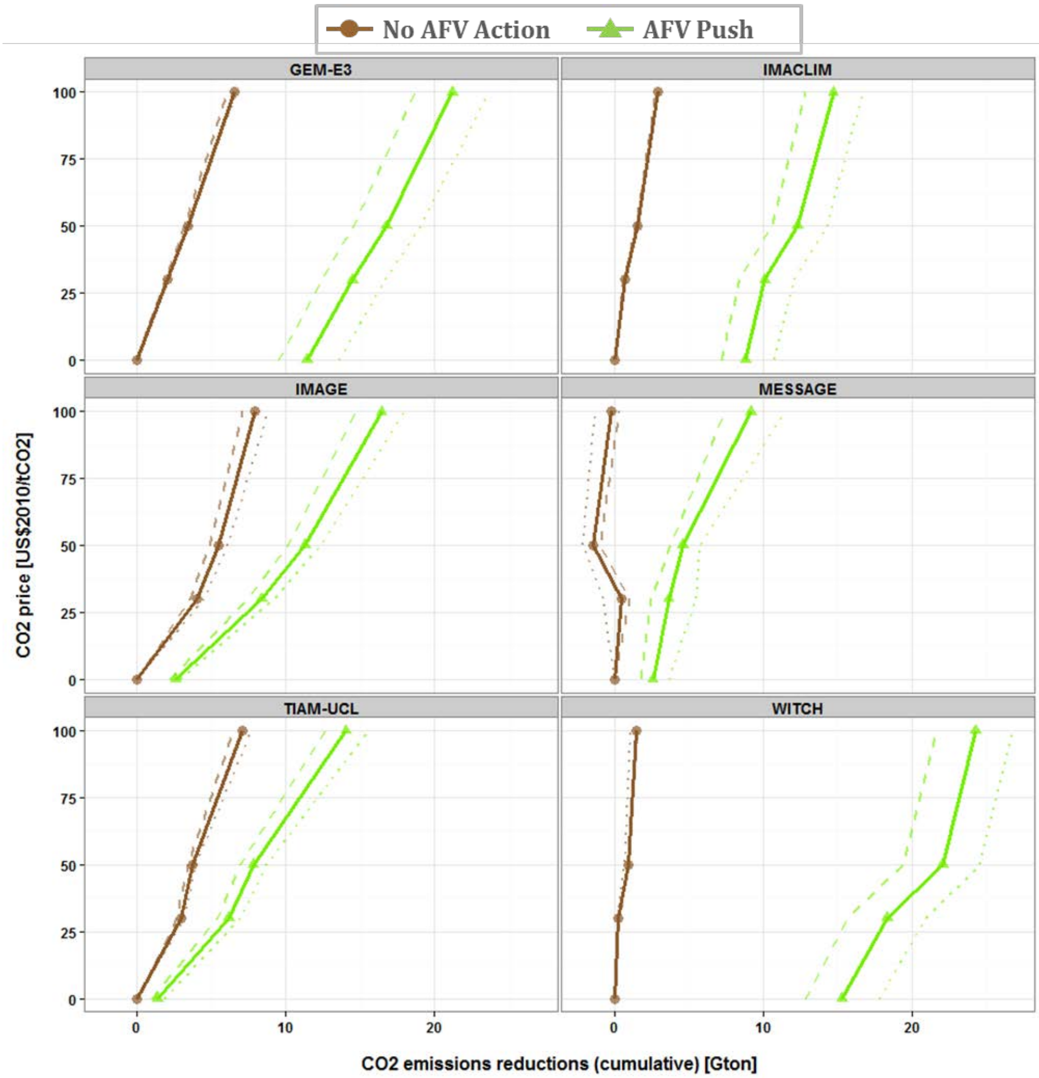
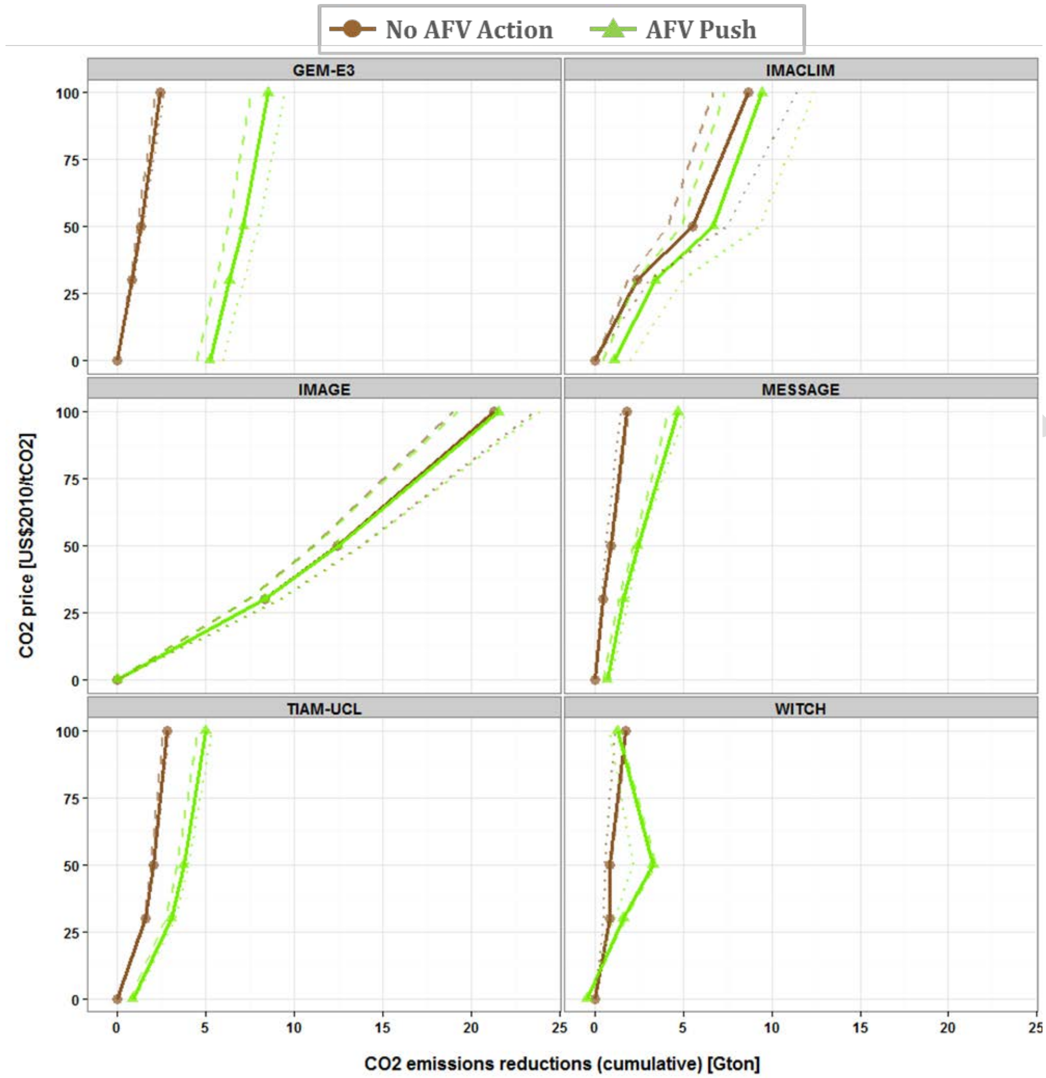


Supplementary Figure 6. Marginal abatement cost (MAC) curves for CO_2 emissions reductions from the OECD light-duty vehicle fleet, assuming strong behavior-influencing measures ('AFV Push'; green curve with triangles) or no such measures ('No AFV Action'; brown curve with circles), across six integrated assessment models. MAC curves from main text shown here, along with additional curves (sensitivity analyses) run with alternative assumptions for fuel carbon intensities. Emissions reductions are cumulative (2010-50) and relative to the counterfactual 'No AFV Action (+ 0 US$/t$CO_2$)' scenario. Global economy-wide carbon pricing starts immediately after 2020 and is then held constant to 2050. For calculating the upstream (indirect) component of emissions, average fuel-specific carbon intensities are in most cases assumed exogenously[1-5]. In the central case (solid lines), these are the following: +20 gCO_2/MJ for gasoline/diesel, +15 gCO_2/MJ for biofuels, +20 gCO_2/MJ for natural gas, +100 gCO_2/MJ for hydrogen, and +50 gCO_2/MJ for fossil synfuels. In the optimistic case (dashed lines), these are: +10 gCO_2/MJ for gasoline/diesel, +0 gCO_2/MJ for biofuels, +10 gCO_2/MJ for natural gas, +25 gCO_2/MJ for hydrogen, and +15 gCO_2/MJ for fossil synfuels. In the pessimistic case (dotted lines), these are: +30 gCO_2/MJ for gasoline/diesel, +50 gCO_2/MJ for biofuels, +30 gCO_2/MJ for natural gas, +200 gCO_2/MJ for hydrogen, and +100 gCO_2/MJ for fossil synfuels. Only for electricity were model-specific carbon intensities estimated and applied. Comprehensive lifecycle assessments based on model results were not conducted for the other fuels, due to insufficient information; hence the exogenous assumptions.



Supplementary Figure 7. Marginal abatement cost (MAC) curves for CO_2 emissions reductions from the DevASIA light-duty vehicle fleet, assuming strong behavior-influencing measures ('AFV Push'; green curve with triangles) or no such measures ('No AFV Action'; brown curve with circles), across six integrated assessment models. MAC curves from main text shown here, along with additional curves (sensitivity analyses) run with alternative assumptions for fuel carbon intensities. Emissions reductions are cumulative (2010-50) and relative to the counterfactual 'No AFV Action (+ 0 US$/t$CO_2$)' scenario. Global economy-wide carbon pricing starts immediately after 2020 and is then held constant to 2050. For calculating the upstream (indirect) component of emissions, average fuel-specific carbon intensities are in most cases assumed exogenously[1-5]. In the central case (solid lines), these are the following: +20 gCO_2/MJ for gasoline/diesel, +15 gCO_2/MJ for biofuels, +20 gCO_2/MJ for natural gas, +100 gCO_2/MJ for hydrogen, and +50 gCO_2/MJ for fossil synfuels. In the optimistic case (dashed lines), these are: +10 gCO_2/MJ for gasoline/diesel, +0 gCO_2/MJ for biofuels, +10 gCO_2/MJ for natural gas, +25 gCO_2/MJ for hydrogen, and +15 gCO_2/MJ for fossil synfuels. In the pessimistic case (dotted lines), these are: +30 gCO_2/MJ for gasoline/diesel, +50 gCO_2/MJ for biofuels, +30 gCO_2/MJ for natural gas, +200 gCO_2/MJ for hydrogen, and +100 gCO_2/MJ for fossil synfuels. Only for electricity were model-specific carbon intensities estimated and applied. Comprehensive lifecycle assessments based on model results were not conducted for the other fuels, due to insufficient information; hence the exogenous assumptions.

Supplementary Discussion

Supplementary Note 1

Because global energy-economy and integrated assessment models (IAMs) have historically been limited in their treatment of the social aspects of human decision making, these and other energy systems modeling tools have faced a fair amount of criticism over the past several years. For instance, of the many critiques of IAMs put forward by ref. [6], one mentioned in passing is that "there are also many types of inherent and deep uncertainties deriving from our inability to predict human behavior" (p. 325). (See also the rejoinder to ref. [6] by ref. [7].) In a similar vein, ref. [8] contend that the bulk of systems models have "unrealistic reliance on the full-rationality of agents", an "inability to properly account for agent heterogeneity", and an "inability to account for mutual influences among agents" (p. 102). A recent editorial in *Nature Climate Change* advocates for an inter-disciplinary "research agenda that integrates understanding of the social processes with technical analysis of climate and energy systems" (ref. [9], p. 539). In that same Collection on Energy, Climate and Society, joint with *Nature Energy*, ref. [10] call for policy analysis/modeling studies to move beyond stylized assumptions of human behavior, which implies "developing understanding of how risk, social networks and governance can influence the pace of transition to a low-carbon future" (ref. [9], p. 539); meanwhile, ref. [11] discuss the critical role of non-financial factors in household energy choices; and ref. [12] suggest that "integrated assessment model-based analysis should be complemented with insights from socio-technical transition analysis and practice-based action research" (p. 576). Though, as ref. [13] explain, such an interaction can be difficult in practice and often proves to be only partially successful. More frequent and purpose-driven dialogue between scientists from different fields is evidently key to addressing the human dimension in model-based analysis. And as ref. [14] note, when discussing the limited exchange of ideas between academic disciplines at present, "A real danger in silo model development is the lack of insights from outside a core modelling community." (p. 1).

Supplementary Note 2

There are a number of known issues with (international) carbon pricing, whether applied to the transport sector or more generally[15,16]. These include, among others, (i) the lack of long-term policy credibility that arises from fluctuating carbon prices, (ii) the potential relinquishing of proprietary information among governments, and (iii) the need for institutional capacity to collect, aggregate and communicate information. Carbon pricing, as a sole policy instrument, is particularly ill-suited for incentivizing change in the transport sector. As noted by ref. [16], "the complexity of transition barriers and the inherent nonlinearity of transition costs make simple policy solutions, such as a carbon or petroleum tax, less efficient than comprehensive strategies targeted to specific barriers" (p. 11) (see also refs. [17,18]).

Supplementary Note 3

Sector-focused strategies and policies in transport seek to influence consumers' financial and non-financial preferences.
Supplementary Table **2** maps the correspondence between these preferences and the main mechanisms currently being used to support AFV adoption throughout the world today. While not all of these measures are equally effective – some have even had perverse effects in certain contexts – the concept of sectoral actions has nevertheless gained considerable traction in transport policy circles in recent years. Certain types of financial incentives, for instance, have been shown to be important, namely those that reduce initial purchase prices through subsidies, grants, or tax credits[19-24]. Vehicle-use incentives such as high-occupancy vehicle (HOV) lane access and parking privileges have also been found to be effective in certain contexts, while counter-effective in others; their success depends in large part on the location-specific severity of the problem they seek to alleviate (e.g., congestion, parking scarcity)[16,21,25,26]. Evidence on the effectiveness of infrastructure build-out is less clear. Hydrogen refueling stations appear to be essential for promoting hydrogen fuel cell vehicles, whereas the need for widely available rapid charging points for battery-electric and plug-in hybrid-electric vehicles depends, to some extent, on a vehicle owner's ability to charge at home or work[16,22,23,27-31].

As
Supplementary Table **2** suggests, different approaches influence different aspects of consumers' vehicle preferences. This is consistent with the evidence that multi-pronged efforts to promote AFV adoption are more effective than a single sectoral or economy-wide policy[16,32,33]. After all, the jurisdictions worldwide that have employed a mix of measures and incentives have proven to be the most successful at promoting AFV deployment to date[34-36]. Whatever this mix, strong coordination across different levels of government (national, state/provincial, and local) appears to be necessary to guarantee AFV success[37,38].

			Transport strategies and policies influencing consumer preferences (Part 1)					
			Targets for cumulative vehicle sales, sales quotas, vehicle mandates	Vehicle efficiency or emission standards	Vehicle sales incentives (purchase subsidies, tax credits, fee-bates, reduced registration fees)	Vehicle manufacturer support (RD&D, production subsidies)	High transport fuel taxes (also carbon taxes or pricing)	Government and company vehicle procurement policies, other demonstration & test fleets
Consumer preferences	***Financial***	***Upfront capital cost***	+		++	++		+
		Fuel cost		+			++	
	Non-financial	***Risk aversion***	+	+	+			++
		Model variety	++			+		+
		Refueling availability	+				+	++
		Range anxiety				+		+
Example countries where strategies and policies have been implemented			Norway, Netherlands, UK, USA (10 states with California mandates), China, France, Germany	Norway, Netherlands, UK, USA, Japan, China, France, Germany	Norway, Netherlands, UK, USA, Japan, China, France, Germany	Norway, Netherlands, UK, USA, Japan, China, France, Germany	Norway, Netherlands, UK, France, Germany	UK, USA, Japan, China, France

			Transport strategies and policies influencing consumer preferences (Part 2)				
			Pilot programs and trialing in car clubs or car-sharing networks	Recharging and refueling public infrastructure investments	Workplace or home charging incentives	Preferential parking or roadway access; reduced congestion charges or tolls	Promotions, social marketing, outreach, information campaigns
Consumer preferences	***Financial***	***Upfront capital cost***					
		Fuel cost		+	+		
	Non-financial	***Risk aversion***	++			+	++
		Model variety	+				+
		Refueling availability	++	++	++		+
		Range anxiety	+	++	++		++
Example countries where strategies and policies have been implemented			France, Germany, Netherlands, USA	Norway, Netherlands, UK, USA, Japan, China, France, Germany	USA, France	Norway, Netherlands, UK, USA, Japan, France, Germany	Norway, Netherlands, UK, USA, Japan, China, France, Germany

Supplementary Table 2. Examples of strategies and policies for encouraging the uptake of AFVs by targeting consumer preferences. Table is divided into two parts. Notes: ++ indicates a strong or direct influence on consumer preference while + indicates a weak or indirect influence on consumer preference; based on authors' own assessment, drawing primarily from refs. [37,39-41]. The selection of countries here represented >90% of global electric vehicle sales in both 2014 and 2015[39,42]. Strategies and policies listed are derived primarily from refs. [37,39].

Supplementary Note 4

The WITCH model shows almost no deployment of electric-drive vehicles in the DevASIA region in the 'AFV Push (+ 100 US$/t$CO_2$)' scenario (Figure 1 of main text). Furthermore, in that same scenario we see that light-duty vehicle CO_2 emissions reductions actually are reduced by an increasingly stringent carbon price above 50 US$/t$CO_2$ (Supplementary Figure 7). The principal reason for this is a "retreat to oil products" in the light-duty vehicle sector when carbon prices reach higher levels. More specifically, in DevASIA, the combination of sectoral actions and economy-wide carbon pricing is insufficient to produce a transition towards electric-drive vehicles before 2050, because the cost of conventional internal combustion vehicles is so much lower than electric vehicles (i.e., a greater cost differential than in other WITCH regions). Decarbonization thus takes place only through (i) a substitution of conventional fossil internal combustion engine vehicles with hybrid-electric vehicles (the latter consuming less fossil fuel than the former), and (ii) a substitution of fossil fuels with biofuels (the latter emitting less CO_2 than the former). Initially, the oil-biofuels substitution predictably grows with increasing taxes, but then the trend is reversed. This reversal is caused by stiff competition for biomass from other parts of the energy system (e.g., biomass demand for electricity production), which starts to become non-negligible above 50 US$/t$CO_2$. From a system-wide perspective, the value of biomass is clearly greater in these other sectors, and as the prices of biofuels are driven upward across the energy-economy, the demand for biomass/biofuels from the light-duty vehicle sector is reduced. Incidentally, this dynamic is common to all world regions; however, electric-drive vehicles do begin to be deployed before 2050 almost everywhere else. This deployment is positively correlated with the carbon tax, and a 100 $/tCO2 carbon price more than compensates the negative effect of the lower biofuel consumption. Hence, the MAC curves for CO_2 reductions for the World and OECD shown in Supplementary Figure 5 and Supplementary Figure 6 remain monotonic.

For the IMAGE model, we see in Figure 1 of the main text that while electric-vehicle deployment in 2050 is strong globally and in OECD countries in the 'AFV Push (+ 100 US$/t$CO_2$)' scenario, deployment is quite weak in DevASIA. The cost differential between electric vehicles (battery-electric and plug-in hybrid-electric) and internal combustion engine vehicles is only a couple thousand dollars depending on the country and time period. Yet, the model's endogenously calculated prices for electricity in those countries (namely India and China) are much higher than for biofuels; this stands in contrast to the electricity prices in certain other countries/regions (e.g., USA and Europe), which see lower electricity prices. Because of the higher electricity prices in DevASIA, there is a disincentive to deploy electric-drive vehicles regardless of what sectoral actions are in place to help lower non-financial costs. In addition, we see that the the MAC curves for CO_2 reductions shown for the IMAGE model in the main text and here in the Supplementary Figures section above often take on a different shape than for the other models. They are more 'elastic' to increasing carbon (i.e., fuel) prices in both the 'No AFV Action' and 'AFV Push' scenarios. Moreover, in the 'No AFV Action' scenario, which sees a limited amount of electric and hydrogen vehicle deployment globally, we see that a significant amount of CO_2 mitigation is found to still be possible. This is because a significant amount of light-duty vehicle emissions reductions can be achieved in IMAGE through the adoption of high-efficiency fossil fuel internal combustion engine vehicles and conventional (non-plug-in) hybrid-electric vehicles. Non-financial costs are essentially zero for these conventional vehicles and therefore the lack of sectoral policies and strategies does not constrain their deployment.

The IMACLIM and TIAM-UCL models tend to exhibit more muted electric-drive vehicle deployment relative to the other models in the 'AFV Push (+ 100 US$/t$CO_2$)' scenario. A key factor influencing this result is the fact that electric vehicles (battery-electric and plug-in hybrid-electric) are significantly more expensive than internal combustion engine vehicles (by up to $20,000 per vehicle, depending on the country and time period). TIAM-UCL is actually unique in that it is the only model of the six not to witness deployment of battery-electric vehicles in 'AFV Push (+ 100 US$/t$CO_2$)'; instead biofuel internal combustion engine vehicles and hybrid-electric vehicles as well as fossil fuel plug-in hybrid-electric vehicles are preferred. (The cost differential with internal combustion engine vehicles is smaller for PHEVs than for BEVs.) This outcome occurs despite TIAM-UCL calculating electricity prices that are roughly the same as, or even somewhat lower than, biofuels prices in the major countries of OECD and DevASIA.

The GEM-E3 and MESSAGE models show the highest levels of electric-drive vehicle deployment globally in the 'AFV Push (+ 100 US$/t$CO_2$)' scenario (see Figure 1 in main manuscript). This is spurred by the relatively low cost differentials between internal combustion engine vehicles and electric vehicles (battery-electric and plug-in hybrid-electric). A marked difference between the GEM-E3 and MESSAGE results has to do with the MAC curves for CO_2 reduction that are calculated by each of the models. GEM-E3 exhibits a much more pronounced shift in the curve when sectoral actions are in place to promote electric vehicle adoption. Because the carbon intensity of electricity production is lower for GEM-E3 than for MESSAGE (as shown in Supplementary Figure 8), the emissions reduction impact of electric vehicle deployment is noticeably greater. In other words, because the electricity in GEM-E3 is more cleanly produced, the emissions benefit associated with the deployment of electric vehicles is greater.

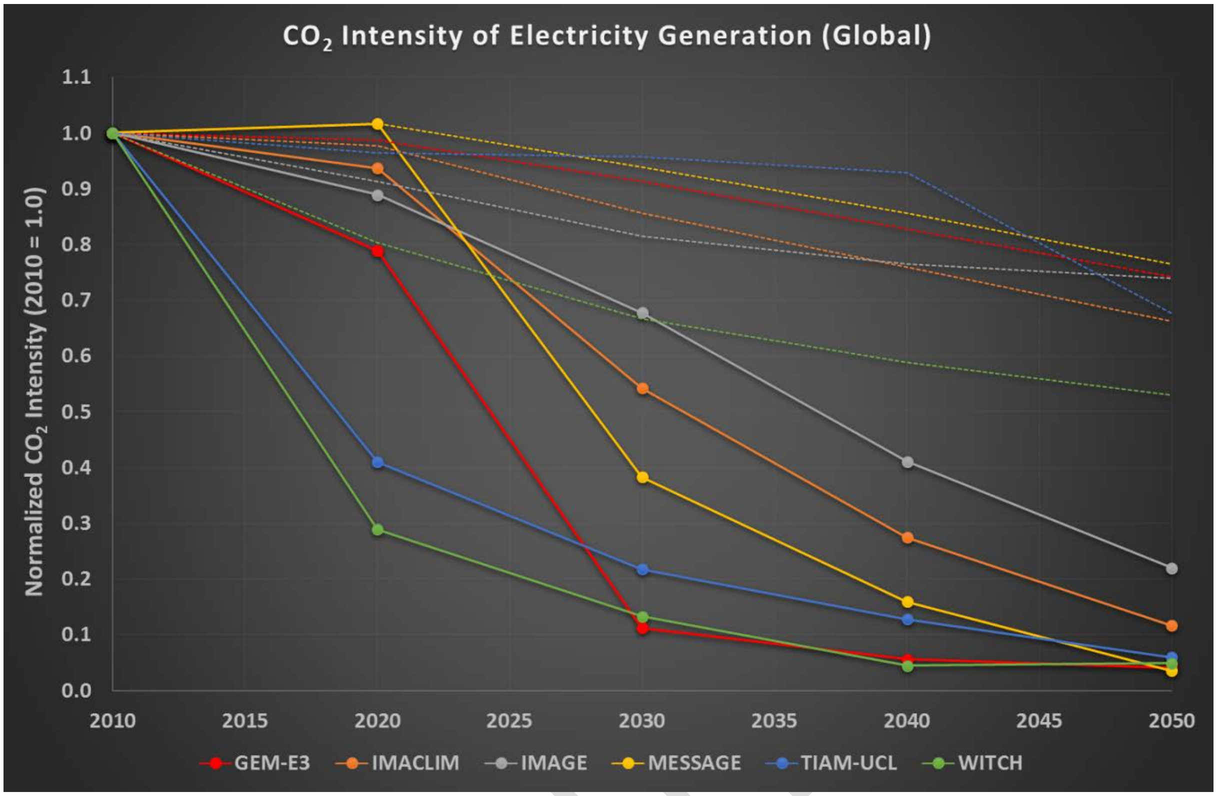
Moreover, we see from the MAC curves shown in Figure 2 of the main manuscript that some of the models (e.g., IMACLIM, MESSAGE and WITCH) exhibit a 'tipping point' in the range of 30–50 US$/t$CO_2$. The shift to vehicles powered by low-carbon biofuels and electricity evidently picks up speed when carbon prices reach this threshold.

Supplementary Note 5

For the most part, the models indicate greater electric and hydrogen vehicle potential in the OECD than in DevASIA. This is the result of two distinct forces at play, both of which are supported by the empirics and which highlight the value of bringing regionally-specific heterogeneity into the modeling. Firstly, social influence effects tend to be stronger in OECD countries (as a weighted average across those countries), meaning that existing perceptions of risk (among the majority of consumers) experience less inertia; consequently, concerns related to risk aversion can potentially dissipate more quickly, at least with regard to vehicle choice[40,43]. Secondly, annual average driving distances are in general greater in OECD countries[44], which means (i) higher-efficiency electric and fuel cell vehicles are more attractive than in Asia from a purely financial perspective, and (ii) non-financial concerns related to lack of refueling station availability and range anxiety are in general more pronounced in the OECD. The latter is especially important, as it shows that overcoming infrastructure-related behavioral barriers can lead to bigger impacts in the OECD context. (For more information, see Supplementary Data 1 and 2 made available with the online version of the paper; these files contain model assumptions for (dis)utility costs, regional multipliers, annual driving distances, and consumer group splits, among other things.) We note that one model, MESSAGE-Transport, shows a different trend here. This is primarily because electricity prices in this model are projected to be considerably cheaper in Asian countries over the next several decades, thereby increasing the attractiveness of electric vehicles from a financial perspective.

Supplementary Note 6

As discussed in the main text of the paper, carbon pricing (or some other form of climate policy adding an implicit price on carbon) is an important driver in the integrated assessment models for ensuring that the electricity used to power electric vehicles is derived from low-carbon sources. This is illustrated in the figure below, which compares the carbon intensities of electricity generation (global level) for two different variants of the 'AFV Push' scenario: one with a strong carbon price and another without a carbon price at all. The values shown are outputs of the models, which endogenously determine their electricity generation mixes based on a variety of factors, including carbon pricing.

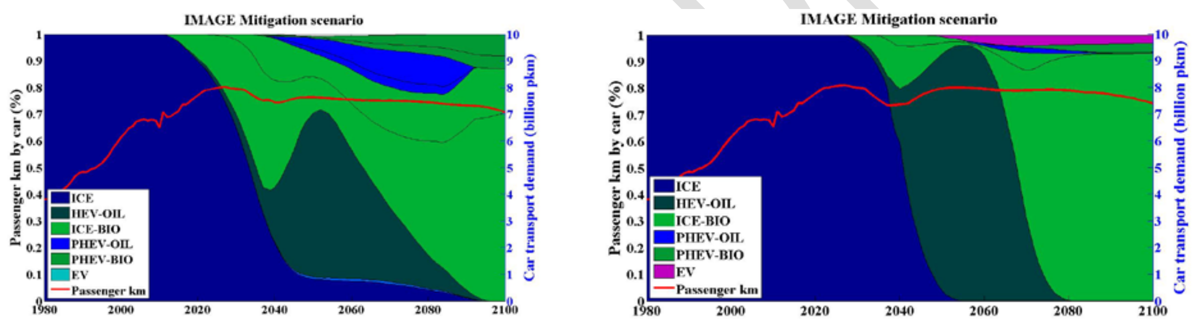


Supplementary Figure 8. Carbon intensities of electricity generation at the Global level as calculated by the models in the 'AFV Push (+ 0 US$/t$CO_2$)' scenario (dashed lines) and 'AFV Push (+ 100 US$/t$CO_2$)' scenario (solid lines) vehicles. Values are normalized to the 2010 historical estimate, which was approximately 150 gCO_2/MJ of electricity produced.

Supplementary Note 7

Introducing consumer heterogeneity and a detailed representation of non-financial behavioral preferences for different types of consumers is shown in the main manuscript and also here in the SI to impact the results obtained by the models. Notably, these model enhancements are also to the benefit of logit-based models (e.g., GEM-E3T-ICCS, IMACLIM-R, and IMAGE), which often capture heterogeneity through generically applied exponent terms in their logit formulations. In other words, in a typical logit-based, global energy-economy model, heterogeneity in vehicle adoption decisions is stylized, rather than coming about via more 'natural' forces (i.e., due to the individual decisions of different consumer types). In our study, our approach was to explore the latter methodology. Thus, it is important to ensure that the logit-based models utilized here avoid any 'double-counting' of heterogeneity and behavior. To achieve this, these modeling teams modified the default logit terms in their models (which were previously applied to the market as a whole and not to unique consumer types), specifically making these parameter settings more optimizing in nature. The outcome is that the market heterogeneity now comes about through an explicit representation of diverse consumer preferences, which are expressed by the (dis)utility costs that vary in magnitude for each consumer group individually. The combination of these two model modifications ensures that heterogeneous behavioral features are 'unpacked' into individual components, thereby allowing modelers to represent these features in a more consumer-specific (less generic) way than more aggregated logit models are typically able to do.

In the figure below, we demonstrate the value of adding diverse consumer groups and a heterogeneous representation of non-financial behavioral preferences to one of the logit-based models utilized in this study (IMAGE). The figure illustrates this value with some 'before-and-after' results. When running a stringent climate mitigation scenario similar to 'No AFV Action (+ 100 US\$/tCO_2)' with the original logit formulation applied to a single consumer group (left panel), we see only modest deployment of plug-in hybrid-electric vehicles and essentially no battery-electric vehicles. Technological heterogeneity does come about, but for this single consumer the higher-cost BEV option is never attractive. In contrast, when consumers are represented in a more heterogeneous way (right panel), the vehicle market takes on a different character over time, as certain consumer groups (namely early adopters in urban areas) find BEVs to be attractive. The latter dynamic is not captured using stylized logit parameter settings, unless the logits were pushed to their limits so as to ensure market heterogeneity in all cases. This can be done, but there is of course great uncertainty in how to 'tune' these logits to represent the future.



Supplementary Figure 9. Shares of light-duty vehicles over time (globally) in a stringent climate change mitigation scenario similar to 'No AFV Action (+ 100 US\$/tCO_2)' run by the IMAGE model. Left panel: original model formulation with a single consumer group and stylized representation of heterogeneity and behavior (default logit settings). Right panel: new model formulation with 27 consumer groups and an explicit, heterogeneous representation of non-financial behavioral preferences.

Supplementary Note 8

An additional scenario, 'AFV Ambition', was also run by the modeling teams for each of the four climate policy cases. The storyline is intentionally optimistic in the policy/strategy and behavioral senses. It assumes current (majority) risk aversion and concerns over limited model variety, lack of refueling station availability, and range anxiety are overcome immediately – they are non-issues for consumers from today onward. Hence, intangible costs are zero for all AFV types in all regions, meaning that all vehicle purchasing decisions are made based solely on pure financial considerations (capital, fuel, maintenance costs). The 'AFV Ambition' scenario, in other words, depicts an environmentally-driven global value shift, perhaps spurred on by climate change concerns and other anticipated co-benefits of AFVs.

As a point of reference, the electric-drive vehicle adoption shares exhibited in the 'AFV Push' scenario with the highest carbon pricing scheme (100 US$/t$CO_2$ after 2020) are somewhat lower than those foreseen in the corresponding 'AFV Ambition' case. In the latter, EDV shares across the models average 31% globally by 2050 [range: 19-42%], compared to 24% [range: 15-34%] in 'AFV Push'. One might expect the shares in 'AFV Ambition' to be greater, especially considering the high carbon tax in place; but this simply underscores the inherent challenge of overhauling the global vehicle fleet and its requisite fuel supply infrastructure, both of which have a considerable amount of inertia associated with them (long technology lifetimes, etc.). As the National Research Council concluded in a recent study of what it would take to transform the U.S. passenger vehicle fleet, "even an aggressive, well planned and supported transition would take well over 25 years to complete" (ref. [45], p. 13).

Supplementary Methods

Brief description of the global integrated assessment modeling frameworks

What follows are concise overviews of each of the energy-economy and integrated assessment models employed in this study: GEM-E3T-ICCS, IMACLIM-R, IMAGE, MESSAGE-Transport, TIAM-UCL, and WITCH. Much lengthier descriptions can be found at the following resource:

The Common Integrated Assessment Model (CIAM) documentation website developed within the context of the ADVANCE project[46]
http://themasites.pbl.nl/models/advance/index.php/ADVANCE_wiki

GEM-E3T-ICCS

The GEM-E3T-ICCS model is a global multi-sectoral, multi-regional, recursive-dynamic Computable General Equilibrium (CGE) framework. The model covers the back-and-forth interlinkages of all industries and calculates the vector of prices that clear all markets (commodity, capital and labor) simultaneously. Trade representation is based on the Armington hypothesis (domestic and imported commodities of the same industry are treated as imperfect substitutes). Demand for commodities, services and production factors derive from utility maximization of households and cost minimization of production firms. Households' income sources are: labor, dividends and social transfers. The model represents involuntary unemployment through endogenous labor supply curves. Capital is fully mobile across sectors, hence a uniform rate of return by country is calculated.

GEM-E3T-ICCS is an enhancement of the standard GEM-E3-ICCS model[47], but with more detail in the transport sector, as well as a representation of fleet choice and energy consumption. It provides results for water-, air- and land-based transport, including for passenger and freight transport modes, covering separately rail, road and a distinction between public and private transport. The model distinguishes technologies for transport means, and makes choice of technologies endogenous in the simulation of investment of sectors providing transport services and the purchasing of durable goods, such as cars, by households. Finally, the model relates the operation of the transport means to sectors producing the energy commodities, including alternative fuels, such as electricity and biofuels. All these extensions are formulated in a way that is consistent with the general equilibrium framework of the model. This extension allows for a link to a detailed transport sector with the rest of the economy, hence capturing feedback effects across sectors. GEM-E3T-ICCS represents explicitly the production of biofuels. Bio-gasoline and biodiesel production is made with feedstocks produced from the agriculture sectors. Biofuels are further disaggregated according to the feedstock and the associated conversion technologies. Transport sectors and households consume oil products, gas, biofuels and electricity for transport purposes. Manufacturing of vehicles was made explicit in GEM-E3T-ICCS by distinguishing sectors producing conventional vehicles and a sector producing electric vehicles. This was done with the aim to capture price differentials of car types and the impacts of global competition on car manufacturing. The sector producing electric vehicles has endogenous learning functions reflecting the possibility of cost reduction, mainly for batteries, as a function of production volume. The stock of vehicles by transport sector and the cars, represented as durable goods in the modelling of behavior of households, change over time as a result of mobility and scrappage. The choice of between vehicle technologies depends on relative costs, which include purchasing cost, running costs and cost factors reflecting uncertainty factors depending on technology maturity and the availability of recharging or refueling infrastructure. The cost of conventional technologies is penalized when they do not comply with CO_2 standards. Taxes are explicitly represented, and the revenues are part of the public budget. Subsidies and expenditures for public infrastructure are also part of the public budget. Deficits or surpluses of the public budget influences the economy through changes in interest rates. In this way, the model aims at capturing the economy-wide effects of public money used in transport sectors and infrastructure, and the effects of fuel taxation or eventual subsidization of new car technologies. More details on transport modelling in GEM-E3T-ICCS can be found in ref. [48].

Of importance for this study, the default settings for the exponent terms in the model's transport sector logit equations (which were previously applied to a single type of consumer in each region) were modified so as to make them more optimizing in nature. In other words, the logits no longer force heterogeneity in vehicle adoption patterns, but rather these patterns emerge naturally from the diverse representation of consumers and their unique behavioral features.

IMACLIM-R

IMACLIM-R is a multi-region and multi-sector model of the world economy that represents the intertwined evolution of technical systems, energy demand behavior and economic growth[49]. It combines a Computable General Equilibrium (CGE) framework with bottom-up sectoral modules in a hybrid and recursive-dynamic architecture (logit formulations used in the transport sector). Furthermore, it describes growth patterns in second-best worlds with market imperfections, partial uses of production factors and imperfect expectations. The model represents endogenous Gross Domestic Product (GDP) and structural change, energy markets and induced technical change. The scope of greenhouse gases represented is restricted to CO_2 emissions from fossil fuel combustion. The main exogenous assumptions are demography and labor productivity growth, the maximum potentials of technologies (e.g., renewable, nuclear, carbon capture and storage, electric vehicles), the learning rates decreasing the cost of technologies, fossil fuel reserves, the parameters of the functions representing energy-efficiency in end-uses, and the parameters of the functions representing energy-demand behaviors and life-styles (e.g., motorization rate, residential space, evolutions in consumption preferences).

Within the broader landscape of integrated assessment models, IMACLIM-R can be labeled as a recursive-dynamic General Equilibrium Model with a medium variety of low-carbon technologies. Diagnostics of its response to carbon pricing places it as a "low response" model, which means that a given carbon price leads to relatively low abatement and high cost per tonne of CO_2 abated compared to other IAMs[50].

Of importance for this study, the default settings for the exponent terms in the model's transport sector logit equations (which were previously applied to a single type of consumer in each region) were modified so as to make them more optimizing in nature. In other words, the logits no longer force heterogeneity in vehicle adoption patterns, but rather these patterns emerge naturally from the diverse representation of consumers and their unique behavioral features.

IMAGE

The IMAGE transport model is described in detail by ref. [51]. The transport model is a state-of-the-art IAM transport implementation, characterized by high detail, in terms of its technological, socio-demographic, and regional resolution. Traveling costs form the basis of the modeling both in determining modal shares, as well as vehicle shares per mode, based on a multi-nominal logit (MNL) model. The model represents 7 passenger transport modes and 6 freight transport modes. Modal costs depend on real costs per passenger-km, non-monetary preferences, and a time weight that represents the importance of time compared to monetary costs. Non-monetary preferences are used to calibrate the model to historical observations and account for factors that go beyond cost (e.g. driving a car is more expensive than other modes, but a popular travel choice). Then, in future years, for the purposes of this study, these default non-monetary preference parameter settings were removed and instead the (dis)utility costs used by all other models were also applied in IMAGE. In addition, the default settings for the exponent terms in the model's transport sector logit equations (which were previously applied to a single type of consumer in each region) were modified so as to make them more optimizing in nature. In other words, the logits no longer force heterogeneity in vehicle adoption patterns, but rather these patterns emerge naturally from the diverse representation of consumers and their unique behavioral features.

The travel money budget (TMB) concept is used to relate travel demand to income. Increasing income leads to increasing travel demand per capita, which results in more time spent travelling. Through the concept of travel time budget (TTB), time gets more weight, and as a result faster modes are valued more. This dynamic relation results in the empirically observed shift to higher speed modes as income increases[51]. The model is calibrated to passenger-km and energy data from 2005 based on refs. [52] and [53].

The costs per vehicle type, which largely determines vehicle choice, depend on energy costs, technology costs, non-energy costs (related to maintenance and vehicle purchase), and the load factor, which is regionally dependent. Energy efficiency in the model is captured in three ways: (i) Price-induced efficiency improvement: in response to higher fuel prices, more efficient vehicles become cost-competitive, (ii) Autonomous efficiency improvement: technology costs of efficient technologies decline over time as a result of technological learning, (iii) Mode shift: increasing fuel prices can also result in a shift toward more efficient modes[51,54]. Reduction of transport GHG emissions can be achieved through a carbon tax, resulting on the one the hand in reduced competitiveness of technologies and modes with high dependency on fossil fuels, and on the other hand through the concept of TMB, as the increased price of travelling leads to less travel demand overall.

MESSAGE-Transport

The MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) is an energy-economic model based on a linear programming (LP) optimization approach which is used for medium- to long-term energy system planning and policy analysis[46,55]. The model minimizes total discounted energy system costs, and provides information on the utilization of domestic resources, energy imports and exports and trade-related monetary flows, investment requirements, the types of production or conversion technologies selected (technology substitution), pollutant emissions, and inter-fuel substitution processes, as well as temporal trajectories for primary, secondary, final, and useful energy. To estimate regionally-aggregated, sector-based air pollutant emissions and related pollution control costs, MESSAGE has been linked to the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model[56]. For the estimation of price-induced changes of energy demand, iterations between the MESSAGE model and the macro-economic model MACRO are relied upon ref. [57]. In MACRO, capital stock, available labor, and energy inputs determine the total output of the economy according to a nested constant elasticity of substitution (CES) production function. Through the linkage to MESSAGE, internally consistent projections of GDP and energy demand are calculated in an iterative fashion that takes price-induced changes of demand and GDP into account. MESSAGE is used in conjunction with MAGICC (Model for Greenhouse gas Induced Climate Change), version 6.8, for calculating internally consistent scenarios for climatic indicators such as atmospheric concentrations, radiative forcing, annual-mean global surface air temperature and global-mean sea level implications[58,59].

The version of the model employed in this study is known as MESSAGE-Transport V.5a. This model version goes beyond previous ones in its detailed representation of the transport sector, meaning individual vehicle technologies are characterized across the various transport modes: light-duty passenger vehicles, two-wheelers, heavy-duty freight trucks, busses, passenger aviation, international shipping, and passenger rail, as well as a residual category that includes freight aviation, domestic shipping, and freight rail[43]. In conjunction with this set-up, the MESSAGE-MACRO linkage is adjusted so that passenger mode choices are responsive to service prices and travel-money and travel-time constraints (via a soft-linked logit-based model). Energy service demands are provided exogenously to MESSAGE; they are then adjusted endogenously based on energy prices thanks to the linkage with MACRO. There are seven demands in the stylized end-use version of the model, one of which is transport. In the more detailed MESSAGE-Transport used in this study, this is adjusted to six non-transport demands (for the industrial and residential/commercial sectors) and seven transport demands (for LDVs; two-wheelers; freight trucks; passenger aviation; buses; passenger rail; and residual category covering freight aviation, freight rail and domestic shipping). Future 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, thereby deviating from the 'scenario generator' approach used in previous applications of MESSAGE (and still used in the non-transport sectors of MESSAGE-Transport). (See ref. [60] for more information about the MESSAGE scenario generator.) MESSAGE-Transport V.5a also contains a detailed representation of energy prices, taxes, and subsidies at both the primary and final energy levels (across all fuels, sectors, and regions). The detailed transport model version described in ref. [43] was combined with the version developed for a separate study on oil price impacts[61]; the combination of these two model versions resulted in MESSAGE-Transport V.5a.

TIAM-UCL

TIAM-UCL[62] is a variant of the original TIMES Integrated Assessment Model[63,64], further developed at University College London (UCL). The model is a technology-rich, bottom-up, partial equilibrium energy systems model, formulated as a linear optimization problem and covering in detail the full energy system from resource extraction to final end use of energy. The world is aggregated into sixteen global regions in the model and the time frame of a model run extends to 2100. A simple climate module, calibrated to MAGICC, is also included in TIAM-UCL. The database of the model includes hundreds of technologies across the energy sector and also describes energy commodity trade between the various regions. Technology/sector-, time period- and region-specific hurdle rates are included for technologies. The 42 energy service demands projected for each region are calculated from a set of exogenously defined drivers (e.g. GDP, population, number of households); the demands respond to prices.

Thirteen of the above mentioned energy demands are for the transport sector, for international and domestic navigation and aviation, for a range of road transport modes (light-duty cars and trucks, two-wheelers, three-wheelers, buses, commercial/medium/heavy-trucks) as well as for rail (passenger and freight). Each of these service demands can be fulfilled with a range of different technologies and all the demands are own-price elastic. The drivers behind the demands differ, but are generally either GDP, population or both and the decoupling factor that governs the relationship between the driver, and the energy service demand is region- and time period-specific. GDP per capita is the main driver for light-duty cars and trucks demand, then further scaled with the size of the population. Mode shifting or cross-price elasticities are not included in the model formulation. For the purposes of this study, which utilizes (dis)utility costs to represent consumers' non-financial preferences for vehicle purchase decisions, the hurdle rates used in the standard TIAM-UCL variant are excluded from the transport sector.

WITCH

WITCH (World Induced Technical Change Hybrid) is an Integrated Assessment Model aiming at studying the environmental, economic, and energy dimensions of climate change over the 21st century, and their interactions. It is defined as hybrid because it is an aggregated macro-economic inter-temporal optimization model with perfect foresight combined with a detailed description of the energy sector. World countries are grouped into thirteen regions, which behave independently optimizing their own decision variables and whose strategic interactions are modeled through a Nash-type dynamic game. One distinguishing feature is the endogenous modeling of technical change, which covers the broad energy efficiency sector as well as specific clean technologies.

The model is structured according to a non-linear Constant Elasticity of Substitution (CES) framework, where the aggregated capital and labor nodes are combined with the energy service node to provide the final output. The energy service node is divided into the capital of energy R&D and the actual energy generation. The former models energy efficiency, since a high R&D stock allows for the provision of the same energy service with lower actual energy supply. The energy node is firstly divided into the electric and the aggregated non-electric sectors, and then further disaggregated down to the single technologies. The electric part is characterized by a rich technology representation, while the non-electric sector nodes are aggregated per type of fuel. Ref. [65] provides further information on the model in general.

Within the transport sector, road passenger (light-duty vehicles only) and road freight are explicitly modeled, while the rest of the sector is indirectly modeled in the non-electric sub-tree described above. The two road transport modules do not explicitly appear in the CES structure, but are linked to the rest of the model through two links. On the one hand, investments and supplementary costs in the transport sector decrease the aggregated consumption, which leads to the need for the cost optimization of the vehicle fleet; on the other hand, transport technologies compete with the other energy technologies for the energy resources. Transport demand is explicitly calculated based on GDP and population projections and it is met with four types of vehicles (traditional, hybrid, plug-in hybrid, battery-electric vehicles) and three types of fuels (oil, biofuel, and electricity). Technical change is accounted for as well, with an exogenous increase of the vehicles' efficiencies and an endogenous decrease of battery costs as a consequence of dedicated R&D investments (learning-by-researching). More details on the transport modeling in WITCH can be found in refs. [66-68].

Approach to modeling heterogeneous behavioral features in the global models

Representing behavioral features of vehicle choice in a global energy-economy model requires the mean representative decision-agent to be divided into distinct consumer segments characterized by different preferences and vehicle use characteristics. This implies a two-step methodology, as first illustrated in a test case by ref. [69] using the TIMES bottom-up modeling framework and then later in a proof-of-concept study by ref. [43] using the MESSAGE-Transport global integrated assessment model framework. The first step is to disaggregate the single, homogenous light-duty vehicle mode (both technologies and demands) along several different dimensions. The second step is to add extra cost terms (so-called "(dis)utility costs", "intangible costs", or "non-financial costs") on top of the vehicle capital costs already assumed in the model. These (dis)utility costs link to the non-financial preferences found to be influential in empirical studies (e.g., range anxiety, lack of refueling station availability, risk aversion; see ref. [43], Table 2), and are specific to particular consumer groups and technologies. They also vary by region and can decline over time, depending on the scenario storyline. Further details about this methodology, as we have applied it in the various global modeling frameworks of this study, are given below and in refs. [43,69]. For an extended discussion of the theoretical underpinnings of this integrated approach, see ref. [70].

Note that as part of the Supplementary Information made available with this paper, we include spreadsheets with calculations for the consumer group splits, the (dis)utility costs, and the regional multipliers. This information will be useful for other modelers who would like to build upon our approach within other energy-economy and integrated assessment model frameworks.

<u>Step 1: introduce heterogeneity</u>

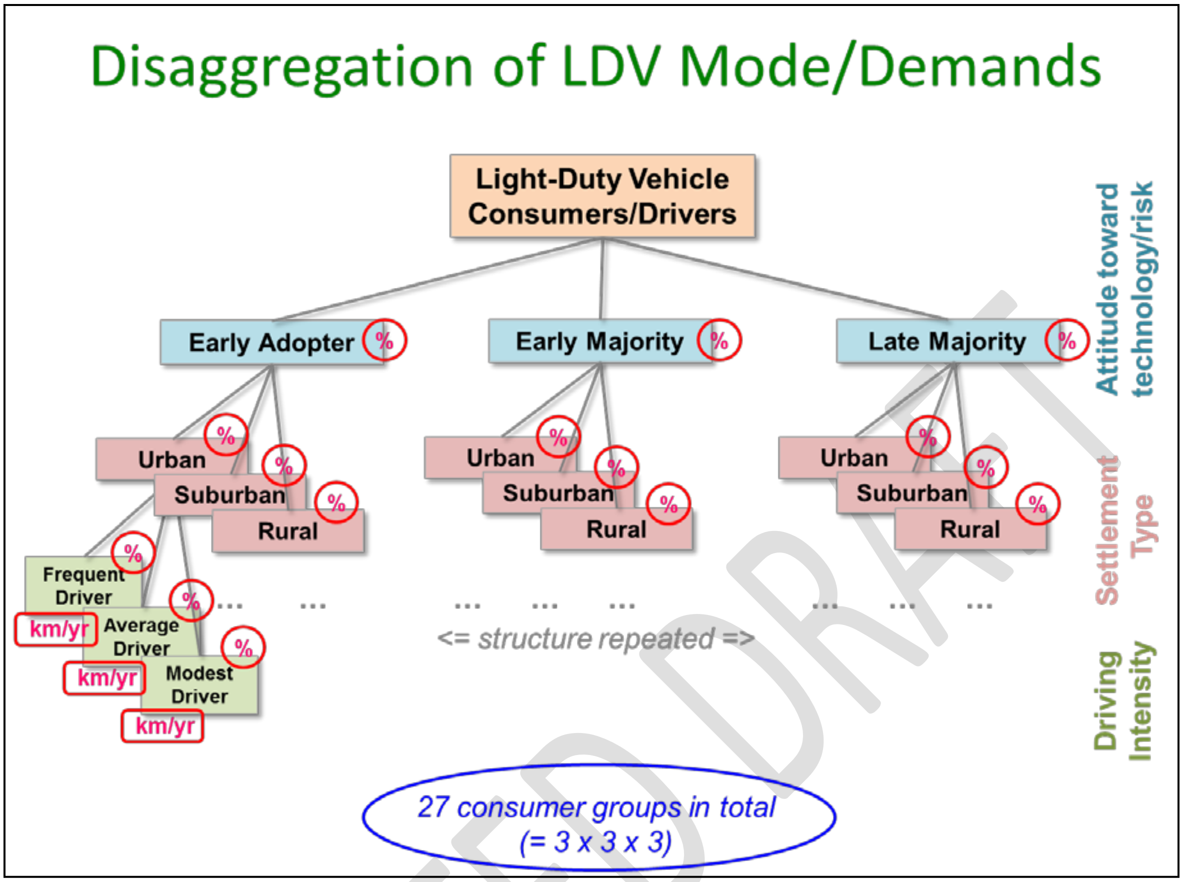
In the most detailed formulation, consumers (potential vehicle buyers) within one of the respective model's native model regions are divided along three separate dimensions. These dimensions are chosen because the empirical evidence base suggests they (or their derivatives) are important behavioral features of vehicle choice (see ref. [43], Table 2).

1. *Settlement pattern*: Urban – Suburban – Rural
2. *Attitude toward technology adoption*: Early Adopter – Early Majority – Late Majority
3. *Vehicle usage intensity*: Modest Driver – Average Driver – Frequent Driver

The combinations possible in this 3x3x3 arrangement led to 27 unique consumer groups (Supplementary Figure 10). All members of the entire driving population (within a particular model region) fall into one of these 27 groups. Division into groups is done with respect to service demands, i.e., passenger-kilometers. Note that two of the models, IMACLIM-R and WITCH, implemented a 9-group disaggregation, collapsing the settlement pattern dimension and thus distinguishing consumers by technology attitude and vehicle usage intensity. (A sensitivity analysis with the (dis)utility cost data indicated that such a simplification could be made without losing much in the way of model insights, while the choice of 9 consumer groups allowed for a less computationally-intensive modeling framework.) Apportionment of current and future vehicle demands by consumer group is determined using base-year transport statistics (for vehicle usage intensity), population projections (for settlement pattern), and diffusion theory (for technology adoption propensity). For making such calculations, we relied on, for example, US National Household Travel Survey (NHTS) data compiled and programmed into the MA^3T model[71] (see below for further details), Rogers's classification of technology adopter types[72], and the urban-rural population projections developed in the Shared Socio-economic Pathways exercise (namely the median-level SSP2 scenario[73-76]).

Introducing heterogeneity into the LDV sub-sector of each model requires that the relative shares among the 27 (or 9) consumer groups are projected over time and by native model region. We then multiplied the time-varying %-share estimates for each consumer group within each region by the previously existing single LDV passenger-km demand trajectories in order to generate a heterogeneous set of service demand projections. In other words, the LDV sub-sector becomes characterized by 27 (or 9) separate demands, each being serviced by the same suite of vehicle technologies as before (e.g., gasoline/diesel/biofuel ICEs and HEVs, H2 FCVs, BEVs, PHEVs). At this point, one could choose to clone these technologies across the 27 (or 9) consumer groups (i.e., making exactly the same assumptions for capital and O&M costs, fuel economies, vehicle lifetimes, occupancy rates, etc.), or the group-specific technologies could be differentiated slightly. Decisions on how to do this were left to each of the teams. In MESSAGE-Transport and WITCH, for instance, the modelers opted to keep all the cost and efficiency assumptions the same but varied the vehicle-specific capacity factors (km/yr) and vehicle lifetimes depending on the (regionally-specific) driving intensities of the different consumer groups (Modest/Average/Frequent).

We have estimated the consumer group shares as best as possible for each region. They are calculated as multiplicative combinations of the share splits for settlement pattern, attitude toward technology adoption, and vehicle usage intensity (see Supplementary Data 1 made available with the online version of the paper). For settlement pattern, urban-rural population projections from the Shared Socio-economics Pathways (SSP) exercise are used. Suburban share splits are then carved out of the urban portion based on modeler judgement; these splits are uncertain since the distinction between urban and suburban is not always clear-cut in many parts of the world. For technology attitude, we hold all shares the same over time and do not differentiate by region. For vehicle usage intensity, share splits for certain US sub-regions (i.e., the 9 Census regions) are pulled directly from MA3T and then used as proxies for other countries/regions. (One method for guiding the choice of proxies has been, for example, to identify similarities in population density between US sub-regions and other countries/regions.) These uncertainties and simplifications should be recognized at the outset, though they are not thought to be any larger than those surrounding the (dis)utility cost estimates themselves.



Supplementary Figure 10. Schematic illustration of heterogeneous consumer groups within the light-duty vehicle sector.

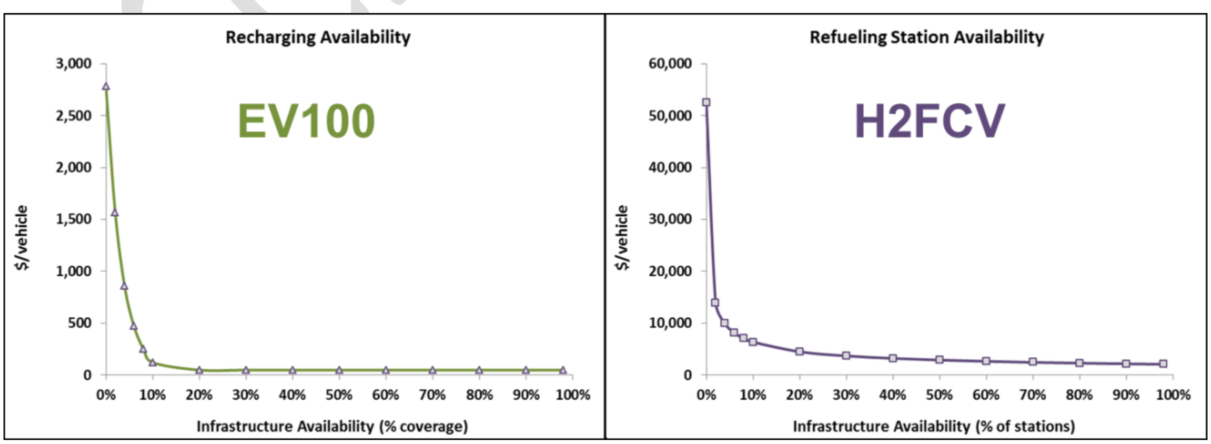
<ins>Step 2: add intangible costs</ins>

Once a disaggregated set of heterogeneous agents has been programmed into the model, the second important step is to assign intangible, or (dis)utility, costs to each of the vehicle technologies that can potentially be purchased by a consumer within a given group. These (dis)utility costs are added as extra cost terms to the vehicle capital costs already assumed, and they vary by technology, by consumer group, by country/region, and over time. (For more information, see Supplementary Data 2 made available with the online version of the paper; this file contains all parameter assumptions and underlying equations for calculating the (dis)utility costs on a technology-, region-, and consumer group-basis.)

The costs have been calculated using a specialized version of the MA^{3}T vehicle choice model (Market Acceptance of Advanced Automotive Technologies) (see http://teem.ornl.gov/ma3t.shtml or refs. [71], [77], [78], [79], [80], [81], [82], and [83] for details), which was made available, upon special request, by the original model developers. MA^{3}T, which utilizes a Nested Multi-Nomial Logit (NMNL) discrete choice approach, has since 2009 been developed by researchers at Oak Ridge National Laboratory, in order to study vehicle transitions in the US light-duty vehicle sub-sector out to 2050. Under standard operation, MA^{3}T estimates choice probabilities for a suite of vehicle technologies within each consumer group (hundreds of groups). In carrying out this calculation, the model calculates a "generalized cost" for each technology within a given group; this cost aggregates both real costs (e.g., capital, fuel and O&M costs) and perceived costs (e.g., range anxiety, technology risk, etc.). By strategically breaking the MA^3T simulation at the point where these generalized costs are tallied, we are able to report the intangible perceived costs (i.e., (dis)utility costs) from the model.

As described more fully below, the (dis)utility cost estimates that we take from MA^3T are comprised of five distinct sub-components, and they come in the form of equations and assumptions that either (i) have been pulled directly from the model (for the risk premium, model variety/availability, and EV charger installation sub-components), or (ii) were estimated based on running an ensemble of scenarios using it (for the range anxiety and refueling station availability sub-components). In the latter case, a structured sensitivity analysis was performed with MA^3T wherein assumptions regarding refueling station and recharging infrastructure availability were varied from 0% to 100% of network coverage in the USA context (with finer gradation at the lower-end below 10% coverage). This allowed us to develop reduced-form relationships for these two (dis)utility cost sub-components as a function of refueling/recharging coverage within a given region and for each of the 27 consumer groups separately. The relationships have either power-law (refueling availability) or piece-wise linear (range anxiety) functional forms. In all cases (whether for electric charger coverage or availability of hydrogen or natural gas refueling), as infrastructure becomes more widespread, the associated (dis)utility costs for a given fuel-vehicle type come down.

Supplementary Figure 11 gives examples – for one of the 27 consumer groups in the USA context – of how the range anxiety and refueling station availability (dis)utility cost components depend on the level of recharging/refueling infrastructure. Range anxiety applies to electric vehicles, while refueling station availability applies to hydrogen vehicles (and also natural gas vehicle, although not shown here.) In both cases, costs drop quickly as the coverage increases from 0% to 10%; and by 20-30% coverage, the costs have leveled off. This finding is consistent with previous studies, some of which used GIS-based spatial optimization and traffic flow models to calculate the average time drivers would need to reach refueling stations offering hydrogen as a function of the number of those stations[84-88]. Coverage of 10-20% was found to offer an acceptable level of convenience in such cases.



Supplementary Figure 11. Example of the relationship between recharging station availability, reflected in vehicle range anxiety (left panel; BEVs with a range of 100 miles) and refueling station availability (right panel; H2FCVs) (dis)utility cost components and the level of recharging or refueling infrastructure availability. USA estimates for a single consumer group are shown (Urban – Early Majority – Average Driver). Cost values in US$2005. Functional forms derived from a sensitivity analysis using the MA³T model.

Although the standard version of MA³T considers a number of non-financial vehicle purchase attributes, we focus on five of these for implementation in the models of this study (i.e., those comprising nearly the entirety of the total summed (dis)utility costs; see Supplementary Figure 13). These (dis)utility cost sub-components are listed below, with more detailed descriptions being given in Supplementary Table 3. Most of these attributes have been found in previous studies to be important determinants of AFV adoption (see ref. [43], Table 2). While there is inherent uncertainty in the magnitude of any single cost component, of the five used here, range anxiety, refueling station availability, and model variety/availability tend to dominate, depending on the particular vehicle technology, consumer group and region under consideration (see Supplementary Table 3). Supplementary Figure 12 provides an illustration of present-day (dis)utility costs of several technologies estimated for two different consumer groups in the USA (the underlying calculations assume extremely low AFV sales/stock and very limited refueling/recharging infrastructure availability). Particularly noteworthy for modeling is the fact that the sum of the five (dis)utility cost sub-components may be as little as ~15% or as much as ~165% of the actual vehicle investment cost (i.e., the retail price).

We also note that risk premiums are estimated to be relatively small on their own, at least according to the framework employed here, which estimates risk premiums individually as part of a larger set of non-financial attributes. (If components like range anxiety, refuelling station availability and model variety/availability were not separated out on their own but were instead lumped into a more generic risk premium component, then the latter would be far larger in magnitude. In other words, this is a definitional issue.) However, according to our methodology a consumer's attitude toward technology risk also affects her valuation of range anxiety as well, so there is an indirect effect. Ref. [70] discusses each of these attributes in detail, including a step-by-step analysis of what happens when each is considered in succession.

1. Range anxiety (limited electric vehicle driving range)
2. Refueling station availability, or lack thereof (for non-electric vehicles)
3. Risk premium (attitude toward new technologies)
4. Model variety/availability (diversity of vehicles on offer)
5. Electric vehicle charger installation (home/work/public)

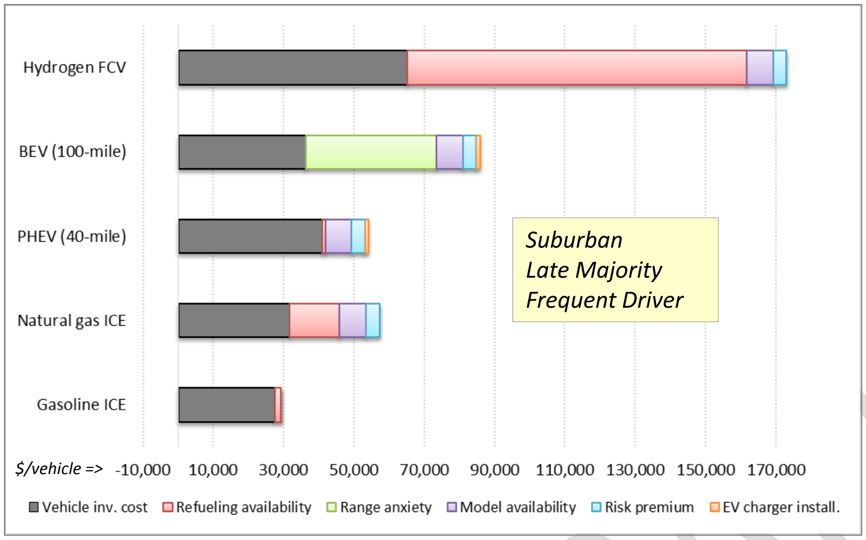
The version of MA³T that we employ also considers vehicle acceleration, cargo space, and towing capability as additional non-financial attributes that may affect consumers' preferences when making vehicle purchase decisions. These three (dis)utility cost sub-components, however, are all estimated to be relatively small by MA³T (based on earlier empirical work); thus, we ignore them for the purposes of our model implementation. This is not to say they are not important though, especially for certain types of consumers. One could actually argue that at an aggregate, non-explicit level the negative (dis)utility costs in our implementation, which are associated with risk premium among early adopters, do actually capture the improved acceleration attribute for electric-drive vehicles, as well as considerations of status/symbolism within peer networks and the potential for quieter driving during vehicle operation. In truth, though, when some of these vehicle platform- and brand-dependent attributes would really become important is when different LDV size classes, makes, and models would be modeled individually (e.g., sports car, small/midsize/large car, small/large SUV, minivan, pickup truck), and at the moment we do not distinguish between separate vehicle types in the IAMs of this study.

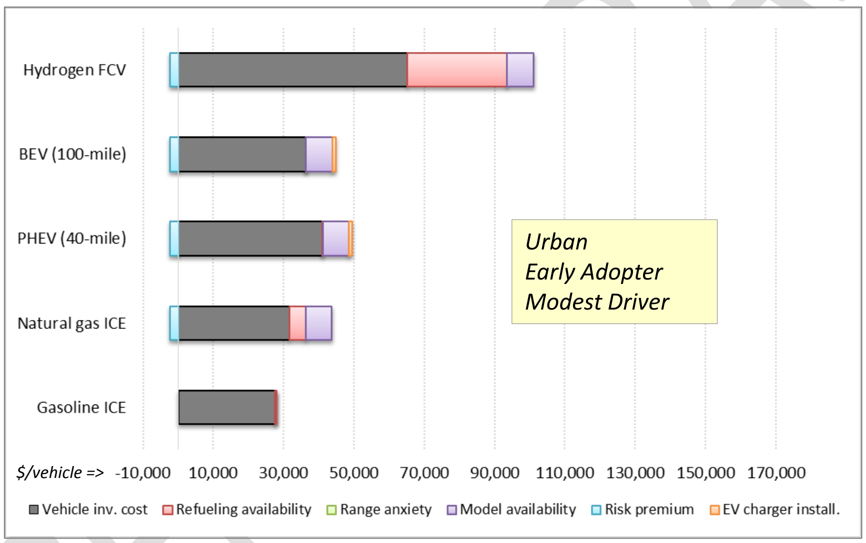
(Dis)utility cost sub-component	Description of attribute	Monetization approach	Regionalization approach
Range anxiety	This attribute monetizes the perceived anxiety felt by a consumer when depending on a limited-range, all-electric vehicle for all of his/her daily driving needs, particularly longer-distance travel. Hence, this sub-component is only relevant for all-electric vehicles.	The cost is proxied based on the estimated amount a consumer would be willing to spend on rental cars over the course of a year in order to satisfy driving needs on those days when the vehicle's all-electric range is insufficient. Costs depend on the charge-sustaining capacities of vehicles (i.e., driving ranges), vehicle efficiencies, daily driving distances, the availability of home/work/public recharging stations, and the attitudes of consumers toward technology risk. In USA, initial costs (@ 0% recharging availability) range from 0 to 40k $/vehicle for BEVs, depending on consumer group. In the original MA^{3}T model, the assumption is that if a rental car would be provided for free to use on those days when the battery-electric vehicle (BEV) range is insufficient, then the consumer would feel indifferent between possessing an electric vehicle or a conventional internal combustion engine vehicle (for which range limitations are not an issue). The cost of rental cars is assumed to be $50 per day[89]. The number of range-insufficient days is calculated based on the specified Gamma distribution of daily distance for each consumer group and is explained in detail in ref. [89]. This Gamma distribution method was proposed and validated with real-world driving data[90,91]. The driving range of a BEV is a function of not just the battery capacity but also the amount of electricity drawn from home, workplace, public and even on-road wireless charging systems, depending on the consumer group's access to these systems and driving patterns. These are scenario assumptions in the model. For example, a consumer that is assumed to charge the BEV every night at home and has a short commute distance will only draw a small amount of electricity to recover the short commute distance, but not the amount calculated based on the charger power and 6-8 hours of at-work vehicle parking. However, if home charging is not available and the BEV leaves home in the morning at a very low state-of-charge (SOC), the electricity drawn from workplace chargers will be significantly much more. The complicated relationships between range, SOC and different charging systems are carefully formulated in a coherent charging infrastructure model, reported in ref. [81].	Regional multipliers (calculated based on differences in WTPs between countries from discrete choice studies focusing on range anxiety) are used to adjust costs between the USA and other countries/regions.
Refueling station availability	This attribute monetizes the perceived	The cost is proxied based on the estimated amount of time a driver would need during each refueling event in order to reach a station supplying the fuel s/he needs.	Regional multipliers (calculated based on differences in WTPs

	inconvenience and hassle felt by a consumer when assessing his/her ease of access to refueling stations. Hence, this sub-component is only relevant for liquid fuel, natural gas, and hydrogen vehicles.	Aggregating those time demands and converting them into a monetary values (also considering, according to other studies, that consumers put more value on the time associated with refueling) results in a (dis)utility cost. Costs depend on vehicle ranges and efficiencies, daily driving distances, and the availability of refueling stations within the transport network. In USA, initial costs (@ 0% refueling availability) range from 30k to 100k $/vehicle for H2FCVs and from 4k to 14k $/vehicle for NGVs, depending on consumer group. In the original MA^{3}T model, the perceived annual cost due to limited refueling station availability is calculated as the refueling inconvenience cost (RIC) for each refueling trip multiplied by the number of refueling trips per year. Gamma distributions in MA^{3}T depict daily driving requirements over the course of the year. RIC is calculated as the product of refueling travel time from a random origin in the network (weighted by traffic volume) to the nearest station, time value and hassle multiplier. Refueling travel time is a power function of fuel availability, i.e. the ratio of the number of stations offering the alternative fuel to a reference number of gasoline stations, similar to the function estimated by ref. [92] for Southern California. MA^{3}T allows users to specify the travel times for 100% and 10% fuel availability for different locations, so that the parameters of the power function can be specified for the given location. The time value is assumed to be $25/hour and the hassle multiplier is estimated to be 3.56, representing the fear of risk of running out of fuel during the search for and travel to stations. These two values are similar to the assumptions of $20/hour and 3.0 made in ref. [45], and they are consistent with stated preference analysis of consumers' preferences for refueling availability[93].	between countries from discrete choice studies focusing on refueling infrastructure) are used to adjust costs between the USA and other countries/regions.
Risk premium	This attribute monetizes the willingness of a consumer to adopt, or avoid, new technologies. It is a measure of perceived technology risk on the part of the consumer; hence, it relates to all alternative fuel vehicle technologies.	Costs depend on the stock of a particular vehicle type within a given region, as this is used to describe "how many people have done it" and therefore affects a consumer's perception of the technology's novelty or unfamiliarity at any point in time. Initial costs (or 'willingness-to-pay', WTP) start out at either -2.4k $/vehicle (early adopters), +0.7k $/vehicle (early majority), or +3.8$/vehicle (late majority) when the respective vehicle technology stock is new (see below); they then approach zero as the stock grows, following an exponential function, as in ref. [45]. Initial costs are the same across all regions, but the rate of decline to zero differs. Early adopters, early majority and late majority consumers are assumed to be 8%, 38% and 54% of the market, respectively, based on standard innovation diffusion theory[72]. In the original MA^{3}T model, technologies are considered new at around 10,000 units of cumulative stock. The WTPs are then assumed to decrease by half at 2 million units of stock. These two WTP points are subsequently used to estimate the two parameters of the exponential function. These estimates are based on the assumptions	Regional multipliers (calculated based on differences in cultural values between countries using World Values Survey data) are used to adjust risk premia between the USA and other countries/regions; in particular, the multipliers are applied to the exponential parameters governing the rate of the (dis)utility sub-component decline as the respective vehicle market share grows.

		that 2% of consumers are willing to pay $100 per month for the sake of trying out a new technology and that all the consumers on average are risk-averse and need $50/month of subsidy to try the new technology. These assumptions are based on private conversations with vehicle manufacturers and are therefore arrived at via expert judgement. To calculate the present-value WTPs from the monthly WTPs, a hypothetical car loan scheme of 48 months at 5.7% interest rate is assumed.	
Model variety/availability	This attribute monetizes the propensity of a consumer to avoid new technologies simply because their desired vehicle type may only be available in a limited number of makes and models (by different automakers, for different vehicle platforms).	The costs, which relate to all alternative vehicle technologies, depend on the sales of a particular vehicle type within a given region at a given point in time, as this affects the diversity of vehicle models on offer. It is assumed that more sales lead to greater model variety and availability. Initial costs start out at +7.5k $/vehicle when sales of the respective vehicle type are new; they then approach zero as sales grow. Initial costs are the same across all consumer groups and regions, and the rate of decline to zero is the same in all cases. In the original MA³T model, model variety is measured by the log of the ratio of the actual number of product models of the technology (n) to the "full availability" number (N), which is represented by the number of product models of the conventional technology available in the base year. Thus, the relationship is ln(n/N) [for a derivation, see ref. [94]]. N is assumed to be 60 as in the U.S. market. The utility coefficient of model variety is assumed to be 0.67, based on ref. [45]. Combined with the price elasticity, this leads to an estimate of costs starting out at +7.5k $/vehicle when sales and model number of the respective vehicle type are one (i.e., when the first model of the technology is offered in the market). Costs decrease following a logarithmic function and quickly approach zero when the model number n reaches 60; they can even become a small negative value if n is allowed to exceed 60. The cost or value here is always relative to that of the current situation with gasoline vehicles. The model number n is assumed to be an exponential function of last-year annual sales (x) of the technology, which is calibrated to be n=80-79*exp(-0.0000006*x) based on the historical sales and model numbers of hybrid-electric vehicles in the United States.	[No differentiation by region]
EV charger	The unit cost of installing a charger for a single electric vehicle. Only relevant for all-electric vehicles and plug-in hybrid-electric vehicles.	Represents either the full cost of installing a dedicated Level-II charger at home or work or the partial cost of a shared Level-III public fast-charger within the transport network (where costs are divided up between the many vehicles that use them). Across all regions and over time, costs are 1k $/vehicle. In the original MA³T model, costs are calculated similarly except that MA³T only considers the installation cost for a home charger, not the costs borne by individual consumers for public chargers.	[No differentiation by region]

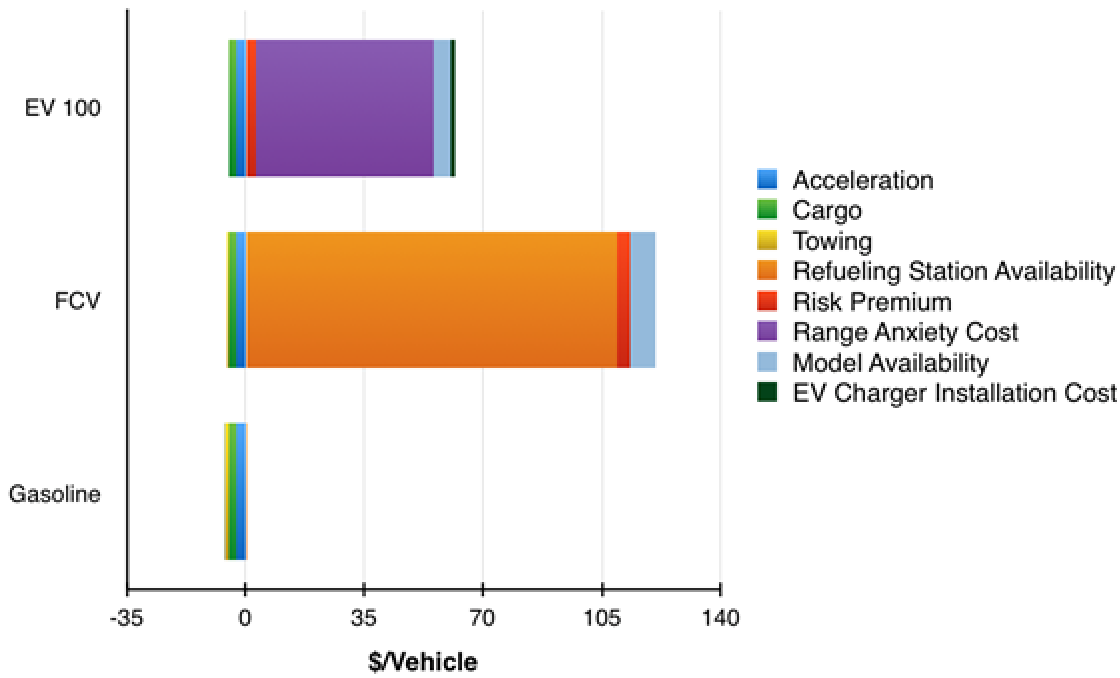
Supplementary Table 3. Sub-components of the (dis)utility costs deriving from the MA³T model. Cost ranges applying to the United States of America (USA) are shown for illustration; other regions would differ. Cost values in US$2005.





Supplementary Figure 12. (Dis)utility cost assumptions for the year 2020, by technology and for two different consumer groups. Estimates for the USA shown: US$2005/vehicle. The underlying calculations assume extremely low AFV sales/stock and very limited refueling/recharging infrastructure availability.

The following illustrative figures presents a breakdown of the (dis)utility cost components for a typical driver in the Suburban – Late Majority – Frequent Driver consumer group in the year 2020. Three different vehicle types are highlighted. Because the attributes "Acceleration", "Cargo", and "Towing Capacity" are relatively small, we ignore them for the purposes of our model implementation.



Supplementary Figure 13. Breakdown of all (dis)utility cost sub-components considered in the original MA^{3}T model. Three different vehicle types are highlighted. Consumer group: Suburban – Late Majority – Frequent Driver. Year: 2020. Estimates for the USA shown: US$2005/vehicle. In order to reduce model complexity, and also because they are small in size, we ignore the attributes "Acceleration", "Cargo", and "Towing Capacity" for the purposes of our global model implementation.

Calculation of regional multipliers for translating (dis)utility costs across regions

While MA^3T was originally developed with the USA light-duty vehicle market in mind, we have determined through our analysis that the (dis)utility costs generated by the model for the USA can be extended to other countries and regions by applying simple "regional multipliers." These multipliers are based on relationships between the different (dis)utility costs and selected predictor variables that are globally available. Specifically, we found that: (i) cultural values predict differences in social influence effect sizes between countries and that these can be applied to risk premium decline rates, and (ii) average driving distances reasonably predict differences in willingness-to-pay estimates (WTPs) for increased vehicle range and refueling infrastructure availability. Once these country-level estimates have been made, multipliers can be calculated that are based on the ratio between each regionally aggregated value and the USA value. The regional multipliers are then applied to three of the five (dis)utility cost sub-components (risk premium, range anxiety, and refueling station availability) in different ways. For range anxiety and refueling station availability, the multipliers act on the sub-component cost terms themselves, whereas for risk premium they act on the exponential parameters governing the rate of the (dis)utility decline as the respective vehicle market share grows.

Empirical data are commonly available in certain regions (e.g., North America) and very sparse in others (e.g., Africa). Empirical estimates of preferences for (or against) alternative fuel vehicles (AFVs) are concentrated in North America, Europe, and Southeast Asia. Certain characteristics of a region can predict how these preferences (or 'intangible' or '(dis)utility' costs) vary between regions. These simple predictive relationships from regions with empirical data can be used to estimate (dis)utilities for regions without empirical data. In the context of the vehicle choice modeling work discussed in this study, for three of the five (dis)utility cost sub-components (related to range anxiety, refuelling station availability, and social influence effects), regional multipliers are estimated to adjust empirical data for a base region (typically North America) to other model regions. Regional multipliers have been calculated for all 26 regions of the IMAGE model[95]. The underlying empirical data are drawn from a large sample of discrete choice analyses and social influence studies, predominantly from North America and Europe.

As an example, range anxieties for AFVs have been estimated in discrete choice studies from the US, Canada, Western Europe, Japan, and South Korea. These range anxieties vary across countries. Average driving distances also vary by country and can therefore be used as a simple predictor of how range anxiety (dis)utilities differ. As average driving distances are known for all model regions, this predictive relationship can be used to adjust or 'rescale' known range anxieties for model regions lacking in AFV discrete choice data.

Risk premium

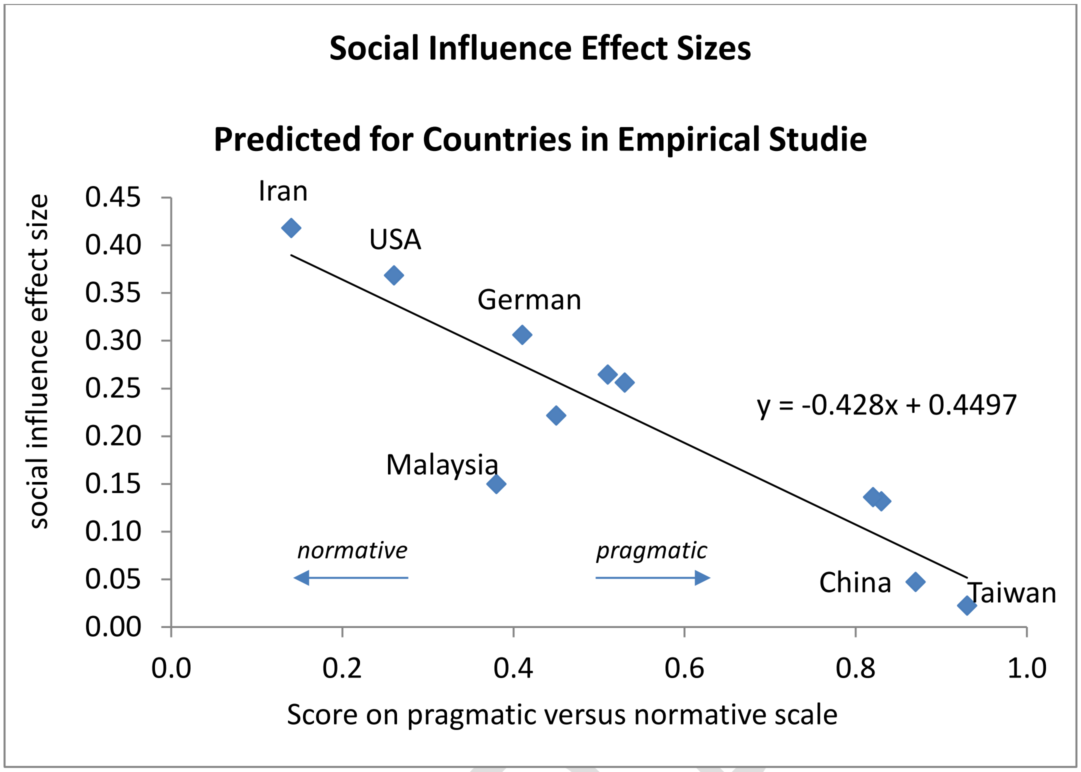
The multipliers related to risk premium (dis)utility costs adjust for cultural variation in the strength of social influence effect across countries, in all cases relative to the USA. At the heart of these multipliers is an average social influence effect size calculated firstly for each country and then aggregated to regional level based on a weighting of country GDP per capita. Multipliers are based on the ratio between each regionally aggregated social influence effect size and the USA effect size of 0.368. Social influence effects for each country are based primarily on a meta-analysis of 21 empirical studies[40] using data from 11 different countries and capturing three broad types of social influence (see Supplementary Table 4).

Social Influence Type	Description
Interpersonal networks	Information exchange and sharing between members of a social group (family, friends, co-workers).
Neighbourhood effects	Visual demonstration of new vehicle technology by neighbours living in close proximity.
Social norms	Increasing motivation to conform as others around have adopted.

Supplementary Table 4. Types of social influence considered in the regional multiplier analysis.

The meta-analysis returned a significant average effect size of beta = 0.241 (95% CI [0.157, 0.322], Z= 5.505, $|p| \leq 0.000$). This average effect size was based on all studies and countries. However, further testing found that the average effect size was moderated by a country's cultural values, measured by a widely-used scale from 'pragmatic' to 'normative'[96]. This scale quantifies differences between countries' receptiveness to social influence, using data from the World Values Survey. Scores on this scale could therefore be used to predict social influence effect sizes for the 11 countries sampled within the meta-analysis. Social influences are stronger for countries at the normative end of the scale (towards zero). In these countries dominant culture is concerned with reinforcing current ways of doing things, established traditions and routines. People prioritize learning from each other as opposed to changing in accordance with new social contexts.

The linear association between country scores on the pragmatic versus normative scale and predicted social influence effects is shown in Supplementary Figure 14. The resultant approximation equation was then used to estimate country-level social influence effects for those countries not included in the meta-analysis, based on their score on the pragmatic versus normative scale (available for over 80 different countries within the 26 regions of the IMAGE model).



Supplementary Figure 14. Association between score on pragmatic versus normative scale and social influence effect size for countries sampled within the meta-analysis.

Countries are then aggregated into model regions again by weighting the social influence effect size according to GDP. If scores on the pragmatic-normative scale are not available for certain countries, social influence effect sizes are calculated from the linear association between country GDP and social influence effect size, taking values from a minimum number of 10% of countries within a particular region (see Supplementary Table 5).

Approach	Countries affected
(a) Included in meta-analysis based on empirical studies, hence directly estimated from score on pragmatic versus normative scale.	Taiwan, China, Germany, Belgium, Sweden, UK, Greece, Malaysia, Finland, USA, Iran.
(b) Scores available on pragmatic versus normative scale. Extrapolation from linear regression (from countries included in (a)): SocInf = -0.428.pn + 0.4497 (where SocInf=social influence effect size and pn=score on pragmatic versus normative scale (R^2= 0.82)).	Mexico, Dominican Republic, El Salvador, Trinidad and Tobago, Bolivia, Chile, Columbia, Peru, Uruguay, Venezuela, Libya, Morocco, Egypt, Cape Verde, Ghana, Nigeria, Austria, Denmark, France, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Switzerland, Albania, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic, Slovenia, Serbia and Montenegro, Russian Federation, Israel, Jordan, Lebanon, Saudi Arabia, Syrian Arab Rep, Hong Kong, Philippines, Singapore, Vietnam, Thailand, Indonesia, Australia, New Zealand, Bangladesh, Sri Lanka, Pakistan, Botswana, Mozambique, Namibia, Tanzania, Zambia.
(c) Scores not available on pragmatic versus normative scale. Estimation from GDP using linear regression between social influence effect size and GDP (from countries included in (a) and (b)): SocInf = 0.000002.GDP + 0.3124 (where SocInf=social influence effect size and GDP=country GDP per capita (US$ 2010)	Ethiopia, Kenya, Madagascar, Mauritius, Rwanda, Sudan, Uganda, Belarus, Moldova, Ukraine, Kazakhstan, Tajikistan, Turkmenistan, Uzbekistan, Korea Rep.

(R^2=0.1214)).	

Supplementary Table 5. Calculation of social influence effect size for representative countries within regions.

Range anxiety

Multipliers are included for willingness to pay (WTP) for increased vehicle driving range (100 miles). These are taken directly from a meta-analysis of 33 studies, which yield over 100 WTP ratios[97], providing robust estimates on five IMAGE regions (based on large sample sizes for USA (n=59), and Europe (n=45), smaller sample size for Australia (n=4), Canada (n=7) and China (n=3). These estimations are used to predict WTP values for other regions by fitting an exponential best-fit to known WTP data points as WTP = $493.914 * e^{0.0001566aam}$ (where aam=average annual mileage), i.e., annual average mileage is used as a simple predictor of WTP for range anxiety in countries with no data. For some IMAGE regions average annual driving distances are not available, and in this case estimates are based on analogous regions. Multipliers are then based on the ratio between each regionally aggregated WTP (100 miles increased driving range) and the USA estimate of US2013_{ppp}$ 2,423.

Refuelling station availability

Multipliers for increased refuelling density (increase of station coverage of 10 %-points) are based on 6 empirical studies providing WTP estimates for three regions: USA, Europe and Japan, again taken from earlier analysis[41]. An exponential best-fit is estimated from these known WTP data points as WTP = $525.73 * e^{0.00009aam}$ (where aam=annual average mileage), i.e., annual average mileage is used as a simple predictor of WTP for refuelling density in countries with no data. Similar to the range anxiety calculations above, if average annual driving distances are not available for certain regions, then estimates are based on analogous regions. Multipliers are then based on the ratio between each regionally aggregated WTP and the USA estimate of US2013_{ppp}$ 2,792.

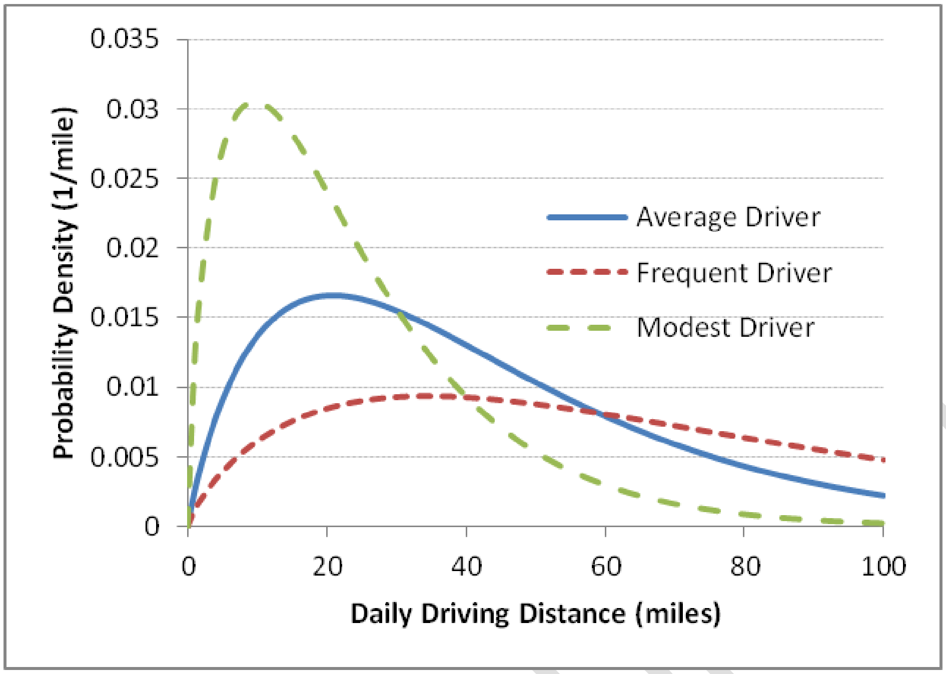
Further details on the original MA^{3}T model

As described briefly above, the Market Acceptance of Advanced Automotive Technologies (MA^{3}T) model was developed by Oak Ridge National Laboratory for the U.S. Department of Energy's Vehicle Technologies Office as a scenario analysis tool for estimating market shares, social benefits and costs of light-duty vehicle powertrain transitions resulting from changes in technology, infrastructure, behavior, and policies. The focus of the model is the U.S. The core of the model is a nested multinomial logit (NMNL) module that estimates choice probabilities for each vehicle type by consumer segment. The 40 vehicle powertrain choices included in original MA^{3}T formulation cover gasoline ICE, diesel ICE, gasoline hybrid, diesel hybrid, natural gas, plug-in hybrid, battery electric, and fuel cell electric technologies. The original 1,458 consumer segments in MA^{3}T cover the entire U.S. light-duty vehicle market; they are distinguished by census division, residential area type, risk attitude, driving type, home charging readiness and workplace charging availability. Note that in the joint MESSAGE-Transport + MA3T implementation, we only include a small subset of these consumer groups (i.e., the 1,458 groups are aggregated up to 27 or 9).

In order to construct a base-year data set for the U.S., census data was used to estimate household shares by census division. This was then combined with the 2009 National Household Travel Survey (NHTS) data to estimate household shares in central cities, suburban areas and rural areas. The approach is based on the residential area type, the census division indicator and the population weights in NHTS. Another important use of NHTS is to estimate the shares of driver type. NHTS records odometer readings, respondent-reported annual distance and vehicle age. Oak Ridge National Laboratory subsequently developed a method to estimate the average annual driving distance for each sample vehicle (coded as 'BESTMILE' in the database). All sample drivers in each census division are separated into Frequent Driver (the top 1/3, based on BESTMILE), the Modest Driver (the bottom 1/3) and the Average Driver (the middle 1/3).

Moreover, there is a need to account for the variation of daily driving distance due to the inclusion of plug-in electric vehicles. The random daily distance is assumed to follow Gamma distributions, as exhibited in Supplementary Figure 15 [71,98,99] – an assumption that has been adopted in several other studies[89,90,100,101] and recently validated by real-world multi-vehicle longitudinal data[91]. Two pieces of information are needed to estimate a Gamma distribution for each driver type. Fortunately, the typical commuting distance by the primary driver in each car is also reported in NHTS, which together with the annual distance BESTMILE allows estimation of the two Gamma distribution parameters (i.e., the mean and the mode). In MA^{3}T, U.S. consumers are divided into Modest, Average, and Frequent drivers, as stated. The mix of these driver types varies across regions and residential areas.

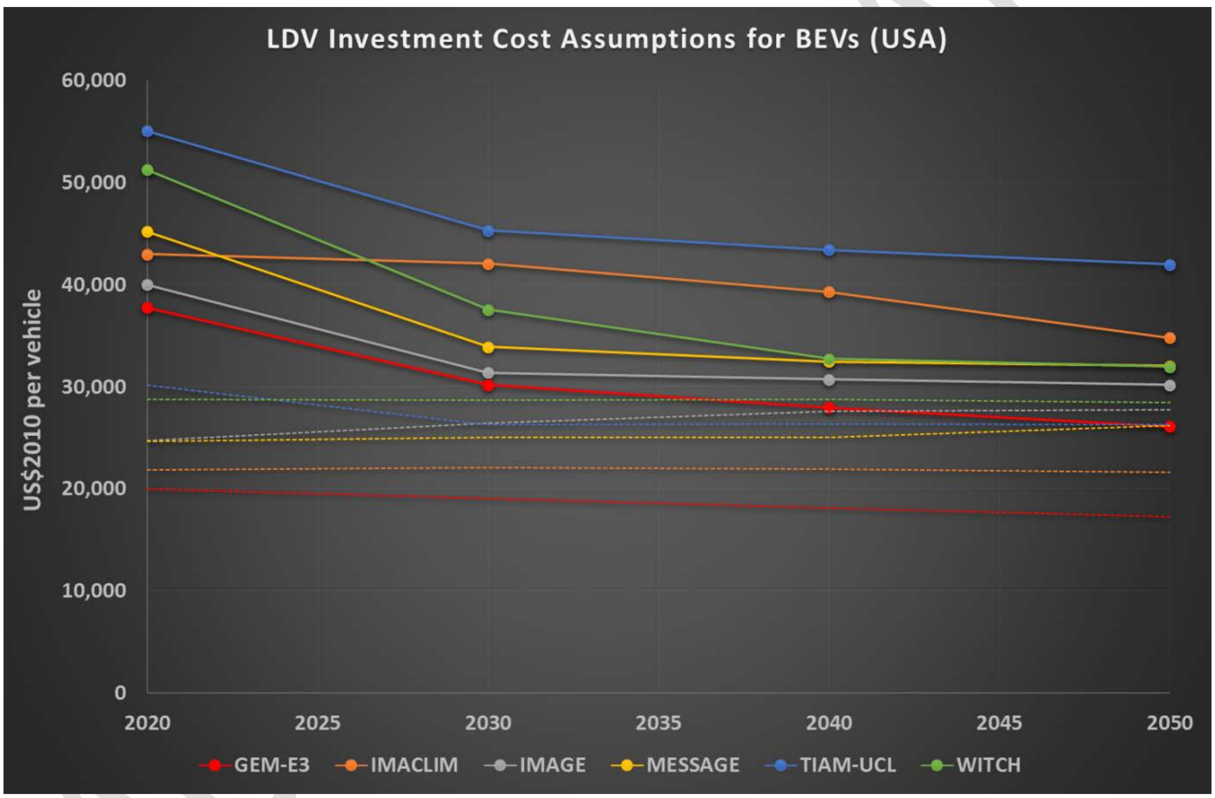
For more information about MA^{3}T, see http://teem.ornl.gov/ma3t.shtml or refs. [80], [81] , [82], and [83].



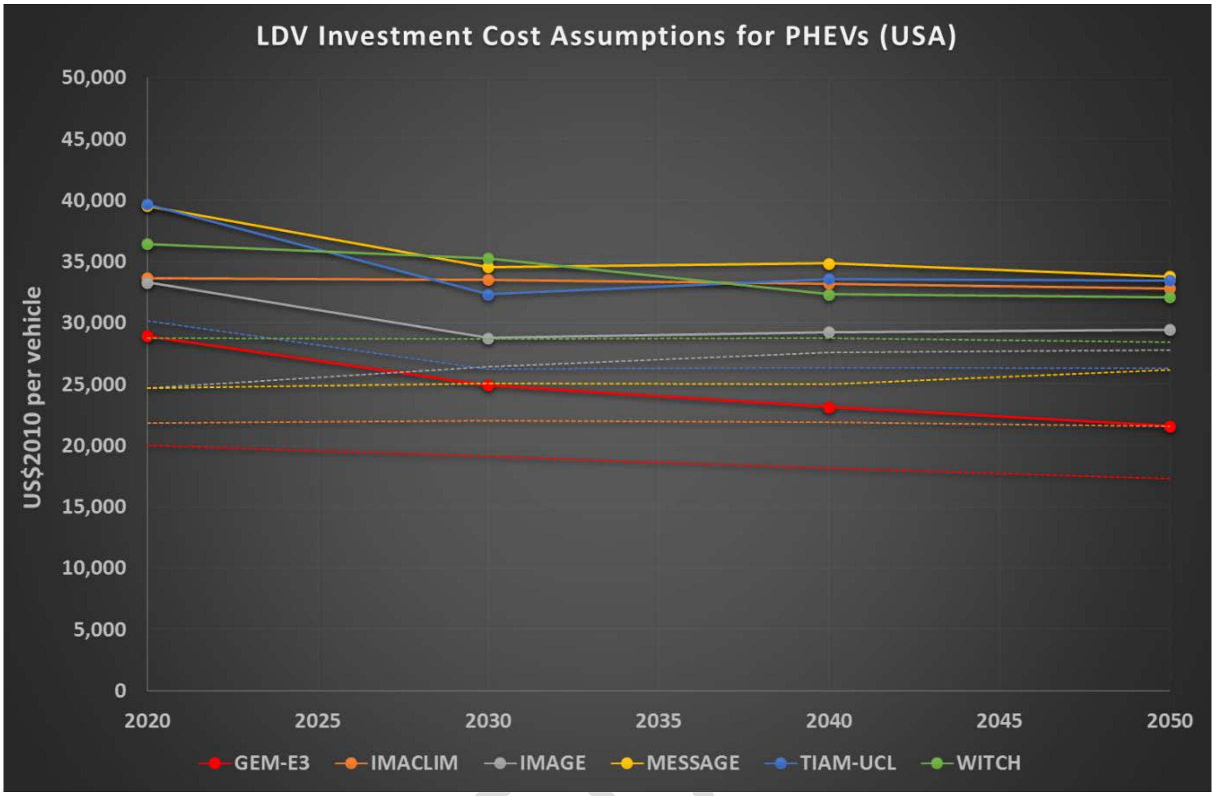
Supplementary Figure 15. Probability distribution of three driver types in MA^{3}T, derived from the U.S. NHTS

Comparison of light-duty vehicle capital costs across the models

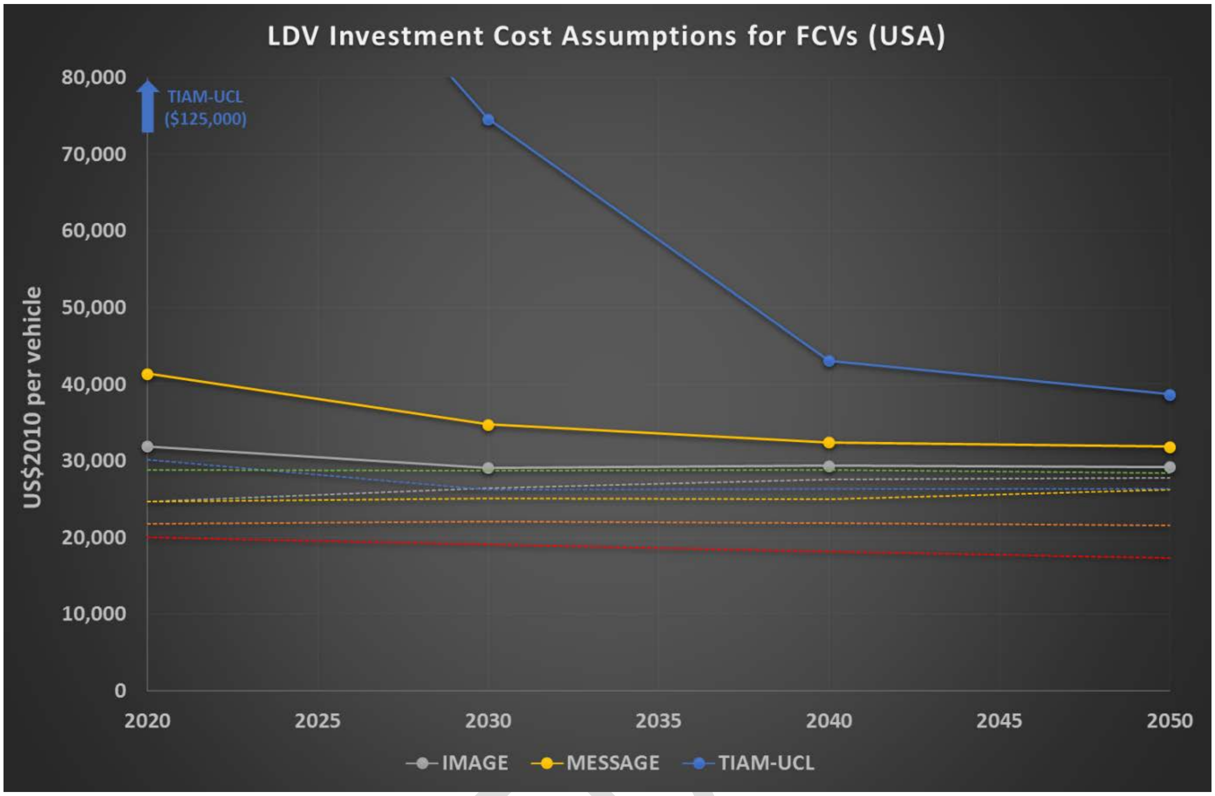
The following figures show the assumed capital costs for light-duty vehicles over time in each of the models (values for the 'AFV Push' scenario with 100 $/t$CO_2$ carbon pricing are shown; see Supplementary Data 3 for exact numbers). The comparison is done strictly for the USA. The models employed in this study generally do not distinguish between light-duty cars and trucks (SUVs, Pick-up trucks, and Mini-vans). These two classes of vehicles, while distinct in reality are generally aggregated in global energy-economy models. Moreover, some of the models make exogenous assumptions about capital costs of vehicles, whereas others employ endogenous learning mechanisms, which ensure that costs are reduced with increased deployment levels (through technological progress and learning-by-doing).



Supplementary Figure 16. Capital costs assumed in the models for battery-electric (BEV; solid lines) and internal combustion engine (ICE; dashed lines) vehicles.



Supplementary Figure 17. Capital costs assumed in the models for plug-in hybrid-electric (PHEV; solid lines) and internal combustion engine (ICE; dashed lines) vehicles.



Supplementary Figure 18. Capital costs assumed in the models for hydrogen fuel cell (FCV; solid lines) and internal combustion engine (ICE; dashed lines) vehicles. FCVs are not available as a technology option in all models.

Example numerical assumptions underlying scenario storylines

AFV Push

Illustration of the evolution of (dis)utility costs relative to upfront capital costs assumed in 'AFV Push' for a BEV-100 (battery-electric vehicle with a range of 100 miles) for one consumer type: early majority – urban – average driving frequency. All costs are for the USA region (in US$/vehicle) as assumed by the IMAGE model. (See Supplementary Data 2 and 3 for details.)

	2020	*2030*	*2040*	*2050*
Upfront capital cost	40,008	31,377	30,730	30,186
(Dis)utility costs (additive terms capturing non-financial attributes)				
Risk aversion	803	507	8	0
Model variety	3,420	0	0	0
Range anxiety	3,081	53	53	53
Upfront costs + (Dis)utility costs = Total (generalized) costs				
Total (generalized) cost	47,312	31,937	30,791	30,239

No AFV Action

Illustration of the evolution of (dis)utility costs relative to upfront capital costs assumed in 'No AFV Action' for a BEV-100 (battery-electric vehicle with a range of 100 miles) for one consumer type: early majority – urban – average driving frequency. All costs are for the USA region (in US$/vehicle) as assumed by the IMAGE model. (See Supplementary Data 2 and 3 for details.)

	2020	*2030*	*2040*	*2050*
Upfront capital cost	40,008	34,569	33,826	33,202
(Dis)utility costs (additive terms capturing non-financial attributes)				
Risk aversion	803	803	803	803
Model variety	8,315	8,315	8,315	8,315
Range anxiety	3,081	3,081	3,081	3,081
Upfront costs + (Dis)utility costs = Total (generalized) costs				
Total (generalized) cost	52,207	46,768	46,024	45,401

Supplementary References

1 Edwards, R., Larive, J.-F., Rickeard, D. & Weindorf, W. Well-to-Wheels Analysis of Future Automotive Fuels and Powertrains in the European Context, Summary of energy and GHG balance of individual pathways, Well-to-Tank Appendix 2 - Version 4a. (European Commission, Joint Research Centre, Institute for Energy and Transport, 2014).

2 Malins, C., Galarza, S., Baral, A., Brandt, A. & Howorth, G. The Development of a Greenhouse Gas Emissions Calculation Methodology for Article 7a of the Fuel Quality Directive, Report to the Directorate General for Climate Action of the European Commission. (The International Council on Clean Transportation (ICCT), Washington, D.C., 2014).

3 Energy-Redefined. Carbon Intensity of Crude Oil in Europe Crude. (2010).

4 Smith, P. *et al.* Agriculture, Forestry and Other Land Use (AFOLU). In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. (Cambridge, United Kingdom, and New York, NY, USA, 2014).

5 CARB. Table 6. Carbon Intensity Lookup Table for Gasoline and Fuels that Substitute for Gasoline. (California Air Resources Board, Sacramento, CA, USA, 2012).

6 Rosen, R. A. Critical review of: "Making or breaking climate targets — the AMPERE study on staged accession scenarios for climate policy". *Technological Forecasting and Social Change* **96**, 322-326, doi:10.1016/j.techfore.2015.01.019 (2015).

7 Kriegler, E. *et al.* A short note on integrated assessment modeling approaches: Rejoinder to the review of "Making or breaking climate targets — The AMPERE study on staged accession scenarios for climate policy". *Technological Forecasting and Social Change* **99**, 273-276, doi:10.1016/j.techfore.2015.07.011 (2015).

8 Mercure, J.-F., Pollitt, H., Bassi, A. M., Viñuales, J. E. & Edwards, N. R. Modelling complex systems of heterogeneous agents to better design sustainability transitions policy. *Global Environmental Change* **37**, 102-115, doi:10.1016/j.gloenvcha.2016.02.003 (2016).

9 NCC. The role of society in energy transitions. *Nature Climate Change* **6**, 539-539, doi:10.1038/nclimate3051 (2016).

10 Stern, P. C., Sovacool, B. K. & Dietz, T. Towards a science of climate and energy choices. *Nature Clim. Change* **6**, 547-555, doi:10.1038/nclimate3027 (2016).

11 Stern, P. C. *et al.* Opportunities and insights for reducing fossil fuel consumption by households and organizations. *Nature Energy* **1**, 16043, doi:10.1038/nenergy.2016.43 (2016).

12 Geels, F. W., Berkhout, F. & van Vuuren, D. P. Bridging analytical approaches for low-carbon transitions. *Nature Clim. Change* **6**, 576-583, doi:10.1038/nclimate2980 (2016).

13 De Cian, E. *et al.* Knowledge Creation between Integrated Assessment Models and Initiative-Based Learning - An Interdisciplinary Approach (FEEM Working Paper No. 66.2016). (2016).

14 Strachan, N., Fais, B. & Daly, H. Reinventing the energy modelling–policy interface. *Nature Energy* **1**, 16012, doi:10.1038/nenergy.2016.12 (2016).

15 Nemet, G. F., Jakob, M., Steckel, J. C. & Edenhofer, O. Addressing policy credibility problems for low-carbon investment. *Global Environmental Change* **42**, 47-57, doi:10.1016/j.gloenvcha.2016.12.004 (2017).

16 Greene, D. L. & Ji, S. Policies for Promoting Low-Emission Vehicles and Fuels: Lessons from Recent Analyses. (Howard H. Baker Center for Public Policy, University of Tennessee, Knoxville, Tennessee, 2016).

17 Bolderdijk, J. W. & Steg, L. in *Handbook of Research in Sustainable Consumption* (eds L.A. Reisch & J. Thøgersen) Ch. 328-342, (Edward Elgar Publishing Limited, 2015).

18 Steg, L., Perlaviciute, G. & van der Werff, E. Understanding the human dimensions of a sustainable energy transition. *Frontiers in Psychology* **6**, 805, doi:10.3389/fpsyg.2015.00805 (2015).

19 Beresteanu, A. & Li, S. Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States. *International Economic Review* **52**, 161-182, doi:10.1111/j.1468-2354.2010.00623.x (2011).

20 Axsen, J., Mountain, D. C. & Jaccard, M. Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. *Resource and Energy Economics* **31**, 221-238, doi:10.1016/j.reseneeco.2009.02.001 (2009).

21 Gallagher, K. S. & Muehlegger, E. Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and Management* **61**, 1-15, doi:10.1016/j.jeem.2010.05.004 (2011).

22 Clinton, B., Brown, A., Davidson, C. & Steinberg, D. Impact of Direct Financial Incentives in the Emerging Battery Electric Vehicle Market: A Preliminary Analysis, NREL/PR-6A20-63263. (National Renewable Energy Laboratory, Golden, Colorado, 2015).

23 Narassimhan, E. & Johnson, C. The Effect of State Incentives on Plug-in Electric Vehicle Purchases, NREL/PR-5400-62884. (National Renewable Energy Laboratory, Golden, Colorado, 2014).
24 Hardman, S., Chandan, A., Tal, G. & Turrentine, T. The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. *Renewable and Sustainable Energy Reviews* **80**, 1100-1111, doi:10.1016/j.rser.2017.05.255 (2017).
25 Sallee, J. M. The Surprising Incidence of Tax Credits for the Toyota Prius. *American Economic Journal: Economic Policy* **3**, 189-219, doi:10.1257/pol.3.2.189 (2011).
26 Bento, A., Kaffine, D., Roth, K. & Zaragoza-Watkins, M. The Effects of Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector. *American Economic Journal: Economic Policy* **6**, 1-29 (2014).
27 Axsen, J. *et al.* Electrifying Vehicles: Insights from the Canadian Plug-in Electric Vehicle Study. (Simon Fraser University, Vancouver, Canada, 2015).
28 Mersky, A. C., Sprei, F., Samaras, C. & Qian, Z. Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D: Transport and Environment* **46**, 56-68, doi:10.1016/j.trd.2016.03.011 (2016).
29 Li, S., Tong, L., Xing, J. & Zhou, Y. The Market for Electric Vehicles: Indirect Network Effects and Policy Design. (School of Applied Economics and Management, Cornell University, Ithaca, New York, 2015).
30 INL. Analyzing Public Charging Venues: Where Are Publicly Accessible Charging Stations Located and How Have They Been Used?, The EV Project, INL/MIS-14-33019. (Idaho National Laboratory, 2014).
31 Melaina, M., Bremson, J. & Solo, K. Consumer Convenience and the Availability of Retail Stations as a Market Barrier for Alternative Fuel Vehicles, NREL/CP-5600-56898. (National Renewable Energy Laboratory, Golden, Colorado, 2013).
32 Bertram, C. *et al.* Complementing carbon prices with technology policies to keep climate targets within reach. *Nature Clim. Change* **5**, 235-239, doi:10.1038/nclimate2514 (2015).
33 Jenkins, J. D. Political economy constraints on carbon pricing policies: What are the implications for economic efficiency, environmental efficacy, and climate policy design? *Energy Policy* **69**, 467-477, doi:10.1016/j.enpol.2014.02.003 (2014).
34 Lutsey, N., Searle, S., Chambliss, S. & Bandivadekar, A. Assessment of Leading Electric Vehicle Promotion Activities in United States Cities. (The International Council on Clean Transportation, 2015).
35 Vergis, S., Turrentine, T. S., Fulton, L. & Fulton, E. Plug-In Electric Vehicles: A Case Study of Seven Markets, Research Report UCD-ITS-RR-14-17. (Institute of Transportation Studies, University of California, Davis, 2014).
36 Searle, S., Pavlenko, N. & Lutsey, N. Leading edge of electric vehicle market development in the United States: An analysis of California cities. (The International Council on Clean Transportation, 2016).
37 Nilsson, M. & Nykvist, B. Governing the electric vehicle transition – Near term interventions to support a green energy economy. *Applied Energy*, doi:10.1016/j.apenergy.2016.03.056 (2016).
38 Langford, B. C. & Cherry, C. R. Planning for Electric Vehicles: Review of Clean Cities' Electric Vehicle Community Readiness Projects, White Paper 5.13. (Howard H. Baker, Jr. Center for Public Policy, The University of Tennessee, Knoxville, 2013).
39 Lutsey, N. Transition to a Global Zero-Emission Vehicle Fleet: A Collaborative Agenda for Governments. (The International Council on Clean Transportation, 2015).
40 Pettifor, H., Wilson, C., Axsen, J., Abrahamse, W. & Anable, J. Social influence in the global diffusion of alternative fuel vehicles – A meta-analysis. *Journal of Transport Geography* **62**, 247-261, doi:10.1016/j.jtrangeo.2017.06.009 (2017).
41 Wilson, C., Pettifor, H. & McCollum, D. Improving the behavioural realism of integrated assessment models of global climate change mitigation: a research agenda (ADVANCE Project Deliverable No. 3.2), Available at www.fp7-advance.eu. (Tyndall Centre for Climate Change Research, Norwich, UK and International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, 2014).
42 IEA. Global EV Outlook 2016. (International Energy Agency (IEA), Paris, France, 2016).
43 McCollum, D. L. *et al.* Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transportation Research Part D: Transport and Environment* **55**, 322-342, doi:10.1016/j.trd.2016.04.003 (2017).
44 PNNL. GCAM Documentation. (Pacific Northwest National Laboratory, 2016).
45 NRC. Transitions to Alternative Vehicles and Fuels. (National Research Council, National Academies Press, Washington, DC, 2013).
46 ADVANCE contributors. *ADVANCE wiki: The Common Integrated Assessment Model (CIAM) documentation website [http://themasites.pbl.nl/models/advance/index.php/ADVANCE_wiki]*, 2017).
47 Capros, P. *et al.* GEM-E3 Model Manual. (2013).

48 Karkatsoulis, P., Siskos, P., Paroussos, L. & Capros, P. Simulating deep CO2 emission reduction in transport in a general equilibrium framework: The GEM-E3T model. *Transportation Research Part D: Transport and Environment* **55**, 343-358, doi:10.1016/j.trd.2016.11.026 (2017).
49 Waisman, H., Guivarch, C., Grazi, F. & Hourcade, J. C. The Imaclim-R model: infrastructures, technical inertia and the costs of low carbon futures under imperfect foresight. *Climatic Change* **114**, 101-120, doi:10.1007/s10584-011-0387-z (2012).
50 Kriegler, E. *et al.* Diagnostic indicators for integrated assessment models of climate policy. *Technological Forecasting and Social Change* **90, Part A**, 45-61, doi:10.1016/j.techfore.2013.09.020 (2015).
51 Girod, B., van Vuuren, D. P. & Deetman, S. Global travel within the 2°C climate target. *Energy Policy* **45**, 152-166, doi:10.1016/j.enpol.2012.02.008 (2012).
52 Schäfer, A., Heywood, J. B., Jacoby, H. D. & I. Waitz. *Transportation in a Climate-Constrained World.* (MIT Press, 2009).
53 IEA. World Energy Outlook 2012. (International Energy Agency (IEA), Paris, France, 2012).
54 Plotkin, S. & Singh, M. Multi-path transportation futures study: vehicle characterization and scenario analyses. (Argonne National Laboratory, 2009).
55 Riahi, K. *et al.* in *Global Energy Assessment - Toward a Sustainable Future* 1203-1306 (2012).
56 Amann, M. *et al.* Cost-effective control of air quality and greenhouse gases in Europe: Modeling and policy applications. *Environmental Modelling & Software* **26**, 1489-1501, doi:10.1016/j.envsoft.2011.07.012 (2011).
57 Messner, S. & Schrattenholzer, L. MESSAGE-MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. *Energy* **25**, 267-282, doi:10.1016/s0360-5442(99)00063-8 (2000).
58 Meinshausen, M., Raper, S. C. B. & Wigley, T. M. L. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. *Atmos. Chem. Phys.* **11**, 1417-1456, doi:10.5194/acp-11-1417-2011 (2011).
59 Wigley, T. M. L. MAGICC/SCENGEN 5.3: User Manual (version 2). (National Center for Atmospheric Research, Boulder, 2008).
60 Riahi, K., Grübler, A. & Nakicenovic, N. Scenarios of long-term socio-economic and environmental development under climate stabilization. *Technological Forecasting and Social Change* **74**, 887-935, doi:10.1016/j.techfore.2006.05.026 (2007).
61 McCollum, D. L. *et al.* Quantifying uncertainties influencing the long-term impacts of oil prices on energy markets and carbon emissions. *Nature Energy* **1**, 16077, doi:10.1038/nenergy.2016.77 (2016).
62 Anandarajah, G., Pye, S., Usher, W., Kesicki, F. & Mcglade, C. TIAM-UCL Global Model Documentation. (University College London, 2011).
63 Loulou, R. ETSAP-TIAM: the TIMES integrated assessment model. part II: mathematical formulation. *Computational Management Science* **5**, 41-66, doi:10.1007/s10287-007-0045-0 (2008).
64 Loulou, R. & Labriet, M. ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure. *Computational Management Science* **5**, 7-40, doi:10.1007/s10287-007-0046-z (2008).
65 Emmerling, J. *et al.* The WITCH 2016 Model - Documentation and Implementation of the Shared Socioeconomic Pathways. (Fondazione Eni Enrico Mattei (FEEM), 2016).
66 Bosetti, V. & Longden, T. Light duty vehicle transportation and global climate policy: The importance of electric drive vehicles. *Energy Policy* **58**, 209-219, doi:10.1016/j.enpol.2013.03.008 (2013).
67 Carrara, S. & Longden, T. Freight futures: The potential impact of road freight on climate policy. *Transportation Research Part D: Transport and Environment* **55**, 359-372, doi:10.1016/j.trd.2016.10.007 (2017).
68 Longden, T. Travel intensity and climate policy: The influence of different mobility futures on the diffusion of battery integrated vehicles. *Energy Policy* **72**, 219-234, doi:10.1016/j.enpol.2014.04.034 (2014).
69 Ramea, K. Integration of Vehicle Consumer Choice in Energy Systems Models and its Implications for Climate Policy Analysis (Doctoral Dissertation). (University of California, Davis, 2016).
70 Bunch, D. S., Ramea, K., Yeh, S. & Yang, C. Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models (Research Report UCD-ITS-RR-15-13). (Institute of Transportation Studies, University of California, Davis, 2015).
71 Lin, Z. & Greene, D. L. Promoting the Market for Plug-In Hybrid and Battery Electric Vehicles. *Transportation Research Record: Journal of the Transportation Research Board* **2252**, 49-56 (2011).
72 Rogers, E. M. *The Diffusion of Innovations*. Fifth Edition edn, (The Free Press, New York., 2003).
73 IIASA. *SSP Database (Shared Socioeconomic Pathways) - Version 1.0*, <https://tntcat.iiasa.ac.at/SspDb/> (2015).
74 Jiang, L. & O'Neill, B. C. Global urbanization projections for the Shared Socioeconomic Pathways. *Global Environmental Change*, doi:10.1016/j.gloenvcha.2015.03.008 (2015).

75 KC, S. & Lutz, W. The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, doi:10.1016/j.gloenvcha.2014.06.004 (2015).
76 O'Neill, B. C. *et al.* The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, doi:10.1016/j.gloenvcha.2015.01.004 (2015).
77 Lin, Z. & Greene, D. L. A Plug-in Hybrid Consumer Choice Model with Detailed Market Segmentation. (Oak Ridge National Laboratory, 2009).
78 Greene, D. L., Lin, Z. & Dong, J. Analyzing the sensitivity of hydrogen vehicle sales to consumers' preferences. *International Journal of Hydrogen Energy* **38**, 15857-15867, doi:10.1016/j.ijhydene.2013.08.099 (2013).
79 Lin, Z., Dong, J. & Greene, D. L. Hydrogen vehicles: Impacts of DOE technical targets on market acceptance and societal benefits. *International Journal of Hydrogen Energy* **38**, 7973-7985, doi:10.1016/j.ijhydene.2013.04.120 (2013).
80 Lin, Z., Greene, D. L. & Ward, J. User Guide of the ORNL MA3T Model (V20130729). (Oak Ridge National Laboratory, 2013).
81 Lin, Z., Li, J. & Dong, J. Dynamic Wireless Charging: Potential Impact on Plug-in Electric Vehicle Adoption. SAE Technical Papers 2014-01-1965. (Society of Automotive Engineers, 2014).
82 Liu, C. & Lin, Z. How uncertain is the future of electric vehicle market: Results from Monte Carlo simulations using a nested logit model. *International Journal of Sustainable Transportation* **11**, 237-247, doi:10.1080/15568318.2016.1248583 (2017).
83 Xie, F. & Lin, Z. Market-driven automotive industry compliance with fuel economy and greenhouse gas standards: Analysis based on consumer choice. *Energy Policy* **108**, 299-311, doi:10.1016/j.enpol.2017.05.060 (2017).
84 Nicholas, M., Handy, S. & Sperling, D. Using Geographic Information Systems to Evaluate Siting and Networks of Hydrogen Stations. *Transportation Research Record: Journal of the Transportation Research Board* **1880**, 126-134, doi:doi:10.3141/1880-15 (2004).
85 Gnann, T. & Plötz, P. A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. *Renewable and Sustainable Energy Reviews* **47**, 783-793, doi:10.1016/j.rser.2015.03.022 (2015).
86 Greene, D. L. Fuel Availability and Alternative Fuel Vehicles. *Energy Studies Review* **8**, 215-231 (1998).
87 Liu, C. & Greene, D. L. Consumer Choice of E85: Price Sensitivity and Cost of Limited Fuel Availability. *Transportation Research Record, Journal of the Transportation Research Board* **2454**, 20-27 (2015).
88 Sperling, D. & Kurani, K. S. Refueling and the Vehicle Purchase Decision: The Diesel Car Case, SAE Technical Paper 870644. (Society of Automobile Engineers, 1987).
89 Lin, Z. Optimizing and Diversifying Electric Vehicle Driving Range for U.S. Drivers. *Transportation Science* **48**, 635-650, doi:10.1287/trsc.2013.0516 (2014).
90 Lin, Z. & Greene, D. Assessing Energy Impact of Plug-In Hybrid Electric Vehicles: Significance of Daily Distance Variation over Time and Among Drivers. *Transportation Research Record: Journal of the Transportation Research Board* **2252**, 99-106, doi:10.3141/2252-13 (2011).
91 Lin, Z., Dong, J., Liu, C. & Greene, D. Estimation of Energy Use by Plug-In Hybrid Electric Vehicles: Validating Gamma Distribution for Representing Random Daily Driving Distance. *Transportation Research Record: Journal of the Transportation Research Board* **2287**, 37-43, doi:10.3141/2287-05 (2012).
92 Lin, Z., Chen, C.-W., Ogden, J. & Fan, Y. The least-cost hydrogen for Southern California. *International Journal of Hydrogen Energy* **33**, 3009-3014, doi:10.1016/j.ijhydene.2008.01.039 (2008).
93 Melaina, M. W., Welch, C., Baumgartner, R. & Rambo, E. in *Annual Conference of the National Hydrogen Association.*
94 Greene, D. L. TAFV Alternative Fuels and Vehicles Choice Model Documentation. ORNL/TM-2001/134. (Oak Ridge National Laboratory (ORNL), 2001).
95 Stehfest, E. *et al. Integrated Assessment of Global Environmental Change with IMAGE 3.0 - Model description and policy applications.* (2014).
96 Minkov, M. & Hofstede, G. Hofstede's Fifth Dimension: New Evidence From the World Values Survey. *Journal of Cross-Cultural Psychology*, doi:10.1177/0022022110388567 (2010).
97 Dimitropoulos, A., Rietveld, P. & van Ommeren, J. N. Consumer valuation of changes in driving range: A meta-analysis. *Transportation Research Part A: Policy and Practice* **55**, 27-45, doi:10.1016/j.tra.2013.08.001 (2013).
98 Dong, J. & Lin, Z. Within-day recharge of plug-in hybrid electric vehicles: Energy impact of public charging infrastructure. *Transportation Research Part D: Transport and Environment* **17**, 405-412, doi:10.1016/j.trd.2012.04.003 (2012).
99 Onar, O. C. *et al.* in *Transportation Electrification Conference and Expo (ITEC)* 1-8 (2013).
100 Lin, Z. Optimizing and Diversifying the Electric Range of Plug-in Hybrid Electric Vehicles for U.S. Drivers. *SAE International Journal of Alternative Powertrains* **1**, 180-194, doi:10.4271/2012.01.0817 (2012).
101 Greene, D. L. Estimating daily vehicle usage distributions and the implications for limited-range vehicles. *Transportation Research Part B: Methodological* **19**, 347-358, doi:10.1016/0191-2615(85)90041-4 (1985).