Supplementary Material

"Improving the behavioral realism of global integrated assessment models: an application to consumers' vehicle choices"

David L. McCollum[a,b*], Charlie Wilson[c], Hazel Pettifor[c], Kalai Ramea[d], Volker Krey[a], Keywan Riahi[a,e], Christoph Bertram[f], Zhenhong Lin[g], Oreane Y. Edelenbosch[h], Sei Fujisawa[a,1]

[a] Energy Program, International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, 2361 Laxenburg, Austria (mccollum@iiasa.ac.at; krey@iiasa.ac.at; riahi@iiasa.ac.at)
[b] Howard H. Baker Jr. Center for Public Policy, University of Tennessee, 1640 Cumberland Avenue, Knoxville, TN 37996, USA
[c] Tyndall Centre for Climate Change Research, University of East Anglia (UEA), Norwich NR4 7TJ, UK (charlie.wilson@uea.ac.uk; h.pettifor@uea.ac.uk)
[d] Institute of Transportation Studies, University of California, Davis, 1605 Tilia Street, Davis, CA 95616, USA (kramea@ucdavis.edu)
[e] Graz University of Technology, Inffeldgasse, 8010 Graz, Austria
[f] Potsdam Institute for Climate Impact Research, Telegrafenberg, 14473 Potsdam, Germany (bertram@pik-potsdam.de)
[g] Oak Ridge National Laboratory, 2360 Cherahala Boulevard, Knoxville, TN 37932, USA (linz@ornl.gov)
[h] PBL Netherlands Environmental Assessment Agency, Antonie van Leeuwenhoeklaan 9, 3721 MA Bilthoven, The Netherlands (Oreane.Edelenbosch@pbl.nl)

[*]Corresponding author

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[1] Present affiliation: FUJISAWA Corporation, 1-10-3 Honmachi, Maebashi-shi, Gunma, 371-0023, Japan (sei@fujisawacorp.jp)

1. A summary of global IAMs and their representation of behavioral features

Supplementary Table 1 provides a high-level overview of a sample of ten global IAMs that are widely used for long-term climate change mitigation analysis. These IAMs cover a wide range of design features, different modelling approaches, technological resolution, and responsiveness to carbon price (Kriegler et al., 2014).

Supplementary Table 1. Key characteristics of IAMs. Based on: (Kriegler et al., 2014).

Model	Modelling approach	Equilibrium type	Time horizon	Resolution of energy supply	Response to carbon price [a]	Key reference
DNE21+	inter-temporal optimization	partial	2050	high	low	(Akimoto et al., 2008)
GCAM	recursive dynamic, simulation	partial	2100	high	high	(Calvin, 2011)
IMACLIM-R	recursive dynamic, simulation	general	2100	medium	low	(Sassi et al., 2010)
IMAGE-TIMER	recursive dynamic, simulation	partial	2100	high	high	(Van Vuuren et al., 2007)
iPETS	inter-temporal optimization	general	2100	low	(high) [a]	(O'Neill et al., 2012)
MESSAGE-MACRO	inter-temporal optimization	general	2100	high	high	(Riahi et al., 2007)
REMIX	optimization	partial	2050	high	-	(Scholz, 2012)
REMIND	inter-temporal optimization	general	2100	high	high	(Luderer et al., 2012)
TIAM-UCL	inter-temporal optimization	partial	2100	high	-	(Anandarajah et al., 2013)
WITCH	inter-temporal optimization	general	2100	low	low	(Bosetti et al., 2006)

Table notes: [a] Not included in Kriegler et al. (2014) diagnostic evaluation study, so response to carbon price is estimated for comparative purposes only.

Within the context of the EU-FP7 ADVANCE project, each of the modeling teams for the ten IAMs described in Supplementary Table 1 completed a questionnaire that asked how behavioral features were represented in their models. Behavioral features were classified using the simple typology described in the main text: individual decision making; social influences; contextual influences; and heterogeneity. These features could be represented using a model-wide approach, or in specific sectors or types of decision.

The principal decisions affecting energy and emission outcomes that are modeled in IAMs relate to technology adoption. Decisions in the buildings and transport sector are made mainly by end-users or consumers (individuals, households). Decisions in the industry and energy supply sectors are mainly made by firms or producers. The main decisions are as follows:

- buildings end-use sector: efficiency investments (retrofits, new builds); appliance adoption and use; levels of demand for energy services (heating, lighting, cooking).

- transport end-use sector: vehicle purchase; mode choice; levels of demand for energy services (mobility).
- industry end-use sector: furnace type (iron and steel).
- energy supply sector: upstream (resource extraction investments), conversion: power plant investments.

The representation of behavioral features in current IAMs is summarized in Supplementary Table 2. The WITCH and REMIX modelling teams reported no current modeling of behavioral features and so do not appear in Supplementary Table 2.

Supplementary Table 2. Representation of behavioral features in ten global IAMs. Blank cells indicate no modelling approach reported.

	Buildings	**Transport**	**Industry**	**Supply**	**General**
	- efficiency - appliances - service demand	- vehicles - modes - service demand	- furnaces	- upstream - power plants	- model wide - all sectors
Heterogeneous decision makers	iPETS MESSAGE				*discount rates:* DNE21+, TIAM *logit calibration:* GCAM, IMAGE
Bounded rationality					implicitly within discount rate formulations (DNE21+, TIAM), and logit calibrations (GCAM, IMAGE)
Non-optimising heuristics					
Non-monetary preferences	IMACLIM IMAGE MESSAGE	GCAM MESSAGE TIAM			
Non-market discount rates	MESSAGE				
Social influence					
Contextual conditions	MESSAGE	GCAM		GCAM	
Political and social institutions					

Economy-wide approaches

Four modelling teams provided information on general, model-wide approaches to behavioral realism. These were substantially different between the inter-temporal optimization-type models (DNE21+, TIAM-UCL) and the recursive-dynamic simulation type models (GCAM, IMAGE-TIMER).

The technology-rich bottom-up IAMs using inter-temporal optimization (DNE21+ and TIAM-UCL) reported using varying discount rates as a general approach to modeling heterogeneous end-user behavior and context-dependent preferences. Discount rates (or investment hurdle rates) were varied as a function of income, technology characteristics, or adoption context (e.g., country or region). The DNE21+ team noted that discount rates were used as a proxy measure of many different behavioral features, and should not be interpreted solely in terms of time preference.

In contrast, the simulation models with limited temporal foresight and a recursive dynamic modelling approach (GCAM, IMAGE-TIMER) reported using multinomial logit functions to model heterogeneous end-user preferences and resulting market shares of competing technologies. These

logit functions were calibrated to empirical data. The calibration parameters were thus used as a proxy for all the non-monetary preferences and other behavioral features influencing observed adoption behavior during the historical calibration period. As the calibration of the logit functions requires historical data, this general modeling approach does not apply to new technologies. The calibration parameters for existing technologies are held constant, implying that the influence of non-monetary preferences on adoption behavior persists over the 100-year model time horizon. This is in contrast to the CIMS modelling approach discussed elsewhere, which assumes the influence of non-monetary preferences decreases as the technology becomes more widely adopted (Rivers and Jaccard, 2006).

Some IAMs use formulations representing behavioral features that are specific to particular decisions or particular sectors.

Heterogeneous decision makers

Buildings: iPETS varies preferences for technology adoption as a function of socio-demographic characteristics. MESSAGE varies price elasticities of electricity use and preferences for technology adoption as a function of income; this is specific to less developed economies as part of work on energy access (Riahi et al., 2012).

Transport: --

Non-monetary preferences

Buildings: IMACLIM uses fixed intangible costs as a proxy for non-monetary preferences for energy-efficient technologies (e.g., disruption and hassle associated with insulation retrofits). MESSAGE uses inconvenience costs as a proxy for non-monetary preferences and barriers to adoption for stove-fuel combinations in less developed economies. REMIND similarly use income-dependent preferences for stove choices.

Transport: GCAM includes the average value of time in transit as a non-monetary preference in both mode choice and total service demands. The value of time in transit is derived from vehicle speed, the wage rate, and an exogenous multiplier reflecting consumers' stated value of time in transit for each mode. IMAGE and MESSAGE include time budgets (and speed) as an influence on mode choice. In both cases, this is related to transport infrastructure.

Recall also the general approach to calibration parameters in GCAM and IMAGE that implicitly include non-monetary preferences for existing technologies.

Context-dependent preferences

Buildings: IMACLIM decomposes aggregate energy consumption into technology adoption (quantity and quality of retrofits) and technology use (level of service demand). Preferences for technology use are therefore conditional on technology adoption in households. MESSAGE modeling of energy access issues recognizes specificity of adoption preferences in less developed economies.

Transport: --

Non-market discount rates

Buildings: MESSAGE uses high implicit discount rates to annualize costs of lighting and cooking equipment in less developed economies.

Transport: --

Contextual conditions

Buildings: IMAGE endogenizes the influence of infrastructure availability on capital investment decisions; this is specific to hydrogen infrastructure.

Transport: GCAM exogenously reduces the market shares of alternative-fuel vehicles due to infrastructure-related constraints.

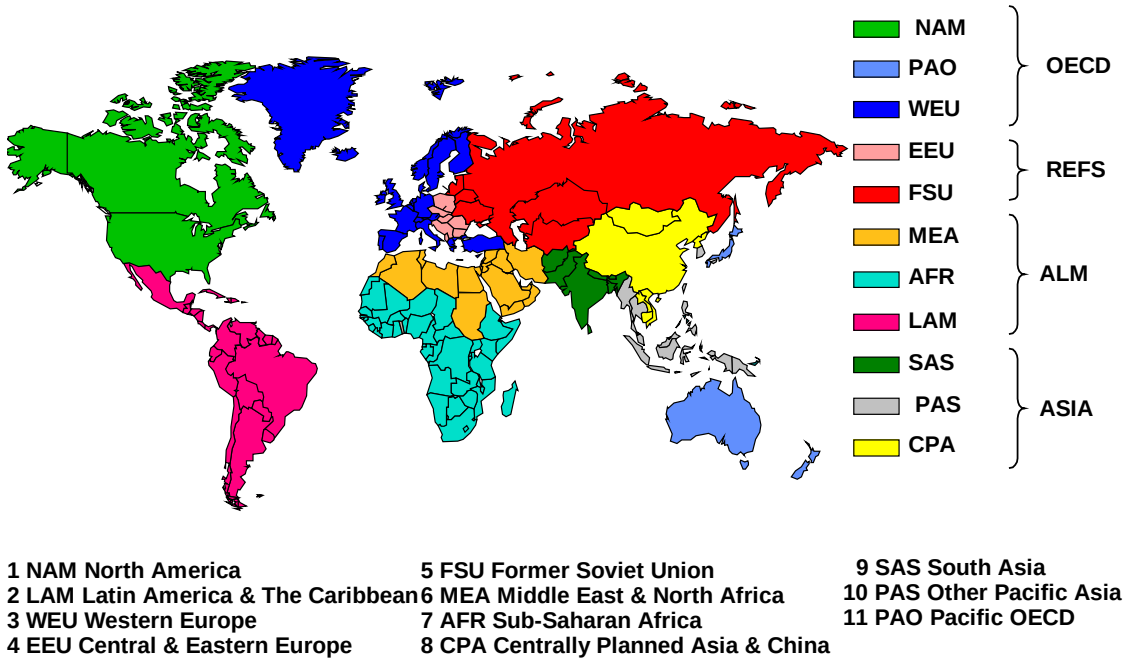
Energy Supply: GCAM lowers the capital cost recovery factors for renewable technologies to represent the favorable financing conditions due to government support programs (mostly in the OECD at present)

2. Overview of the MESSAGE integrated assessment modeling framework

The MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) integrated assessment model (IAM) is a global systems engineering optimization model used for medium- to long-term energy system planning, energy policy analysis, and scenario development (Messner and Strubegger, 1995, Riahi et al., 2012, van Vliet et al., 2012, ADVANCE, 2015). Developed and maintained at the International Institute for Applied Systems Analysis (IIASA) over nearly three decades, MESSAGE is an evolving framework that, like other global IAMs in its class (e.g., MERGE, ReMIND, IMAGE, WITCH, GCAM, etc.), has gained wide recognition over time through its repeated utilization in developing global energy and emissions scenarios (e.g., Nakicenovic and Swart (2000)). (Note that the version of MESSAGE employed in this study, MESSAGE-Transport, includes a more detailed representation of the transport sector than has been utilized in previous studies. Section 3 discusses this further, while the current section focuses on the more general aspects of the MESSAGE framework.)

The MESSAGE model divides the world up into eleven (11) regions (Supplementary Figure 1, Supplementary Table 3) in an attempt to represent the global energy system in a simplified way, yet with many of its complex interdependencies, from resource extraction, imports and exports, conversion, transport, and distribution, to the provision of energy end-use services such as light, space conditioning, industrial production processes, and transportation. Trade flows (imports and exports) between regions are monitored, capital investments and retirements are made, fuels are consumed, and emissions are generated. In addition to the energy system, the model includes also the other main greenhouse-gas emitting sectors, agriculture and forestry. MESSAGE tracks a full basket of greenhouse gases and other radiatively active gases – CO_2 , CH_4 , N_2O , NO_x , volatile organic compounds (VOCs), CO, SO_2, PM, BC, OC, NH_3, CF_4, C_2F_6, HFC125, HFC134a, HFC143a,

HFC227ea, HFC245ca, and SF_6 – from both the energy and non-energy sectors (e.g., deforestation, livestock, municipal solid waste, manure management, rice cultivation, wastewater, and crop residue burning). In other words, all Kyoto gases plus several others are accounted for.



Supplementary Figure 1. Map of 11 regions in MESSAGE model

Supplementary Table 3. Listing of 11 MESSAGE regions by country

11 MESSAGE regions	Definition (list of countries)
NAM	**North America** (Canada, Guam, Puerto Rico, United States of America, Virgin Islands)
WEU	**Western Europe** (Andorra, Austria, Azores, Belgium, Canary Islands, Channel Islands, Cyprus, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Greenland, Iceland, Ireland, Isle of Man, Italy, Liechtenstein, Luxembourg, Madeira, Malta, Monaco, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom)
PAO	**Pacific OECD** (Australia, Japan, New Zealand)
EEU	**Central and Eastern Europe** (Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, The former

	Yugoslav Rep. of Macedonia, Hungary, Poland, Romania, Slovak Republic, Slovenia, Estonia, Latvia, Lithuania)
FSU	**Former Soviet Union** (Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Republic of Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, Uzbekistan)
CPA	**Centrally Planned Asia and China** (Cambodia, China (incl. Hong Kong), Korea (DPR), Laos (PDR), Mongolia, Viet Nam)
SAS	**South Asia** (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka)
PAS	**Other Pacific Asia** (American Samoa, Brunei Darussalam, Fiji, French Polynesia, Gilbert-Kiribati, Indonesia, Malaysia, Myanmar, New Caledonia, Papua, New Guinea, Philippines, Republic of Korea, Singapore, Solomon Islands, Taiwan (China), Thailand, Tonga, Vanuatu, Western Samoa)
MEA	**Middle East and North Africa** (Algeria, Bahrain, Egypt (Arab Republic), Iraq, Iran (Islamic Republic), Israel, Jordan, Kuwait, Lebanon, Libya/SPLAJ, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria (Arab Republic), Tunisia, United Arab Emirates, Yemen)
LAC	**Latin America and the Caribbean** (Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Bermuda, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, French Guyana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Mexico, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Santa Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Venezuela)
AFR	**Sub-Saharan Africa** (Angola, Benin, Botswana, British Indian Ocean Territory, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Cote d'Ivoire, Congo, Democratic Republic of Congo, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Saint Helena, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe)

A typical model application is constructed by specifying performance characteristics of a set of technologies and defining a Reference Energy System (RES) that includes all the possible energy chains that MESSAGE can make use of. In the course of a model run, MESSAGE determines how much of the available technologies and resources are actually used to satisfy a particular end-use demand, subject to various constraints (both technological and policy), while minimizing total discounted energy system costs over the entire model time horizon (1990-2110). It does this based on a linear programming, optimization solution algorithm. The representation of the energy system includes vintaging of the long-lived energy infrastructure, which allows for consideration of the timing of technology diffusion and substitution, the inertia of the system for replacing existing facilities with new generation systems, clustering effects (technological interdependence) and – in certain versions of the model – the phenomena of increasing returns (i.e., the more a technology is applied the more it improves and widens its market potentials). Combined, these factors can lead to "lock-in" effects (Arthur, 1989, Arthur, 1994) and path dependency (change occurs in a persistent direction based on an accumulation of past decisions). As a result, technological change can go in multiple directions, but once change is initiated in a particular direction, it becomes increasingly difficult to alter its course.

Important inputs for MESSAGE are technology costs and technology performance parameters (e.g., efficiencies and investment, variable, and O&M costs). For the scenarios included in this paper, technical, economic and environmental parameters for over 100 energy technologies are specified explicitly in the model. Costs of technologies are assumed to decrease over time as experience (measured as a function of cumulative output) is gained. For assumptions concerning the main energy conversion technologies see the following references: Riahi et al. (2007), Nakicenovic and Swart (2000), Riahi et al. (2012), van Vliet et al. (2012), and the Global Energy Assessment Scenario Database (IIASA, 2012). For information on carbon capture and storage technologies specifically, see Riahi et al. (2004).

MESSAGE is able to choose between both conventional and non-conventional technologies and fuels (e.g., advanced fossil, nuclear fission, biomass, and renewables), and in this respect the portfolio of technologies/fuels available to the model obviously has an important effect on the model result. In the version of the model used in this study, we consider a portfolio of technologies whose components are either in the early demonstration or commercialization phase (e.g., coal, natural gas, oil, nuclear, biomass, solar, wind, hydro, geothermal, carbon capture and storage, hydrogen, biofuels, and electrified transport, to name just a subset). Notably, this portfolio includes bio-CCS, a technology that can potentially lead to negative emissions (i.e., permanent underground storage of CO_2 which was originally pulled out of the atmosphere by photosynthesis). Exceedingly futuristic technological options, such as nuclear fusion and geo-engineering, are, however, not considered.

Other important input parameters for our modeling include fossil fuel resource estimates and potentials for renewable energy. For fossil fuel availability, the model distinguishes between conventional and unconventional resources for eight different categories of (oil, gas, coal) occurrences (Rogner, 1997, Riahi et al., 2012). For renewable potentials we rely on spatially explicit analysis of biomass availability and adopt the assumptions discussed in Riahi et al. (2012).

Price-induced changes in energy demand (i.e., elastic demands) are also modeled in MESSAGE via an iterative link to MACRO, a top-down, macro-economic model of the global economy (Messner and Schrattenholzer, 2000). Through an iterative solution process, MESSAGE and MACRO exchange information on energy prices, energy demands, and energy system costs until the demand responses are such that (for each of the six end-use demand categories in the model: electric and thermal heat demands in the industrial, residential, commercial, and transportation sectors) the two models have reached equilibrium. This process is parameterized off of a baseline scenario (which assumes some autonomous rate of energy efficiency improvement, AEEI) and is conducted for all eleven MESSAGE regions simultaneously. Therefore, the demand responses motivated by MACRO are meant to represent the additional (compared to the baseline) energy efficiency improvements and conservation that would occur in each region as a result of higher prices for energy services. The macro-economic response captures both technological and behavioral measures (at a high level of aggregation), while considering the substitutability of capital, labor, and energy as inputs to the production function at the macro level.

MESSAGE is also linked to MAGICC (Model for the Assessment of Greenhouse-gas Induced Climate Change), version 6.8, which has is used to estimate the climate system impacts of the varying greenhouse gas emission trajectories that derived from the MESSAGE-MACRO scenarios. MAGICC is a reduced-complexity coupled global climate-carbon cycle model, in the form of a user-friendly software package that runs on a personal computer (Wigley, 2008, Meinshausen et al., 2011). In its standard form, MAGICC calculates internally consistent projections for atmospheric concentrations, radiative forcing, global annual-mean surface air temperature, ice melt, and sea level rise, given emissions trajectories of a range of gases (CO_2, CH_4, N_2O, CO, NO_x, VOCs, SO_2, and various halocarbons, including HCFCs, HFCs, PFCs, and SF_6), all of which are outputs from MESSAGE. The time horizon of the model extends as far back as 1750 and can make projections as far forward as 2400. The climate model in MAGICC is an upwelling-diffusion, energy-balance model, which produces output for global- and hemispheric-mean temperature and for oceanic thermal expansion. Climate feedbacks on the global carbon cycle are accounted for through the interactive coupling of the climate model and a range of gas-cycle models. When reporting our results from MAGICC, atmospheric CO_2-eq concentrations (in parts per million, ppm) are calculated from radiative forcing (RF) levels – from all greenhouse gases and forcing agents, excluding contributions from albedo change, nitrate aerosols, and mineral dust – relative to the pre-industrial era (1750), using the standard approximation formula: $C_0 \exp(RF/\alpha)$, where C_0 = 278 ppm and α=5.35.

Further and more detailed information on the MESSAGE modeling framework is available, including documentation of model set-up and mathematical formulation (Messner and Strubegger, 1995, Riahi et al., 2012, ADVANCE, 2015) and the model's representation of technological change and learning (Rao et al., 2006, Riahi et al., 2004, Roehrl and Riahi, 2000).

3. Further information on the transport module MESSAGE-Transport

The version of MESSAGE employed in this study includes a more detailed representation of the transport sector than has been utilized previously, e.g., in McCollum et al. (2014). The following brief

description elaborates the main characteristics of this transport module, which we distinguish from the previous version by referring to it as "MESSAGE-Transport".

While the stylized transport model formulation only includes fuel switching and price-elastic demands (via MACRO linkage) as the main responses to energy and climate policy, MESSAGE-Transport has much greater end-use technological detail, meaning individual vehicle technologies are characterized across the various transport modes (light-duty, heavy-duty, aviation, shipping, rail, etc.). In conjunction with this, 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). Moreover, 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 Riahi et al. (2007) for more information about the MESSAGE scenario generator.[2]) The characteristics of MESSAGE-Transport explained here apply to all scenarios modeled in the current study, whether they include consumer heterogeneity or disutility costs in the LDV sub-sector or not.

The following bulleted list summarizes the different vehicle types that are available for deployment in each of the different transport modes:

Light-duty vehicles

- Internal combustion engine using gasoline/diesel (low, medium, and high efficiency versions)
- Internal combustion engine using natural gas
- Internal combustion engine using biofuels
- Internal combustion engine using methanol/synthetic fossil liquids
- Hybridized internal combustion engine using gasoline/diesel
- Hybridized internal combustion engine using natural gas

[2] 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, 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). The non-transport demands are generated using an R-based model called the scenario generator. This model uses country-level historical data of GDP per capita (PPP) and final energy use, as well as projections of GDP|PPP and population, to extrapolate the six non-transport energy service demands into the future. The sources for the historical and projected datasets come from, for example, the World Bank, UN, OECD, and IEA. Using the historical datasets, the scenario generator conducts regressions that describe the historical relationship between the independent variable (GDP|PPP per capita) and several dependent variables, including total final energy intensity (MJ/2005USD) and the shares of final energy in several energy sectors (%).The historical data are also used in quantile regressions to develop global trend lines that represent each percentile of the cumulative distribution function (CDF) of each regressed variable. Given the regional regressions and global trend lines, final energy intensity and sectoral shares can be extrapolated forward in time based on projected GDP per capita. Several user-defined inputs allow the user to tailor the extrapolations to individual socio-economic scenarios. The total final energy in each region is then calculated by multiplying the extrapolated final energy intensity by the projected GDP|PPP in each time period. Next, the extrapolated shares are multiplied by the total final energy to identify final energy demand for each of the six non-transport energy service demand categories. Finally, final energy is converted to useful energy in each region by using the average final-to-useful energy efficiencies reported by the IEA for each country.

- 7Hybridized internal combustion engine using biofuels
- Hybridized internal combustion engine using methanol/synthetic fossil liquids
- Hybridized fuel cell vehicle using hydrogen
- Hybridized fuel cell vehicle using methanol/synthetic fossil liquids via onboard steam reformation
- Hybridized fuel cell vehicle using natural gas via onboard steam reformation
- Battery-electric vehicle using electricity-only
- Plug-in hybrid-electric vehicle using gasoline/diesel

Two-wheelers

- High-efficiency internal combustion engine using gasoline/diesel
- Battery-electric vehicle using electricity-only

Freight truck

- Internal combustion engine using gasoline/diesel (low, medium, and high efficiency versions)
- Internal combustion engine using natural gas
- Internal combustion engine using biofuels
- Hybridized internal combustion engine using gasoline/diesel
- Hybridized fuel cell vehicle using hydrogen
- Hybridized fuel cell vehicle using methanol/synthetic fossil liquids via onboard steam reformation
- Hybridized fuel cell vehicle using natural gas via onboard steam reformation

Aviation (passenger)

- Conventional jet engine using light oil petroleum products (kerosene jet fuel)
- Conventional jet engine using methanol/synthetic fossil liquids
- Conventional jet engine using biofuels
- Conventional jet engine using hydrogen

Buses

- Internal combustion engine using gasoline/diesel (medium and high efficiency versions)
- Internal combustion engine using natural gas
- Internal combustion engine using biofuels
- Hybridized internal combustion engine using gasoline/diesel
- Hybridized fuel cell bus using hydrogen
- Hybridized fuel cell bus using natural gas via onboard steam reformation
- Hybridized fuel cell bus using methanol/synthetic fossil liquids via onboard steam reformation
- Electric trolleybus connected to power cables
- Plug-in hybrid-electric bus using gasoline/diesel

Rail (passenger)

- Electrically-powered urban public rail transport (aggregate of metro/underground, streetcars/trams, commuter trains, and regional trains)
- Diesel-powered urban public rail transport
- Coal-powered urban public rail transport (aggregate of metro/underground, streetcars/trams, commuter trains, and regional trains)
- Electrically-powered long-distance high-speed rail transport
- Electrically-powered long-distance medium-speed rail transport

- Diesel-powered long-distance medium-speed rail transport

In contrast to the more detailed representation of the modes mentioned above, the demand for freight aviation, freight rail, domestic shipping (via inland waterways), and international shipping is not explicitly modeled, but rather a number of different energy carrier options (light and heavy fuel oil, biofuels, natural gas, and hydrogen) are available for supplying energy demand. Demand is accounted for via an exogenous energy demand trajectory that is subject to price-induced demand response via the MACRO linkage. The following transport modes are not modeled in MESSAGE-Transport: walking, bicycle, three-wheelers, pipelines, and off-road devices.

The model determines which vehicle types are used within a given transport mode based on least-cost optimization considering the discounted net present cost of each technology at each point in time (including vehicle investment costs, fixed and variable O&M costs, and fuel costs). The techno-economic parameters for each technology are exogenously assumed and change over time. There is also some regional differentiation for certain technologies and parameter assumptions. Vehicle registration fees, insurance, and taxes are not currently considered in the model.

The demand projections for freight trucking are exogenously assumed. They are, however, subject to endogenous price-induced demand response via the MACRO linkage.

The demand projections for passenger travel in the various modes, as well mode-switching decisions, are endogenously determined.

The demand projections for passenger travel in the various modes, as well mode-switching decisions, are endogenously determined. In a first step, total travel demand (*TV*) per region in a reference scenario without climate policy (business-as-usual, BAU) is determined via equation 1 (Schafer and Victor, 2000). The two parameters *e* and *f** are calculated for each region with 2005 base-year values obtained from (Schäfer et al., 2009) and a globally harmonized assumed convergence point for annual travel and income of 150,000 pkm/yr at US$330,000/capita (which is not reached in any of the regions during the modeling time frame).

$$\frac{TV}{cap} = \left(\frac{GDP}{cap}\right)^{e} \cdot f^{*} \qquad \text{(eq. 1)}$$

Service demands (in passenger-km) for the different modes are determined by calculating the share $S_{i,r,t}$ of each mode *i* in region *r* at time *t* via multi-nomial logit functions (as in eq. 2) and multiplying this with the total regional pkm demand as obtained by eq. 1.

$$S_{i,r,t} = \frac{(SW_{i,r})(P_{i,r,t})^{\lambda}}{\sum_{i}^{n}(SW_{i,r})(P_{i,r,t})^{\lambda}} \qquad \text{(eq. 2)}$$

with the logit exponent λ = -2 as used in Kyle and Kim (2011), and share weights $SW_{i,r}$ that partially converge across regions as a function of income.

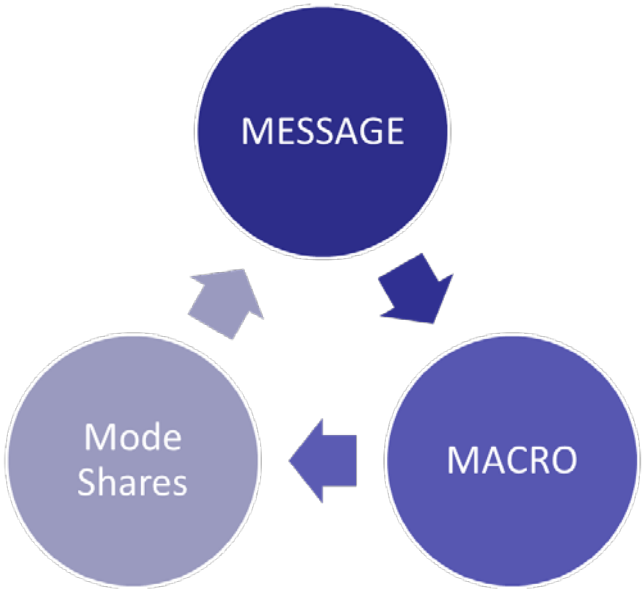
The structure and parameterization of the mode-sharing approach is based on Kyle and Kim (2011) and Girod et al. (2012) and considers the generalized price per mode $P_{i,r,t}$, consisting of a fuel price, non-fuel price and value of time component (eq. 3).

$$P_{i,r,t} = FP_{i,r,t} + NFP_{i,r,t} + \frac{Wage_{r,t} \cdot VOTM_{r,t}}{Speed_{i,r,t}} \qquad \text{(eq. 3)}$$

where

- Endogenous value of time multiplier *VOTM* increasing from 0.2 – 0.9 with higher income
- Speeds per mode as from Schäfer et al. (2009)

The logit-based mode-choice algorithms described above are incorporated within the combined MESSAGE-Transport + MACRO framework, thereby creating a triangular arrangement of three soft-linked models, as is illustrated in the schematic diagram in Supplementary Figure 2. In short, the partial-equilibrium model MESSAGE starts with finding the least-cost energy system configuration for fulfilling exogenously-given demand levels for a total of 5 aggregate useful energy types covering the non-transport sectors and the 6 modes in the more detailed transport sector. Information on service-demand prices and quantities is transferred from MESSAGE-Transport to MACRO, with the 5 passenger transport modes aggregated into one energy service category (the sixth transport category is freight). The 5 aggregate useful energy types and the 2 aggregate transport energy services (pkm and freight ton-kilometers, tkm) are inputs to a nested production function with constant elasticity of substitution in the general equilibrium growth model MACRO, which then computes the demand response for each of the 7 demand categories, either increasing or decreasing the demands depending on prevailing prices. New passenger mode-shares are calculated using equations 2 and 3 (based on the updated income from MACRO and fuel-price information from MESSAGE), and these shares are subsequently used to split up the new level of total passenger transport demand resulting from MACRO. Finally, the updated demands of all energy service categories are fed in as inputs for the next iteration, which starts again with a run of MESSAGE-Transport. By iteratively running this triangular, soft-coupled model arrangement, the quantities and prices of the various transport modes and other energy inputs converge within well under 10 iterations.



Supplementary Figure 2. Schematic diagram illustrating the inter-linked framework of MESSAGE-Transport, MACRO, and the logit-based mode choice and demand projection algorithms.

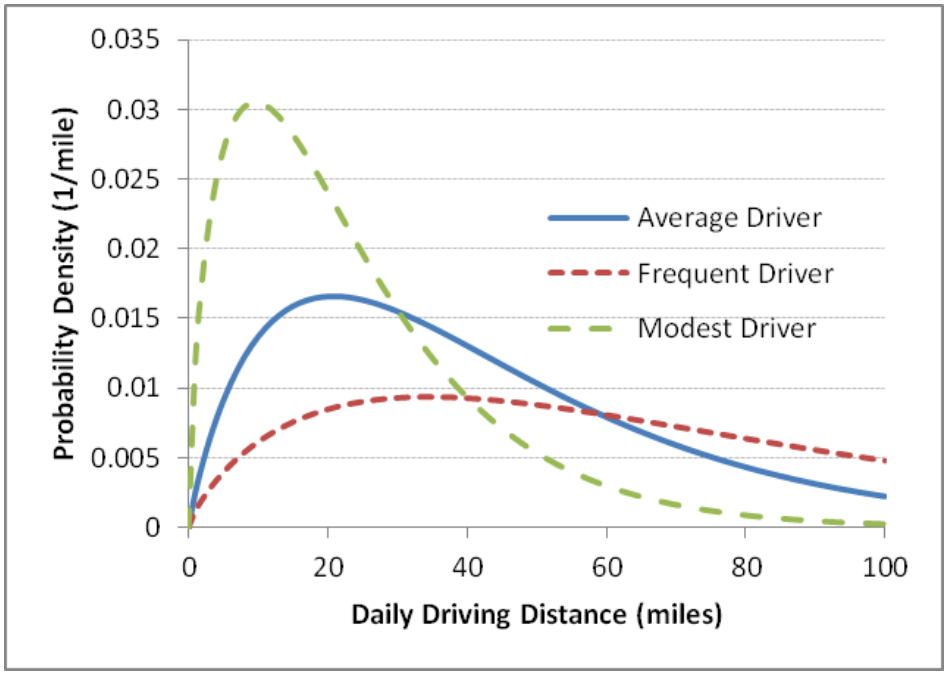
4. Further details on the original MA^{3}T model

As described briefly in the main text, 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).

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 (2)-(4). The random daily distance is assumed to follow Gamma distributions, as exhibited in Supplementary Figure 3 (Dong and Lin, 2012, Lin and Greene, 2011b, Onar et al., 2013) – an assumption that has been adopted in several other studies (Lin and Greene, 2011a, Lin, 2012a, Greene, 1985, Lin, 2012b) and recently validated by real-world multi-vehicle longitudinal data (Lin et al., 2012). 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://cta.ornl.gov/ma3t/ or Lin et al. (2013) and Lin et al. (2014).



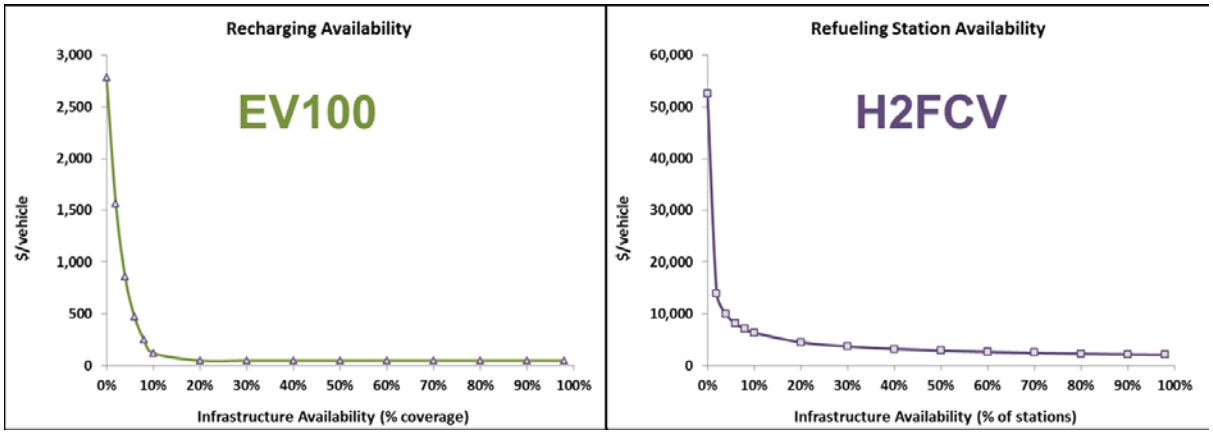
Supplementary Figure 3. Probability distribution of three driver types in MA^{3}T, derived from the U.S. NHTS

5. *Additional information about the joint MESSAGE-Transport + MA^{3}T implementation*

Estimation of functional forms for range anxiety and refueling availability disutility costs

The following figures give examples – for one of the 27 consumer groups in the North American context – of how the range anxiety and refueling station availability disutility 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

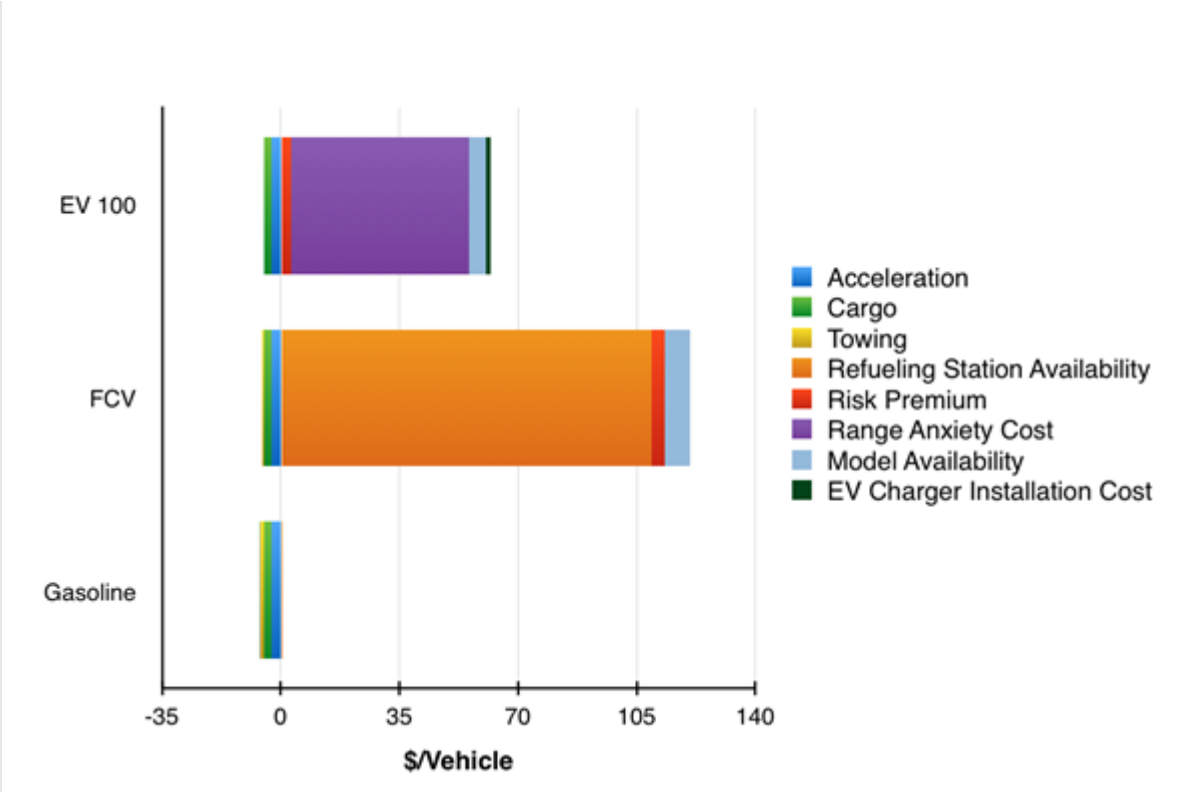
studies, which used GIS-based spatial optimization and traffic flow models to calculate the average time drivers would need to reach refueling stations offering hydrogen as a function of the number of those stations (Nicholas et al., 2004). Coverage of 10-30% was found to offer an acceptable level of convenience in such cases.



Supplementary Figure 4. Example of the relationship between range anxiety (left panel; BEVs with a range of 100 miles) and refueling station availability (right panel; H2FCVs) disutility cost components and the level of recharging or refueling infrastructure availability. North American estimates for a single consumer group are shown. Functional forms derived from a sensitivity analysis using the MA^{3}T model.

Breakdown of all disutility cost sub-components considered in the original MA^{3}T model

The following illustrative figures presents a breakdown of the disutility 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 5. Illustration of disutility cost components for different vehicle types, deriving from the original MA^{3}T model. Consumer group: Suburban – Late Majority – Frequent Driver. Year: 2020.

6. *Details on the calculation of the regional multipliers applied to the disutility costs deriving from MA^{3}T and implemented in MESSAGE-Transport*

Introduction

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 (sometimes referred to as 'disutilities') vary between regions. These simple predictive relationships from regions with empirical data can be used to estimate disutilities for regions without empirical data. In the context of the vehicle choice modeling work discussed in this study, for three of the five disutility 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 IMAGE model regions (Stehfest et al., 2014). 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 disutilities 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.

Calculation of regional multipliers

Risk premium

The multipliers related to risk premium disutility 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 (US$2010). 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 (Pettifor et al., forthcoming) using data from 11 different countries and capturing three broad types of social influence (see Supplementary Table 4).

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

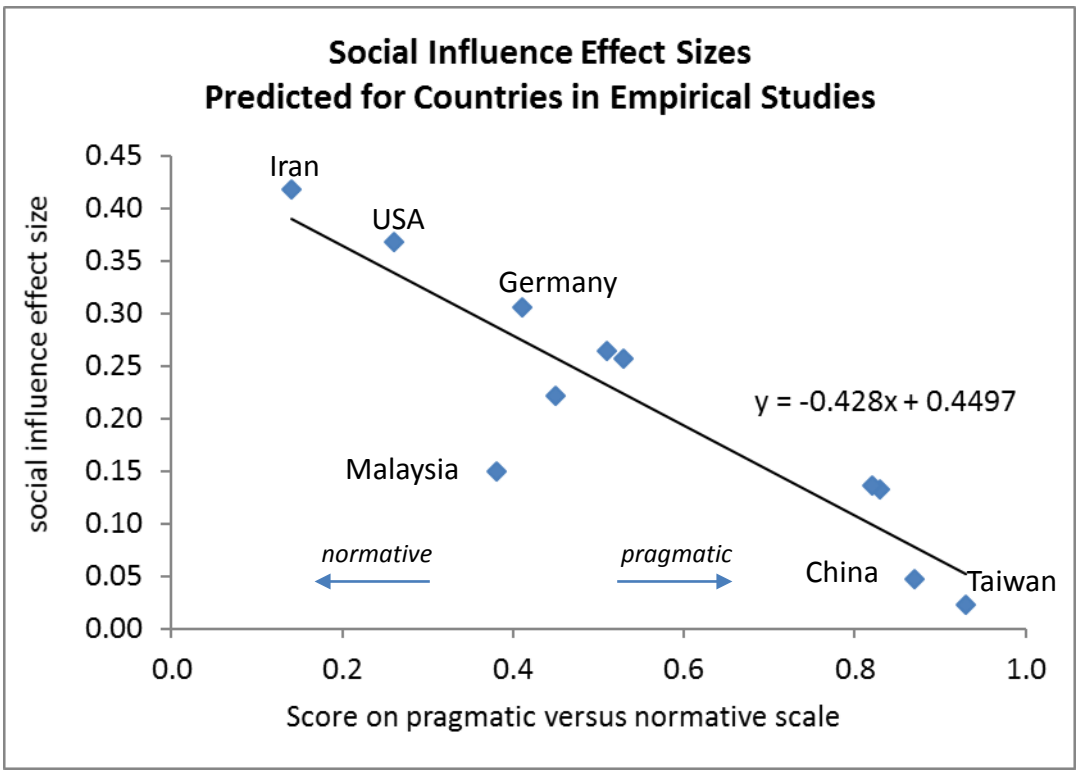
Social Influence Type	Description
Interpersonal networks	Information exchange and sharing between members of a social group (family, friends, co-workers).
Neighbourhood effects	Visual demonstration of new vehicle technology by neighbours living in close proximity.
Social norms	Increasing motivation to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

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'[3] (Minkov and Hofstede, 2010). 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.

The linear association between country scores on the pragmatic versus normative scale and predicted social influence effects is shown in Supplementary Figure 6. The resultant linear equation was then used to estimate country-level social influence effects for those countries not included in

[3] A scale measuring the extent to which a country is receptive to social influences. 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 meta-analysis, based on their score on the pragmatic versus normative scale (available for over 80 different countries within the 26 IMAGE regions).



Supplementary Figure 6. Linear association between score on pragmatic versus normative scale and social influence effect size for countries sampled within 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).

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

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)):	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,

SocInf = -0.428.pn + 0.4497 (where SocInf=social influence effect size and pn=score on pragmatic versus normative scale (R^2= 0.82)).	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) (R^2=0.1214)).	Ethiopia, Kenya, Madagascar, Mauritius, Rwanda, Sudan, Uganda, Belarus, Moldova, Ukraine, Kazakhstan, Tajikistan, Turkmenistan, Uzbekistan, Korea Rep.

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 (Dimitropoulos et al., 2013), 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 $US\$2013_{ppp}$ 2,423.

Refuelling station availability

Multipliers for increased refuelling density (increase 10% station coverage) are based on 6 empirical studies providing WTP estimates for three regions: USA, Europe and Japan, again taken from earlier analysis (Wilson et al., 2014). 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 (increase 10% stations) and the USA estimate of $US\$2013_{ppp}$ 2,792.

7. Results referred to in the main text but only briefly discussed

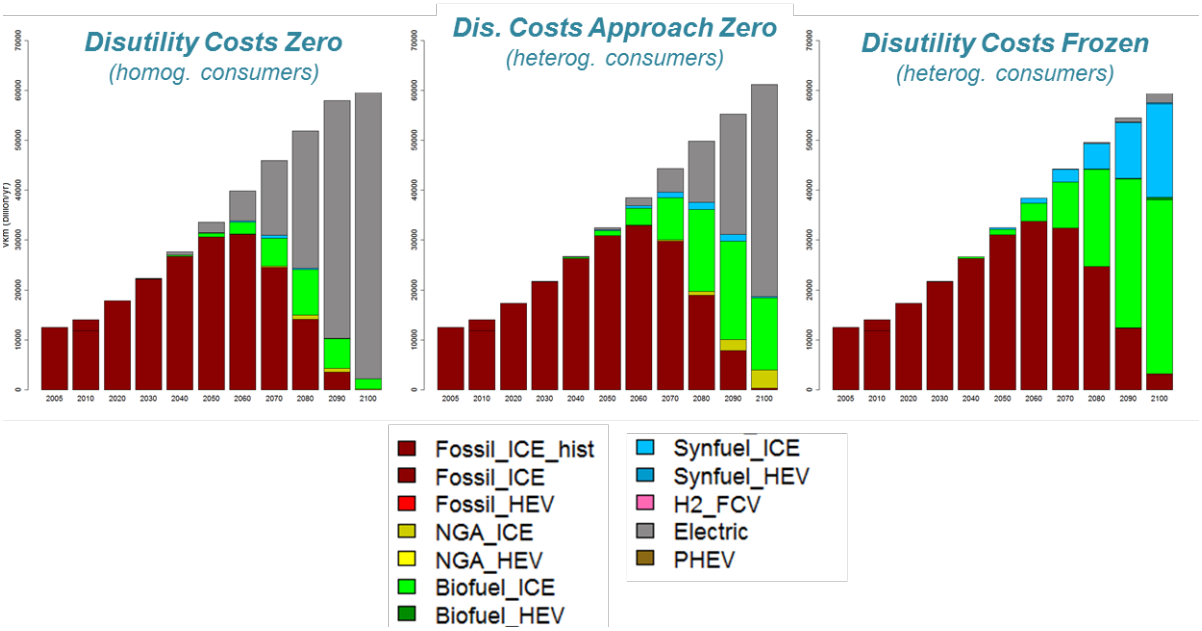
Results for a modified version of scenario Heterog_DivBeh that assumes non-frozen disutility costs

The scenarios in the main text that capture non-monetary preferences make a simplifying assumption that disutility costs stay constant at today's levels throughout the time horizon of the model. An alternative approach would have them approach zero (i.e., the levels of conventional gasoline/diesel vehicles) over time, as AFVs become more commonplace and their requisite refueling/recharging availability expands. For illustrative purposes, we ran one such scenario; it includes a pre-defined trajectory for the principal drivers in the disutility cost equations. More specifically, the exogenously chosen values shown in Supplementary Table 6 were assumed for all regions simultaneously. The scenario storyline underlying these assumptions is that AFVs become more common by the middle part of the century and that consumer familiarity with each grows in parallel. Model results obtained from running MESSAGE-Transport with these non-frozen disutility costs (see Supplementary Figure 7) show that AFV deployment is more rapid in this scenario than in the "frozen disutility costs" case. In particular, all-electric BEVs manage to capture a fairly large share of the LDV market in the second half of the century (though still less than in the case where disutility costs are assumed to be zero in all years, i.e., when non-monetary preferences are not captured at all). Furthermore, Supplementary Figure 8 illustrates that in scenarios assuming non-frozen disutility costs, the differences brought about by including heterogeneity are considerably more pronounced than in the frozen cost case (since the disutility costs are higher/lower and approach zero faster/slower for certain consumer groups than others).

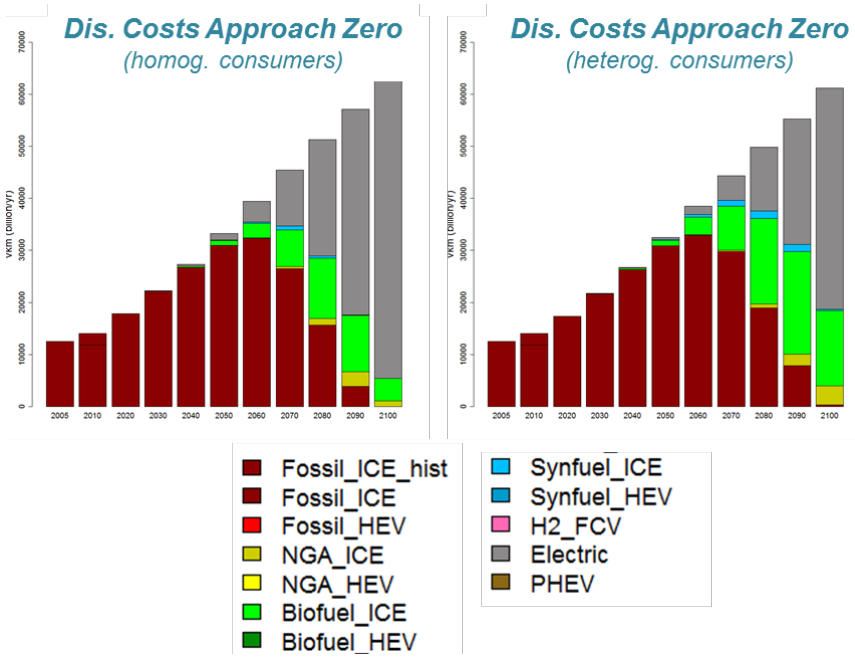
It should be noted that for the purposes of this paper, we have not attempted to closely tie the exogenous assumptions for the disutility cost drivers to the AFV deployment and refueling/recharging infrastructure levels deriving from the scenarios. Doing this would allow for a more internally consistent story for developments on both the supply and demand sides of the energy system and therefore should be the subject of future work.

Refueling and Recharging Infrastructure Availability										
	2010	*2020*	*2030*	*2040*	*2050*	*2060*	*2070*	*2080*	*2090*	*2100*
Electric vehicles (EV & PHEV)	0.0%	0.0%	2.0%	8.0%	25.0%	40.0%	80.0%	100.0%	100.0%	100.0%
H2 vehicles	0.0%	0.0%	2.0%	8.0%	25.0%	40.0%	80.0%	100.0%	100.0%	100.0%
Natural gas vehicles	0.0%	0.0%	2.0%	8.0%	25.0%	40.0%	80.0%	100.0%	100.0%	100.0%
* Relevant for the "Range Anxiety" and "Refueling Station Availability" disutility cost sub-components										
Share of New Vehicle Sales										
	2010	*2020*	*2030*	*2040*	*2050*	*2060*	*2070*	*2080*	*2090*	*2100*
Electric vehicles (EV & PHEV)	0.0%	0.0%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%	45.0%
H2 vehicles	0.0%	0.0%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%	45.0%
Natural gas vehicles	0.0%	0.0%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%	45.0%
* Relevant for the "Model Availability" disutility cost sub-component										
Share of Total Vehicle Stock										
	2010	*2020*	*2030*	*2040*	*2050*	*2060*	*2070*	*2080*	*2090*	*2100*
Electric vehicles (EV & PHEV)	0.0%	0.0%	0.5%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%
H2 vehicles	0.0%	0.0%	0.5%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%
Natural gas vehicles	0.0%	0.0%	0.5%	1.0%	5.0%	20.0%	25.0%	30.0%	35.0%	40.0%
* Relevant for the "Risk Premium" disutility cost sub-component										

Supplementary Table 6. Exogenous assumptions for disutility cost drivers in the scenario where they approach zero over time.



Supplementary Figure 7. Light-duty vehicle deployment from 2005 to 2100, by technology, in a modified version of scenario Heterog_DivBeh that assumes non-frozen disutility costs (middle panel). Also shown for comparison are results from scenario Heterog_DivBeh discussed in the main text, which assumes frozen disutility costs (right panel), and from scenario Homog_NoBeh, which assumes that disutility costs are zero in all years. All scenarios assume the same climate policy of moderate stringency; see text for details. Global results shown: vehicle-km/yr.

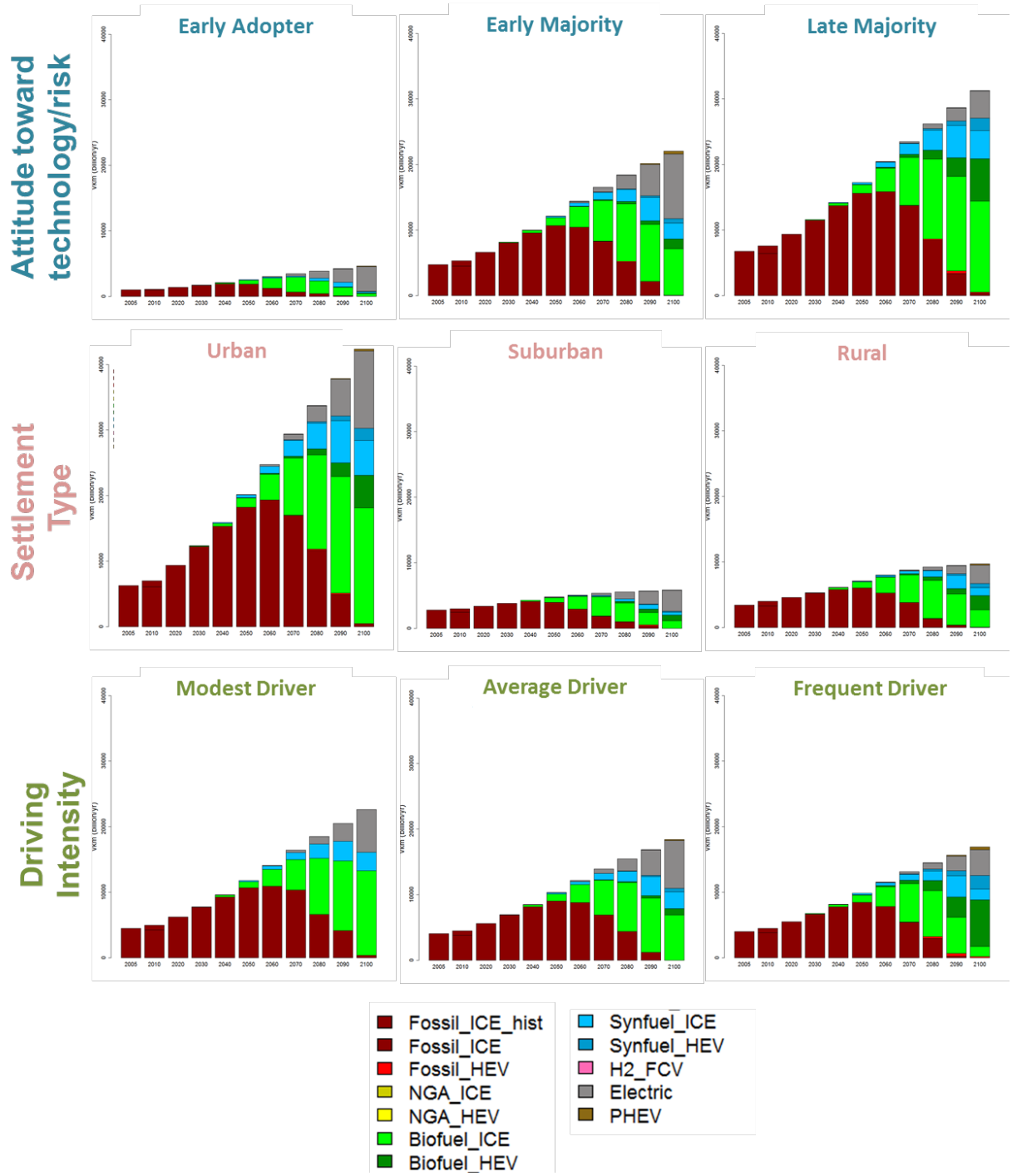


Supplementary Figure 8. Light-duty vehicle deployment from 2005 to 2100, by technology, in modified versions of scenarios Homog_LimBeh and Heterog_DivBeh that assume non-frozen disutility costs (left and

right panels, respectively). All scenarios assume the same climate policy of moderate stringency; see text for details. Global results shown: vehicle-km/yr.

Results for a modified version of scenario Heterog_DivBeh that assumes higher carbon prices

At higher carbon prices, i.e., when there is a greater incentive for the model to bring electric and hydrogen vehicles into the vehicle mix, more divergent behavior between the consumer groups can be observed. This is exhibited in Supplementary Figure 9 for a scenario which is in the same family as scenario Heterog_DivBeh in the main text but which sees an alternative carbon price trajectory reaching 90 $/t$CO_2$eq in the year 2040 (rising at 5%/yr interest both before and after). This more stringent policy framework leads to roughly 520 ppm CO_2eq in 2100 and global mean temperature increase of 2.2 °C. Moreover, in this scenario electric vehicles are brought online in significant numbers post-2050, making inroads noticeably earlier (1-2 decades) in the early adopter and early majority groups (vs. the late majority) and ultimately capturing higher shares of the vehicle market among modest and average drivers (vs. frequent drivers). In short, the behavioral barriers associated with adopting these more advanced technologies can vary considerably by consumer group (namely along the risk attitude and driving intensity dimensions, due to varied range anxiety and refuelling/recharging availability concerns) and, thus, so can their timing of adoption between groups.

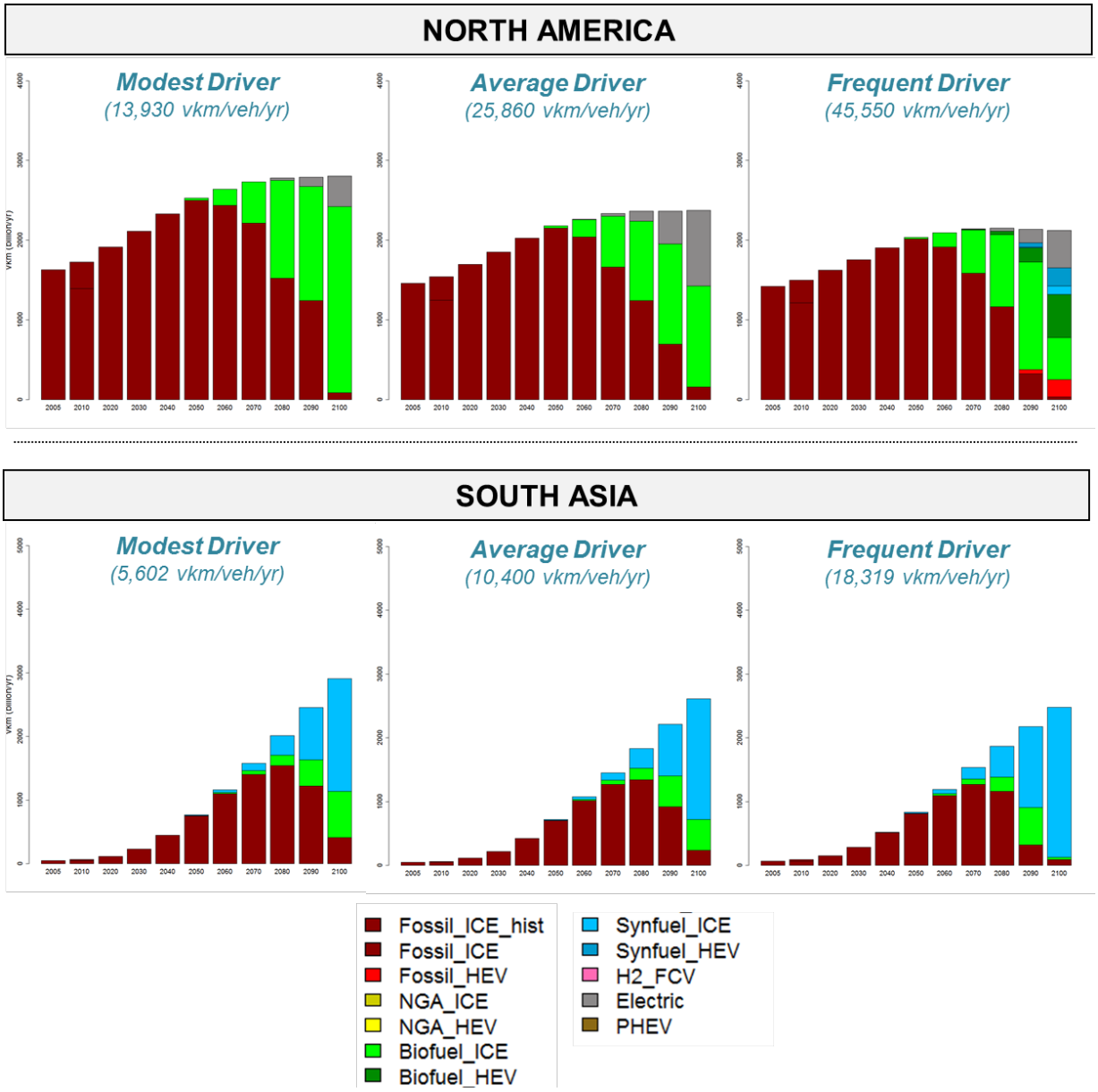


Supplementary Figure 9. Light-duty vehicle deployment from 2005 to 2100, by technology and along alternative consumer group dimensions, in scenario with higher carbon prices (see text). This scenario assumes climate policy of relatively high stringency; see text for details. Global results shown: vehicle-km/yr.

Results for the standard scenario Heterog_DivBeh: regional comparison

A key reason for representing behavior heterogeneously within the model relates to the balancing of real costs (capital, fuel, O&M) vs. perceived/non-monetary costs (disutilities) in the financial calculations. This point can be clearly illustrated by comparing scenario results for scenario Heterog_DivBeh across consumer groups in two very different regions: North America and South

Asia. Supplementary Figure 10 shows that while BEVs make inroads in the North American context post-2050, they never penetrate the market in South Asia. Instead, fossil synfuels (principally gas-to-liquids with CCS) and, to a lesser extent, biofuels come to dominate in South Asia after 2050. Given that the disutility costs for BEVs are lower in South Asia than North America (owing to regional multipliers below 1.0, as derived from the empirical analysis described previously), it is somewhat counter-intuitive that electric vehicle deployment would be less in the former than in the latter. The explanation for this behavior underscores an important point related to how fuel-vehicle choices are made in the model, and by extension in reality. The driving intensity levels assumed for South Asia are relatively low compared to those in North America. In fact, an average driver in South Asia is found to drive less per year than even a modest driver in North America. At these lower levels of driving, the incrementally higher capital costs of BEVs fail to be recovered by the fuel savings achieved over the lifetimes of the vehicles. Hence, BEVs are less economically attractive from the perspective of the model – and this, despite the disutility costs of BEVs being lower in South Asia.



Supplementary Figure 10. Light-duty vehicle deployment from 2005 to 2100, by technology and driver intensity type, in scenario Heterog_DivBeh. This scenario assumes climate policy of moderate stringency; see text for details. Regional results shown for both North America and South Asia: vehicle-km/yr.

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