Originally published as:

McCollum, D. L., Wilson, C., Pettifor, H., Ramea, K., Krey, V., Riahi, K., Bertram, C., Lin, Z., Edelenbosch, O. Y., Fujisawa, S. (2017): 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

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

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Abstract:
A large body of transport sector-focused research recognizes the complexity of human behavior in relation to mobility. Yet, global integrated assessment models (IAMs), which are widely used to evaluate the costs, potentials, and consequences of different greenhouse gas emission trajectories over the medium-to-long term, typically represent behavior and the end use of energy as a simple rational choice between available alternatives, even though abundant empirical evidence shows that real-world decision making is more complex and less routinely rational. This paper demonstrates the value of incorporating certain features of consumer behavior in IAMs, focusing on light-duty vehicle (LDV) purchase decisions. An innovative model formulation is developed to represent heterogeneous consumer groups with varying preferences for vehicle novelty, range, refueling/recharging availability, and variety. The formulation is then implemented in the transport module of MESSAGE-Transport, a global IAM, although it also has the generic flexibility to be applied in energy-economy models with varying set-ups. Comparison of conventional and 'behaviorally-realistic' model runs with respect to vehicle purchase decisions shows that consumer preferences may slow down the transition to alternative fuel (low-carbon) vehicles. Consequently, stronger price-based incentives and/or non-price based measures may be needed to transform the global fleet of passenger vehicles, at least in the initial market phases of novel alternatives. Otherwise, the mitigation burden borne by other transport sub-sectors and other energy sectors could be higher than previously estimated. More generally, capturing behavioral features of energy consumers in global IAMs increases their usefulness to policy makers by allowing a more realistic assessment of a more diverse suite of policies.

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Keywords: consumer choice, human behavior, transport, light-duty vehicles, climate change mitigation

1 INTRODUCTION & MOTIVATION

The future direction of the world's energy and transport systems, and in particular society's ability to mitigate climate change and overcome a variety of other sustainable development challenges, hinges critically on both technological and socio-behavioral factors. These factors, many of which are associated with large uncertainties, have been studied in detail by diverse research communities employing a variety of methodological approaches: from engineers to natural scientists to social scientists. Somewhere in the middle of these communities sit modelers, drawing, in an interdisciplinary way, on the thinking of individual disciplines. Models come in all shapes and sizes: some, for instance, focus only on the transport sector in a particular country whereas others cover the energy-economic system of the entire world. Many models are forward-looking and therefore are used for medium-to-long-term scenario analyses, with an eye toward informing energy, transport, and sustainable development policy; some of these models consider both technological and socio-behavioral elements in developing their scenarios. Bridging the gap between these dimensions has historically presented a challenge (Turnheim et al., 2015, Avineri, 2012). This paper attempts to make progress by using transport sector-focused behavioral research to enhance the state-of-the-art of energy-economic and integrated assessment models.

1.1 Global integrated assessment and energy-economy models in brief

Models of the global energy-economy are widely used to evaluate the costs, potentials, and consequences of different greenhouse gas emission trajectories over the medium-to-long term. These models are increasingly coupled to atmospheric, land use, agricultural, forestry and other sectoral models: hence, 'integrated assessment models' (IAMs). Representation of the global energy-economy within IAMs is inevitably – and often intentionally – stylized, simplified, and selective. Their purpose is to derive robust insights – qualitative and quantitative – on the systemic consequences of socio-economic development and technology and policy choices (Krey, 2014).

Krey (2014) distinguishes IAMs along three main dimensions: (i) the 'mathematical solution concepts' - optimization or simulation, partial or general equilibrium, limited or perfect foresight; (ii) system boundaries - sectoral, regional, temporal; and (iii) the level of detail or heterogeneity - technological, spatial (urban/rural), income. Meanwhile, Sathaye and Shukla (2013) summarize the eight main sources of variation across model structures and assumptions that yield differences in results. These include energy demand drivers, resource costs and technology performance parameters, endogenous technological change, and solution algorithms (e.g., intertemporal optimization, myopic with recursive dynamics). (Details for a sample of global IAMs are provided in the Supplementary Material).

IAMs also differ in their representation of energy end-user or consumer behavior. This 'behavioral realism' of models has not, heretofore, been meaningfully discussed in the literature. The objectives of this paper are: (i) to review relevant empirical literature on the behavioral characteristics of energy end-use; (ii) to assess the ways in which IAMs currently endogenize or reproduce key features of human behavior; and (iii) to develop and test a novel IAM formulation for representing heterogeneous consumer groups with varying preferences. Throughout, the focus is on light-duty vehicles and consumers' purchase decisions.

1.2 Why behavioral realism in IAMs is important

Climate change mitigation scenarios and the IAMs that generate them are increasingly being designed to be more 'realistic' by incorporating features observed in the real world. Such real-world features include delays in concerted global mitigation action (e.g., Riahi et al. (2015)), fragmented policy approaches (e.g., Tavoni et al. (2013)), and the absence from mitigation portfolios (either for political or social reasons) of specific low-carbon technologies or resources, such as nuclear power or biofuels (Riahi et al., 2012, Kriegler et al., 2014, Krey et al., 2014). Such features are for the most part modeled using exogenous assumptions that are consistent with the overarching scenario narrative.

Another important feature of the 'real world' relates to human behavior. IAMs generally represent the behavior of consumers or energy end-users in a stylized way through simplified economic relationships: energy demand as a function of price, technology investments to minimize levelized costs, and so on. (The same basic arguments apply equally to producers or firms (e.g., Laitner et al. (2003)), but the emphasis in this paper is on energy consumers.)

With their necessary levels of aggregation, IAMs do not represent individual interacting decision makers, but rather 'representative agents' that describe aggregate behavior at the mean (Conlisk, 1996, Laitner et al., 2000). Representative agents act 'as if' they were perfectly rational. Rational choice implies: (i) decision makers with known and fixed preferences; (ii) utility-maximizing decisions; and (iii) perfect information about all decision alternatives and their attributes. As Laitner et al. (2000) argue: "the crucial question is whether the behavior that is actually carried out by the economic agents has different consequences for economic modeling of climate policy than the 'as if' presumption of maximisation" (p. 19).

A cursory review of the evidence suggests this is indeed the case. Behaviorally-realistic models of many different forms show the important influence of behavioral assumptions on policy-relevant outcomes in the energy economy (e.g., Rivers and Jaccard (2006); Sun and Tesfatsion (2007)). In addition, a mass of empirical evidence has accumulated on behavioral influences on energy use, end-use technology adoption, and resulting emissions (e.g., Lutzenhiser (1993); Ayres et al. (2009)). Rivers and Jaccard (2006) argue that because characteristic 'real world' features of human behavior are notably absent from IAMs, the models have inherent limits for informing policy making. In addition, IAMs are largely unable to explore the detailed consequences of explicit behavior change policies.

In sum, there are various reasons for trying to improve how IAMs represent end-user behavior and decision-making:

- Empirical evidence clearly shows that end-user behavior has many features that are not captured by representations of unbounded rationality (Gillingham et al., 2009, Lutzenhiser, 1993, Stern, 1992).
- Theories and concepts of behavior and decision-making across the social sciences variously emphasize the many influences on end-user behavior beyond costs and prices (Wilson and Dowlatabadi, 2007).
- Models lacking behavioral realism are limited in their ability to evaluate energy efficiency policies and other influences on end-user demand (Rivers and Jaccard, 2006).
- Improving the behavioral realism of models substantially affects policy-relevant model analysis of climate change mitigation (Mattauch et al., 2015).

1.3 Behaviorally realistic energy end-users

There is extensive microeconomic evidence for features of real-world decision making that deviate from the axioms of rational choice (Camerer et al., 2004, Kahneman and Tversky, 2000, Avineri, 2012). Gillingham et al. (2009) review these behavioral features in relation to energy end-users and find that: (i) consumers are loss-averse and so respond asymmetrically to expected losses and gains (e.g., upfront costs and future cost savings) (Greene, 2011); (ii) decisions are boundedly rational in the sense that finding and processing information is costly and imperfect; (iii) decision making uses heuristic (short-cut) rules which are non-optimizing (e.g., a habit heuristic - do what you did last time) (Shogren and Taylor, 2008). Investments into energy efficiency, in which an upfront cost is traded off against uncertain expectations for future cost savings, are particularly susceptible to such behavioral features.

Empirical research on the 'energy efficiency gap' has shown that end-users do not adopt energy-efficient technologies based solely on a cost-effectiveness criterion (using levelized costs at market discount rates) (Gillingham et al., 2009, Jaffe and Stavins, 1994). Explanations and perspectives vary, but most tend to invoke 'barriers' to otherwise cost-effective technology adoption decisions: "Certain characteristics of markets, technologies and end-users can inhibit rational, energy-saving choices …" (p. 148, Levine et al. (2007)).

The complexities of energy end-user behavior are illustrated by Mundaca et al. (2010) who review the empirical literature and find that preferences for energy-efficient technologies are expressed over a wide range of non-monetary attributes and that decisions are non-optimizing and based on imperfect information. They conclude "the literature shows that … capital and operating costs … represent only a part of a great variety of determinants that drive consumers' energy-related decisions regarding technology choices … even in the presence of perfect information, a larger set of determinants can still lead to irrational ... decisions" (p. 317, Mundaca et al. (2010)). Other research shows the importance of decision makers' attitudes and socio-demographic characteristics (Guerin et al., 2000). The status and position of decision makers within social networks is also influential as technology adoption signals status and prompts social recognition (Axsen and Kurani, 2012).

Table 1 describes behavioral features associated with energy end-use, and specifically vehicle choice. The table provides an initial bridge from diverse theoretical and empirical literatures on behavior and decision making to the more specific challenge of modeling behavioral influences on vehicle choice. It uses a simple typology that distinguishes behavioral features related to (i) individual decision making, (ii) social influences, and (iii) contextual conditions within which decisions are made. Each of these is illustrated for vehicle choice drawing on examples from empirical studies (see also Avineri (2012).

This typology is analogous to the approach of Mattauch et al. (2015), who apply behavioral economic evidence reviewed by DellaVigna (2009) to mobility-related behavior, with a particular emphasis on modal choices and mode-shifting. They distinguish behavioral features relating to choice mechanisms (preferences, beliefs, decision-making), physical environment, and social context.

The typology of behavioral features in Table 1 also includes heterogeneity, i.e., variation or differences between end-users. Heterogeneity cuts across the three other types of behavioral features. Allowing for heterogeneity in decision preferences or influences enables other types of behavioral features to be considered (Element Energy, 2013, Axsen et al., 2015). As an example, heterogeneous adoption propensities among end-users are an enabling feature for social influence effects (Rogers, 2003). Introducing heterogeneity among consumers is also important for addressing the problems with mean representative-agent assumptions (Kirman, 1992). Avineri (2012) find that “specific attention should be given to the notion of heterogeneity in travel choice making and in travellers’ responses to interventions”. With reference to general equilibrium IAMs, Laitner et al. (2000) argue that “… the device of the representative agent is highly questionable … even if one accepts the utility-maximizing consumer as a model for individual decision making, it is not valid for aggregate decision making … [unless] one makes the explicit assumption that consumers are virtually identical. But this is clearly at odds with reality” (p. 26, our emphasis). Mercure et al. (2016) draw a similar conclusion in relation to global IAMs more generally. Heterogeneous end users are therefore central to the behavioral realism of IAMs. The potential downside of modeling heterogeneity is that it can significantly increase computational requirements, though previous experience has shown this to be tractable (Rausch and Rutherford, 2010).

TABLE 1. BEHAVIORAL FEATURES OF ENERGY END-USERS, EXAMPLES RELATED TO VEHICLE CHOICE, AND EXISTING IAM REPRESENTATIONS (SEE TEXT FOR DETAILS).

Behavioral Feature		**Description of Behavioral Feature of Energy End-Users**	**Examples of Behavioral Features Related to Vehicle Choice**	**Examples of Current Methods Used to Represent Behavioral Features in IAMs**
Heterogeneity		Differences in decision maker characteristics and responses to external influences, including socio-demographics and propensity for technology adoption.	e.g., early adopters are attracted by new vehicle types. e.g., younger, female drivers are more likely to purchase alternative fuel vehicles (Baltas and Saridakis, 2013, Beggs and Cardell, 1980, Belgiawan et al., 2013, Choo and Mokhtarian, 2004, Axsen et al., 2015)	logit function parameters calibrated to ensure heterogeneous market share of technologies + see under non-market discount rates
Individual	**Bounded rationality**	Costs of searching for and acquiring information on decision alternatives.	e.g., myopia, limited search (Baltas and Saridakis, 2013, Hocherman et al., 1983, Jansson et al., 2010)	not modeled
	Non-optimizing heuristics	Decisions in familiar, repeated contexts influenced by past experience (habit, inertia, loyalty).	e.g., current vehicle ownership and use patterns determine future vehicle type (Baltas and Saridakis, 2013, Hocherman et al., 1983, Mannering and Winston, 1985, Mannering et al., 2002)	not modeled
	Non-monetary preferences	‘Intangible’ non-monetary costs and benefits specific to particular decision contexts.	e.g., influence on vehicle purchase decisions of aesthetics, brand, status, functionality, performance, refueling (Baltas and Saridakis, 2013, Darzianazizi et al., 2013, Wu et al., 2014)	value of time or time budgets included in preference function + see under heterogeneity

	Non-market discount rates	Implicit discount rates estimated from market behavior are significantly higher than interest rates.	e.g., strong immediacy effects in preferring lower capital costs to lower discounted fuel costs (Beggs and Cardell, 1980, Allcott and Wozny, 2014) e.g., loss aversion in relation to uncertainty about net value of future fuel savings weakens preferences for fuel efficient vehicles (Greene, 2011)	varying discount rates per consumer segment as a function of income, location (e.g., urban-rural)
Social	**Social influence**	Imitation (herding, bandwagon) effects, distinction (status-seeking), or neighborhood effects linked to visibility of others' behavior.	e.g., social influences have an important effect on purchase decisions relative to purchase price (Gaker et al., 2010) or fuel economy (Peters et al., 2015)	not modeled
Contextual	**Contextual conditions**	Behavior is influenced, constrained, or determined by infrastructure, the physical environment, or other contextual factors.	e.g., influence of refueling infrastructure on alternative fuel vehicle adoption (van Bree et al. 2010; Tran et al. 2010) e.g., transit accessibility linked to residency and residential density predict vehicle type (Kitamura et al., 2000, McCarthy and Tay, 1998)	exogenous constraints linked to infrastructure availability
	Political and social institutions	Institutions and culture shape decisions and behavior through social norms, availability and type of choices.	e.g., marked cultural variation in preferred vehicle attributes (size, speed, designs) (Dijk et al., 2013)	not modeled

1.4 Behavioral realism in current energy-economy models and IAMs

Current modeling of behavioral features in energy-economy and integrated assessment models is relatively limited. Mundaca et al. (2010) review 20 modelling studies evaluating energy-efficiency policy in households using 12 different bottom-up models at either global or national scales. They find that all the models represent homogeneous end-users making unboundedly rational investment decisions. In some cases, high (above-market) discount rates are used as a means of reproducing sub-optimal adoption rates of cost-effective energy-efficient technologies. The CIMS model of the Canadian energy-economy is different in that it draws on empirical studies of either observed market behavior or stated preferences in discrete choice surveys in order to estimate non-monetary preferences, end-user heterogeneity, and non-market discount rates (Jaccard and Dennis, 2006, Rivers and Jaccard, 2006). The heterogeneity of end-user decisions is simulated by multinomial logit functions allocating market shares to competing technologies. Non-market discount rates capture end-users' strong aversion to delayed financial benefits. The parameters describing these behavioral features are context-specific to different decision nodes in the model (e.g., vehicle purchase, commuting mode, and so on) (Rivers and Jaccard, 2006). Other models making an explicit attempt to better represent behavioral realism include (i) BLUE (Behaviour Lifestyles and Uncertainty Energy model for the UK), which considers features such as market heterogeneity, intangible costs and benefits, hurdle rates, replacement and refurbishment rates and demand elasticities (Strachan and Warren, 2011, UCL, 2015); and (ii) Res-IRF, which assesses future household energy demands in France, considering barriers to energy efficiency in the form of intangible costs, consumer heterogeneity, and learning-by-doing (Giraudet et al., 2011). The UK Transport Carbon Model provides an example of how a transport sector-focused, logit-based discrete choice framework can be linked to an optimization-based energy systems model at the country level, in order to model vehicle choice and service demand projections across all modes of transport (Brand et al., 2012, Anable et al., 2012).

Laitner et al. (2000) examine top-down, general equilibrium models, which similarly characterize decision making in the aggregate as consistent with rational choice. These models generally exclude the behavioral features summarized in Table 1, although to some extent, social and contextual influences are implicit in the econometric estimation of parameters such as income and price elasticities, or the elasticities of substitution between capital, labor and energy. Mercure et al. (2016) provide a more recent critique of global IAMs for their lack of behavioral realism, emphasizing the importance of consumer heterogeneity.

Table 1 summarizes the approaches to behaviorally-realistic modeling in a group of ten widely-used global IAMs (see Supplementary Material, SM, for details). General, model-wide approaches for incorporating behavioral realism are substantially different between model set ups (see also IRGC (2015)). Technology-rich bottom-up IAMs using inter-temporal optimization (e.g., DNE21+, TIAM-UCL, MESSAGE) commonly vary discount rates as a general approach to modeling heterogeneous end-user behavior as a function of income, technology characteristics, or adoption context (e.g., country or region). For example, Ekholm et al. (2010) introduce heterogeneous discount rates for cooking appliances in less-developed economies to improve the modeling of energy access. Discount rates are thus used as a proxy measure of many different behavioral features and should not be interpreted solely in terms of time preference. In contrast, simulation models with limited temporal foresight and a recursive-dynamic modeling approach (e.g., GCAM, IMAGE) use multinomial logit functions to model heterogeneous end-user preferences and resulting market shares of competing technologies. These logit functions are calibrated to empirical data (when available), and the calibration parameters are used as a proxy for all the non-monetary preferences and other behavioral features influencing observed adoption behavior during the historical calibration period. Modeling approaches specific to vehicle choices are also summarized in Table 1. These include, for instance, incorporating time budgets or the value of time in transit (linked to the wage rate) within the consumer preference functions; technology-specific discount rates have also been used in some models.

In sum, current modeling of behavioral features in global IAMs is relatively limited and quite varied, both between models and across a single model's different sectors. It is also dominated by model-wide formulations that aggregate behavioral influences, masking the specific underlying behavioral features. Furthermore, as is the case with future-oriented modeling more generally, there is the issue is that the uptake of new technologies is commonly based on historically calibrated parameters derived from consumer experiences with established technologies, even if those new technologies may be wholly different from the status quo in numerous ways.

2 BEHAVIORAL FEATURES OF VEHICLE CHOICE

2.1 The importance of vehicle choice to energy use and emissions

Our principal aim in this paper is to explore how the behavioral realism of IAMs can be improved, given their current structure and function. We use the specific case of new vehicle choice (vehicle adoption) to illustrate our argument. End-user choices of vehicles are important for many reasons. In

IAMs in particular, vehicle purchase is a technology adoption decision that strongly influences energy and emission outcomes (Girod et al., 2013). The global transport sector already comprises ~20% of total energy use and carbon dioxide emissions, with light-duty vehicles (LDVs; passenger cars and trucks/SUVs) accounting for just under half of energy and emissions within the sector (IEA, 2015). Moreover, transportation is arguably the hardest end-use sector to decarbonize, making end-user vehicle choices a critical determinant of low-emission futures (Riahi et al., 2012). Mobility is an energy service that is written into the fabric of social and economic activity, is strongly associated with development and modernity (Urry, 2008), and involves a wide range of socio-economic actors (Marletto, 2014). Vehicle preferences are highly heterogeneous, and vehicles are socially-visible technologies with many non-financial attributes. The behavioral features identified in Table 1 are therefore quite relevant for vehicle choice, as highlighted by examples in the table.

Previous integrated assessment modeling studies exploring the role of transport in low-carbon worlds (Bosetti and Longden, 2013, Gül et al., 2009, Hedenus et al., 2010, Kyle and Kim, 2011, Rösler et al., 2014, McCollum et al., 2014, Pietzcker et al., 2014, Girod et al., 2013) have not explicitly taken heterogeneity- and/or behavior-related considerations into account when developing their scenarios, or have only done so in a limited way (e.g., by using empirics to parameterize logit formulations, but still for mean representative-agents). The work described here intends to fill this gap in the literature.

2.2 Evidence for behavioral features relevant to vehicle choice

There is a mass of empirical studies examining vehicle choices using a range of methodologies, data and theoretical approaches. Wilson et al. (2014) review over 80 such studies focusing on alternative fuel vehicles (AFVs). They find evidence across the typology of behavioral features set out above. Table 1 includes specific examples and illustrative studies. The strength of the evidence base is summarized below in Table 2.

Social and contextual influences on vehicle choice are consistently found to be important (see also Mattauch et al. (2015)). As examples, the availability and proximity of refueling/recharging infrastructure for alternative fuels (hydrogen, electricity) as well as the social signaling and early experiences communicated by the visible use of novel vehicles by early adopters mean that diffusion has spatial, neighborhood characteristics.

Vehicle attributes in addition to price and operating cost (fuel efficiency) are also influential on choices. Non-monetary attributes of vehicles include range, carbon dioxide emissions, engine power, model availability, and so on. Discrete choice experiments using stated preferences are particularly useful for identifying important attributes of novel vehicle types not yet available in the mass market. Discrete choice studies also model revealed preferences to estimate the relative weighting of observable non-monetary attributes in relation to price. In this way, non-monetary preferences can be expressed in monetary equivalents in an overall utility function describing vehicle choice.

2.3 Vehicle choice representations in current IAMs

Vehicle choices in IAMs depend on a variety of assumptions, ranging from demand projections to technology-specific characteristics. (See SM for full details in one particular IAM, MESSAGE). Total service demand for mobility is typically exogenous and/or linked to GDP or prices through parameterized price and income elasticities. Optimization-based models then find least-cost vehicle fleets to meet these demands, often subject to constraints on vehicle shares and growth. Available vehicle types (fuel, drive-train) vary in complexity, but most models distinguish at least the main fuel types (fossil liquid fuels, biofuels, electricity, hydrogen, natural gas). At each time step, the model deploys a certain number of vehicles of a particular type (or in the more aggregated models, a certain quantity of fuel), in an effort to minimize the lifecycle costs (amortized capital + fuel + operation and maintenance) of meeting the service demand requirements. Capital costs and fuel efficiency per vehicle type are exogenously specified, while fuel costs are calculated endogenously. (Some models may use cost per unit of service as alternative inputs; or they may endogenize capital cost declines over time through learning.) Average operating lifetimes define capital stock turnover and vehicle replacement rates. Models additionally use diffusion constraints (or in the case of simulation models, market heterogeneity parameters) to ensure that transitions away from previously cost-competitive vehicle types are not overly abrupt.

From a behavioral perspective, models therefore have representative decision makers with perfect (global) knowledge of all technologies' capital and operating costs, conversion efficiencies, and other technical parameters. Although this example is specific to optimization-based models, Laitner et al. (2000) discuss very similar issues with general equilibrium-type IAMs.

2.4 Modelling behavioral features of vehicle choice in IAMs

Laitner et al. (2000) note the difficulty of behaviorally-realistic modeling, particularly given the time and resource investments in design, construction and parameterization of IAMs. Focusing on top-down, general equilibrium-type IAMs, they suggest various improvements that are more or less compatible with model designs, including: (i) sector or technology-specific discount (i.e., investment hurdle) rates, which can be reduced by non-price policies and programs, (ii) co-benefits of energy technologies in decision functions, (iii) heterogeneity among agents and their interactions.

This is in broad agreement with our review of the evidence base, as summarized in Table 2 (for further details, see Wilson et al. (2014)). Sector- and technology-specific discount rates correspond with heterogeneous preferences and contextual conditions. (Some models already differentiate discount rates by technology, but not for different types of consumers.) Co-benefits correspond with non-monetary preferences. Heterogeneous agents distinguished by adoption propensity, location, or driving patterns are a necessary enabling feature of the other behavioral features.

TABLE 2. REPRESENTING BEHAVIORAL FEATURES OF VEHICLE CHOICE IN GLOBAL IAMS. EACH FEATURE IDENTIFIED IN THE LITERATURE IS SUBJECTIVELY ASSESSED (YES-MAYBE-NO) IN TERMS OF WHETHER IT WOULD BE POSSIBLE (TRACTABLE TO MODEL), USEFUL (IMPROVING POLICY-RELEVANT ANALYSIS), AND CONSEQUENTIAL (IMPACTING RESULTS) TO BE REPRESENTED IN GLOBAL IAMS.

Behavioral Feature	Description	strength of evidence	tractable	policy lever	impact
Heterogeneous socio-economic characteristics	Age	medium	maybe	no	maybe
	Gender	medium-low	maybe	no	no
	Number of children	low	maybe	no	maybe
	Education	medium-low	maybe	no	maybe
Heterogeneous preferences	Adoption propensity	high-medium	maybe	maybe	yes
	Driving practices	low	no	no	maybe
	Environmental concern	medium	maybe	no	yes

	Attitudes to vehicles	high-medium	maybe	no	less
Non-monetary preferences	Refueling network	high	yes	yes	yes
	CO_2 emissions	high-medium	yes	yes	yes
	Range, battery time, warranties	high	yes	maybe	yes
	Vehicle range	high-medium	yes	no	yes
Social influences	Neighborhood effects	high	maybe	yes	yes
	Information transmission	high	maybe	maybe	yes
Contextual conditions	Refueling availability	high	maybe	yes	yes
	Refueling location	medium	maybe	yes	yes
	Incentives	high	yes	yes	yes

For each type of behavioral feature evidenced empirically in relation to vehicle choice, Table 2 also summarizes – based on the authors' qualitative judgement – whether it would be possible (tractable), useful (policy-relevant), and consequential (affects outcomes) to be represented in global IAMs.

If the inclusion of heterogeneous decision agents within modeling frameworks is a necessary condition for representing behavior, then modelers must decide what is possible to represent and how best to do this. Table 2 evaluates whether including such features in IAMs would be tractable; in many cases the answer is not clear. It is neither appropriate nor reasonable to propose a single, standardized approach for incorporating behavioral realism into IAMs, as no two IAMs are exactly alike, and IAM research groups have distinct research interests, focusing on different sets of research questions. While the disaggregation of end-users is clearly important, whether this is done directly within the core part of the IAM or simply reserved for an external model to deal with depends on the particular modeling arrangement. Logit and other types of discrete choice models are a common means of representing vehicle purchase decisions in the empirical literature. Hence, simulation-based IAMs, which already make use of logit functions, may be able to endogenize such heterogeneous information more directly within their solution frameworks. Optimization-based IAMs, on the other hand, may find this task more difficult and therefore may instead prefer to soft-link with an external model. Under that arrangement, an IAM would continue to represent average, per-capita characteristics of end-users within its core, while the external, more detailed model would contain all of the heterogeneity and a range of non-optimal characteristics of real-world vehicle choices. Hybrid approaches are also possible, as demonstrated by a model application later in this paper.

The question of how much heterogeneity and how many behavioral features to include in a modeling framework (whether endogenized or soft-linked) is also an important one. As a simple heuristic, IAMs should only explicitly represent what is needed to address the relevant research questions under study. This is why 'policy lever' and 'impact' are included in Table 2 as key criteria for selecting which behavioral features to prioritize: would inclusion of these features allow IAMs to examine a range of policy instruments, and which features would impact key energy and emission outcomes? In the case of vehicle purchase decisions, models should, if possible, disaggregate the consumers of their light-duty vehicle sectors (passenger cars and trucks/SUVs) in ways that allow for explicit representation of the most influential behavioral features: non-monetary preferences (e.g., vehicle range), social influence (e.g., risk aversion), and contextual conditions (e.g., refueling infrastructure).

The remainder of this paper explores how consumer heterogeneity and non-monetary preferences can be introduced into IAMs, using one such model, MESSAGE, to demonstrate and test the approach. More specifically, we detail a novel model formulation that is flexible and simple enough to be applied to global IAMs with different structures and solution algorithms, yet richly detailed enough to capture the most influential behavioral features that have been identified in the empirical evidence base, as summarized above. First, we briefly describe the concept and methodological approach in a way that should be accessible to other transport-energy analysts and modelers. Then we present scenario results both before and after the new model implementation to illustrate the usefulness of the method. Finally we reflect on ways to improve the modeling further as well as new areas of research that future work could explore. We consider a variety of alternative fuel vehicles in our analysis: biofuel and natural gas internal combustion engine (ICE) and hybrid-electric vehicles (HEVs), plug-in hybrid-electric vehicles (PHEVs), hydrogen fuel cell vehicles (FCVs), and battery-electric vehicles (BEVs).

3 CONCEPT AND METHODOLOGICAL APPROACH

The MESSAGE integrated assessment modeling framework[2] provides a suitable platform for demonstrating our proof-of-concept approach, given its sufficient level of detail within the transport sector and considering that the model is able to capture the complex interplay between this sector and all other energy producing and consuming sectors of the global economy. MESSAGE combines a global (multi-region, multi-sector) systems engineering, inter-temporal optimization model (Riahi et al., 2007, van Vliet et al., 2012), an aggregated macro-economic model, and a simple climate model, all within a consistent, inter-linked framework. MESSAGE is rich in technological detail on the supply side of the energy system (e.g., resource extraction, secondary fuel conversion, and fuel delivery and transport). In contrast to previous versions described elsewhere in the literature (Riahi et al., 2012, McCollum et al., 2014), the version of MESSAGE we employ here also includes a considerable amount of end-use detail in the transport sector. We distinguish this model version by referring to it as 'MESSAGE-Transport' in this paper. The detailed transport module in MESSAGE-Transport represents individual transport modes and the various technologies that can be used to satisfy demands therein. Passenger mode-shifting is also modeled, considering the relative costs (in terms of time and money) of traveling by the different modes. Such demand-side detail is necessary for improving the representation of heterogeneity and behavior in the light-duty vehicle sub-sector, which is the focus of the current work. (Detailed information on the standard version of MESSAGE, the novel features of MESSAGE-Transport, and the extended representation of vehicle choice are all provided in the SM.)

3.1 Including heterogeneity and behavior in the MESSAGE-Transport model

Representing behavioral features of vehicle choice in an IAM requires the mean representative decision-agent to be divided into distinct consumer segments characterized by different preferences

[2] The acronym 'MESSAGE' stands for: Model for Energy Supply Strategy Alternatives and their General Environmental Impact.

and vehicle use characteristics. This implies a two-step methodology, as first illustrated in Bunch et al. (2015) using the TIMES bottom-up modeling 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 "disutility costs", "intangible costs", or "non-monetary costs") on top of the vehicle capital costs already assumed in the model. These disutility costs link to the non-monetary preferences found to be influential in empirical studies (e.g., range anxiety, lack of refueling station availability, risk aversion; see Table 2), and are specific to particular consumer groups and technologies. They also vary by region and can decline over time, depending on the overarching scenario storyline. Further details about this methodology, as we have applied it in MESSAGE-Transport, are given below. For an extended discussion of the theoretical underpinnings of this integrated approach, see Bunch et al. (2015).

Step 1: introduce heterogeneity

In the most detailed formulation, LDV drivers within one of the eleven MESSAGE-Transport 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 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 lead to 27 unique consumer groups (Figure 1). All members of the entire driving population (within a particular model region) fall into one of these 27 groups. 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^{3}T model (Lin and Greene, 2011) (see below for further details, as well as the SM), Rogers's classification of technology adopter types (Rogers, 2003), and the urban-rural population projections developed in the Shared Socio-economic Pathways exercise (namely the median-level SSP2 scenario (KC and Lutz, 2015, Jiang and O'Neill, 2015, O'Neill et al., 2015, IIASA, 2015)).

Introducing heterogeneity into the LDV sub-sector requires that the relative shares among the 27 consumer groups be projected over time and by model region.[3] We then multiplied the time-varying

[3] We have estimated these 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 Excel workbook as part of SM). 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 MA^{3}T 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

%-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 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 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. For instance, in MESSAGE-Transport we have opted to keep all the cost and efficiency assumptions the same but have varied the capacity factors (veh-km/vehicle/yr) and vehicle lifetimes depending on the (regionally-specific) driving intensities of the different consumer groups (Modest/Average/Frequent).

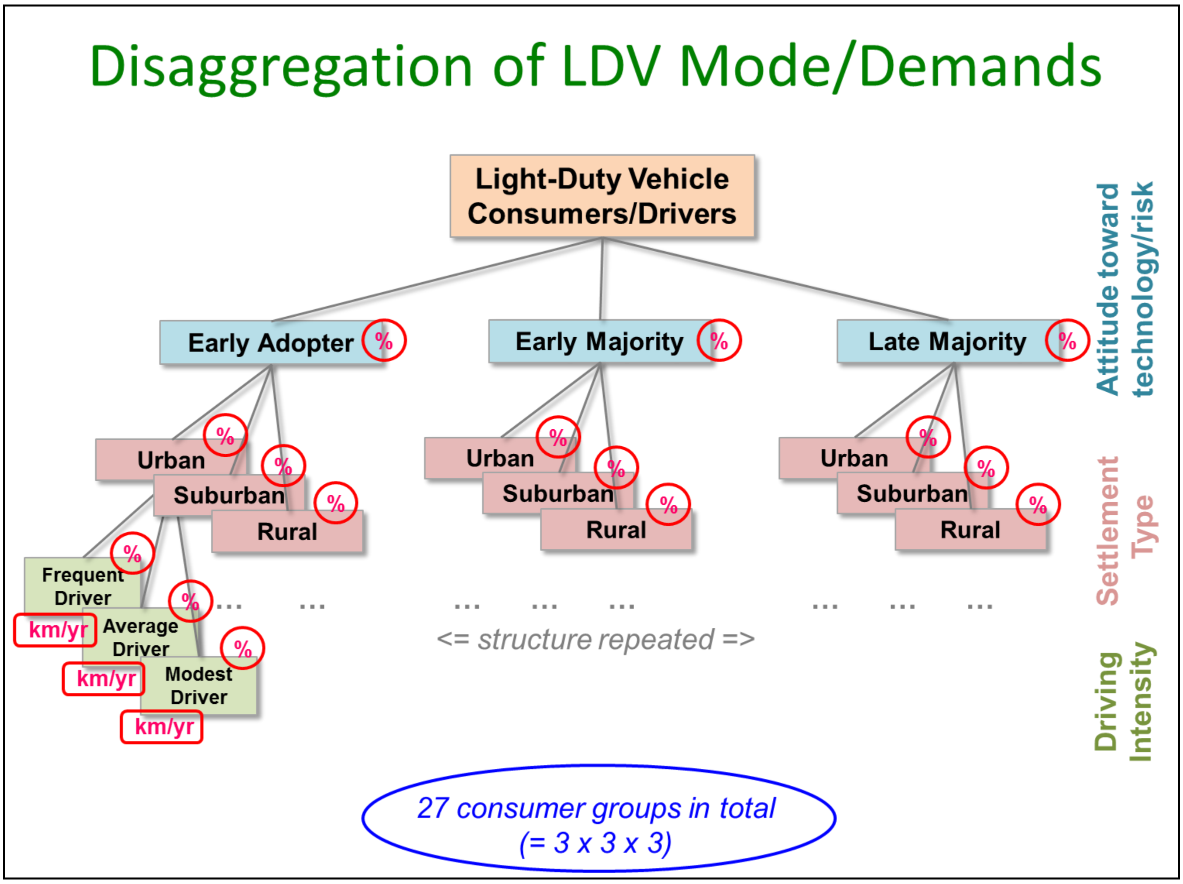

FIGURE 1. SCHEMATIC ILLUSTRATION OF HETEROGENEOUS CONSUMER GROUPS WITHIN THE LIGHT-DUTY VEHICLE SECTOR.

Step 2: add disutility costs

Once a disaggregated set of heterogeneous agents has been programmed into the model, the second important step is to assign disutility costs to each of the vehicle technologies that can potentially be purchased by a consumer within a given group. These disutility 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. The costs have been calculated using a

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and simplifications should be recognized at the outset, though they are not thought to be any larger than those surrounding the disutility cost estimates themselves.

specialized version of the MA^{3}T vehicle choice model (Market Acceptance of Advanced Automotive Technologies) (see http://cta.ornl.gov/ma3t/ or Lin et al. (2013b) and Lin et al. (2014) 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 for several years been developed by researchers at Oak Ridge National Laboratory (Lin and Greene, 2009, Lin and Greene, 2011, Greene et al., 2013, Lin et al., 2013a, Lin et al., 2014) 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^{3}T simulation at the point where these generalized costs are tallied, we are able to report the perceived costs (i.e., disutility costs) from the model.

As described more fully below, the disutility cost estimates we take from MA^{3}T 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 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^{3}T wherein assumptions regarding refueling station and recharging infrastructure availability were varied from 0% to 100% of network coverage in the US context (with finer gradation at the lower-end below 10% coverage). This allowed us to develop reduced-form relationships for these two disutility 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 disutility costs for a given fuel-vehicle type come down. (See SM for further details.)

Although the standard version of MA^{3}T considers a number of non-cost vehicle purchase attributes, we focus on five of these for implementation in MESSAGE-Transport (i.e., those comprising nearly the entirety of the total summed disutility costs; see SM for an illustrative comparison of all eight attributes considered in the original MA^{3}T formulation).[4] These disutility cost sub-components are listed below, with more detailed descriptions being given in Table 3. Most of these attributes have

[4] The version of MA^{3}T we employ also considers vehicle acceleration, cargo space, and towing capability as additional non-monetary attributes that may affect consumers’ preferences when making vehicle purchase decisions. These three disutility cost sub-components, however, are all estimated to be relatively small by MA^{3}T (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 disutility costs in our MESSAGE-Transport 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 really become important is when different LDV size classes, makes, and models are 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 MESSAGE-Transport.

been found in previous studies to be important determinants of AFV adoption (see 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 availability tend to dominate, depending on the particular vehicle technology, consumer group and region under consideration (see Table 3). Figure 2 provides an illustration of present-day disutility costs of several technologies for two different consumer groups in North America (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 disutility cost sub-components may be as little as ~15% or as much as ~165% of the actual vehicle investment cost. We also note that risk premiums are estimated to be relatively small on their own[5]; 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. Bunch et al. (2015) 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 availability (diversity of vehicles on offer)
5. Electric vehicle charger installation (home/work/public)

TABLE 3. SUB-COMPONENTS OF THE DISUTILITY COSTS DERIVING FROM THE MA^3T MODEL. COST RANGES APPLYING TO NORTH AMERICA (NAM) ARE SHOWN FOR ILLUSTRATION; OTHER REGIONS WOULD DIFFER.

Disutility 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. 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. (Gamma distributions in MA^3T depict daily driving requirements over the course of the year.) 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 NAM, initial costs (@ 0% recharging coverage) range from 0 to 40k $/vehicle for BEVs, depending on consumer group.	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 US and other countries/regions.
Refueling station availability	This attribute monetizes the perceived inconvenience and hassle felt by a consumer when	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. (Gamma distributions in MA^3T depict daily driving requirements over the course of the year.) Aggregating those time demands and converting them	Regional multipliers (calculated based on differences in WTPs between countries from discrete choice studies focusing on

[5] At least according to the framework employed here, which estimates risk premiums individually as part of a larger set of non-monetary attributes. If components like range anxiety, refuelling station availability and model 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.

	assessing his/her ease of access to refueling stations. Hence, this sub-component is only relevant for liquid fuel, natural gas, and hydrogen vehicles.	into a monetary values (also considering, according to other studies, that consumers put more value on the time associated with refueling) results in a disutility cost. Costs depend on vehicle ranges and efficiencies, daily driving distances, and the availability of refueling stations within the transport network. In NAM, initial costs (@ 0% refueling availability) range from 30k to 100k \$/vehicle for H2FCVs and 4k to 14k \$/vehicle for NGVs, depending on consumer group.	refueling infrastructure) are used to adjust costs between the US 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 affects a consumer's perception of the technology's novelty or unfamiliarity at any point in time. Costs start out at either -2.4k \$/vehicle (early adopters), +0.7k \$/vehicle (early majority), or +3.8\$/vehicle (late majority) when the respective vehicle stock is nil; they then approach zero as the stock grows, following an exponential function. Initial costs are the same across all regions, but the rate of decline to zero differs.	Regional multipliers (calculated based on differences in cultural values between countries using World Values Survey data) are used to adjust risk premia between the US and other countries/regions; in particular, the multipliers are applied to the exponential parameters governing the rate of the disutility sub-component decline as the respective vehicle market share grows.
Model 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. Costs start out at +7.5k \$/vehicle when sales of the respective vehicle type are nil (i.e., when the models on offer are limited); they then approach zero as sales grow (and numerous models become available), following a logarithmic function. Initial costs are the same across all consumer groups and regions, and the rate of decline to zero is the same in all cases.	[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).[6] Across all regions and over time, costs are 1k \$/vehicle.	[No differentiation by region]

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[6] This is a deviation from the original MA^{3}T paradigm. Normally, MA^{3}T only considers the installation cost for a home charger, not the costs borne by individual consumers for public chargers.

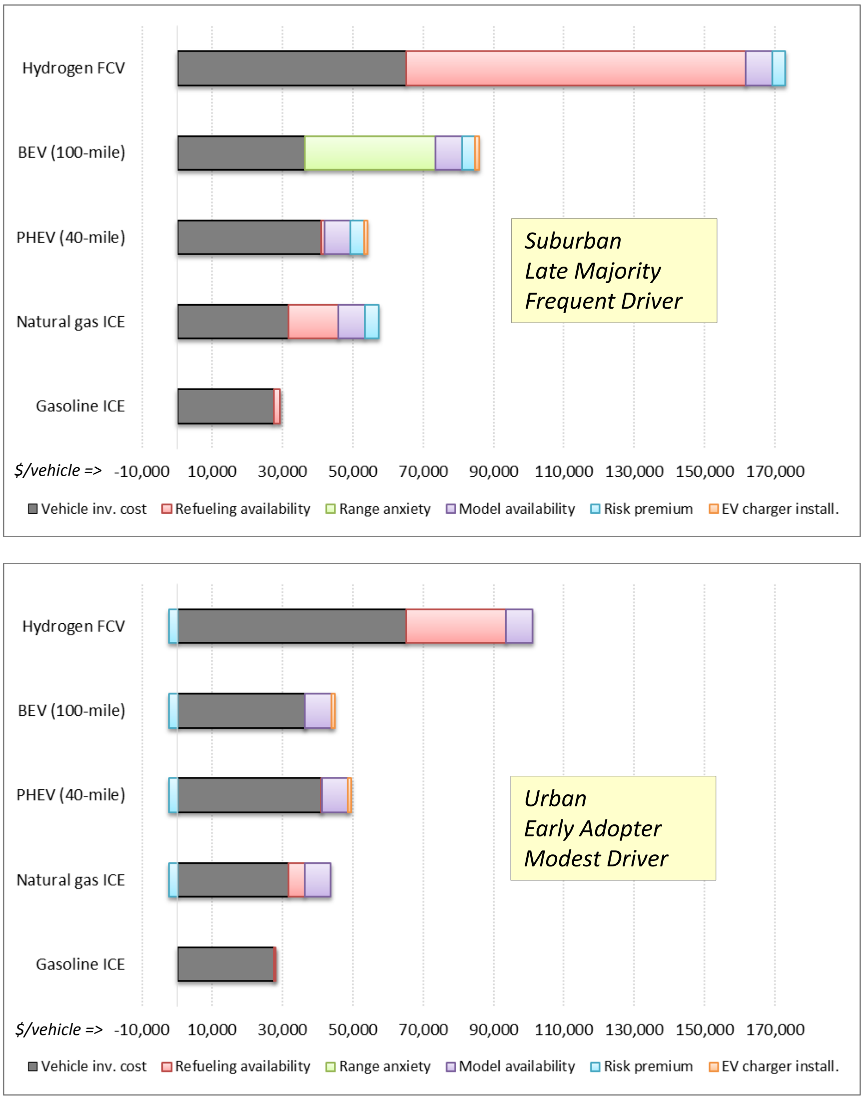

FIGURE 2. DISUTILITY COST ASSUMPTIONS FOR THE YEAR 2020, BY TECHNOLOGY AND FOR TWO DIFFERENT CONSUMER GROUPS. ESTIMATES FOR NORTH AMERICA SHOWN: $/VEHICLE. THE UNDERLYING CALCULATIONS ASSUME EXTREMELY LOW AFV SALES/STOCK AND VERY LIMITED REFUELING/RECHARGING INFRASTRUCTURE AVAILABILITY.

While MA^3T was originally developed with the US light-duty vehicle market in mind, we have determined through our analysis that the disutility costs generated by the model for the US can be extended to other countries and regions by applying simple “regional multipliers.” These multipliers are based on relationships between the different disutility 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; (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. (Further details are provided in the SM.) The regional multipliers are then applied to three of the five disutility 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 disutility sub-component decline as the respective vehicle market share grows.

Note that as part of the Supplementary Material made available with this paper, we include spreadsheets with calculations for the consumer group splits, the disutility 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.

3.2 Scenario design for illustrating the novel model formulation

To demonstrate the aforementioned approach to improving behavioral realism in the transport modules of IAMs, this paper primarily relies on four scenarios that sequentially incorporate an increasingly greater level of detail in the light-duty vehicle sub-sector. The scenarios move from a model implementation where light-duty vehicle choices are made by a single representative consumer (highly *homogeneous*) to one where non-monetary considerations are captured uniquely for a diverse array of consumers (highly *heterogeneous*). Table 4 summarizes the major characteristics of these four scenarios, focusing in particular on the dimensions where they differ. These differences reflect alternative model implementations of heterogeneity and behavior within the MESSAGE-Transport framework.

In two of these cases, disutility costs deriving from the MA^3T model are brought into MESSAGE-Transport, in order to capture non-monetary behavioral preferences through monetization. The empirical evidence suggests that the disutility costs should approach zero over time (i.e., the levels of conventional gasoline/diesel vehicles) as AFVs become more commonplace and their requisite refueling/recharging availability expands (see Table 2 and Table 3). How rapidly these costs might fall is uncertain, however. Hence, for a simple, stylized illustration of our proof-of-concept methodology, we have opted in this paper to hold the disutility costs constant at today's levels throughout the time horizon of the model. The embedded assumption here is that even if AFVs and their refueling/recharging infrastructure make inroads going forward, the disutility costs fail to come down over time (or come up to zero from negative values in the case of early adopters). This leads to future levels of AFV deployment in our scenarios that are on the conservative end of the spectrum; indeed, some auto markets (e.g., California, Norway) have already seen non-trivial levels of deployment of BEV/PHEVs and recharging infrastructure. We recognize that the stylized nature of our illustrative scenarios presented here misses some of these recent market developments, but again we stress that the focus of this paper is on detailing the theoretical and empirical basis for including behavioral realism in global IAMs and then highlighting the utility of doing so through a proof-of-concept implementation. Results for a modified version of our highly heterogeneous scenario that assumes non-frozen disutility costs can be found in the SM; future work could build on such scenario storylines.

TABLE 4. CHARACTERISTICS OF THE FOUR SCENARIOS USED TO ILLUSTRATE THE USEFULNESS OF CAPTURING HETEROGENEITY AND BEHAVIOR IN TRANSPORT.

Scenario name, ordering	Consumer group diversity	Representation of behavior
Homog_NoBeh	*Homogeneous* Single LDV service demand projection for each region. Vehicle technologies in this single group are	*None* Disutility costs are set at zero in all years.

	characterized by default model assumptions (e.g., for efficiencies, costs, driving intensities, lifetimes, etc.).	
Heterog_NoBeh	*Heterogeneous* LDV service demand projection for each region is disaggregated into 27 separate consumer groups, each with a differing market share. Vehicle technologies in different consumer groups are characterized differently (e.g., driving intensities, lifetimes, etc.).	*None* Disutility costs are set at zero in all years.
Homog_LimBeh	*Homogeneous* Single LDV service demand projection for each region. Vehicle technologies in this single group are characterized by default model assumptions (e.g., for efficiencies, costs, driving intensities, lifetimes, etc.).	*Limited* Disutility costs are frozen at today's levels throughout time. Costs for a single, representative group (UREMA) are applied. Costs vary regionally.
Heterog_DivBeh	*Heterogeneous* LDV service demand projection for each region is disaggregated into 27 separate consumer groups, each with a differing market share. Vehicle technologies in different consumer groups are characterized differently (e.g., driving intensities, lifetimes, etc.).	*Diverse* Disutility costs are frozen at today's levels throughout time. They vary across, and are unique for, each consumer group. Costs vary regionally.

All four scenarios are consistent with a global climate policy framework of moderate stringency. More specifically, a uniform carbon price (applying to all regions and economic sectors simultaneously) is implemented in 2020 and grows at an interest rate of 5%/yr until the end of the century, reaching 30 $/tCO_2eq$ (in US$2010) in the year 2040. Prior to 2020, a baseline path for energy use, vehicle deployment and emissions is followed (i.e., no major climate policies are assumed). The greenhouse gas emission trajectories resulting from these policies lead to atmospheric concentrations of CO_2 that are approximately 600 ppm CO_2eq in 2100 across the four scenarios; meanwhile, global mean surface temperature increase (relative to the pre-industrial level) amounts to 2.7 °C by the same year. Such a storyline for international climate policy is not meant to be entirely representative of how events are likely to play out in reality; rather, the simple narrative is used here for diagnostic purposes. Importantly, at this level of policy stringency, both oil products and alternative fuels are attractive in the standard model formulation, scenario Homog_NoBeh, i.e., neither completely dominates the market; and this is useful for gauging the impact of sequentially incorporating heterogeneity and behavior in the modeling.

4 RESULTS & DISCUSSION

4.1 <u>Impacts on light-duty vehicles</u>

Light-duty vehicle deployment portfolios over the century are shown in Figure 3 for each of the four scenarios described above. Significant differences in the portfolios are evident when moving sequentially from the highly homogeneous, single representative consumer implementation (Homog_NoBeh) to the highly heterogeneous implementation where various non-monetary considerations are captured uniquely for a diverse array of consumers (Heterog_DivBeh). The differences result from the compound effects of (i) making light-duty vehicle drivers more heterogeneous, and (ii) adding disutility costs to better represent non-monetary considerations. The magnitude of these two effects is by no means balanced, however: incorporating greater consumer detail has only a small impact (Heterog_NoBeh), whereas adding the disutility costs is seen to lead to large differences in the model results (Homog_LimBeh). Such outcomes are mainly driven by the scenario design, but are nevertheless informative, as they evidence the greater influence of adjustments to vehicle investment costs in the model solution than simply vehicle usage intensities and lifetimes (see below). The results can also be viewed in Table 5, which compiles a range of LDV-related metrics for the scenarios.

TABLE 5. SELECTED RESULTS FOR THE LIGHT-DUTY VEHICLE SUB-SECTOR IN EACH OF THE FOUR SCENARIOS. GLOBAL RESULTS ARE SHOWN ACROSS A RANGE OF METRICS; CUMULATIVE FROM 2010 TO EITHER 2050 OR 2100.

Metric of comparison	Scenario name, ordering							
	2010-2050				2010-2100			
	Homog_NoBeh	Heterog_NoBeh	Homog_LimBeh	Heterog_DivBeh	Homog_NoBeh	Heterog_NoBeh	Homog_LimBeh	Heterog_DivBeh
Oil products (gas./diesel) use (EJ)	1827	1771	1853	1805	3428	3252	4155	4039
Fossil synfuels use (EJ)	0.7	0.8	5.1	4.4	21	28	580	528
Biofuels use (EJ)	12	12	16	17	454	591	1523	1541
Natural gas use (EJ)	0	2.8	0	0	32	96	0	0
Electricity use (EJ)	15	16	0	0	1009	917	31	19
Hydrogen use (EJ)	0	0	0	0	0	0	0	0
Sales of BEV/PHEVs (mill. vehicles)	112	104	0	0	7443	6783	131	94
Carbon dioxide emissions, direct ($GtCO_2$)	134	130	136	133	255	246	342	330

Heterogeneity alone (Heterog_NoBeh) – without any consideration of non-monetary preferences– has an effect because of the varied driving intensities (vehicle-km/veh/yr; and, hence, vehicle lifetimes and fixed O&M costs) that are assumed for the different consumer groups. This means that certain vehicle types, such as natural gas ICEs, become more economically attractive for those drivers that travel substantial distances per year. Put another way, the fuel savings over the lifetimes of these vehicles – thanks to efficiency gains relative to gasoline/diesel ICEs, and also considering the lower fuel prices seen in the model for natural gas compared to gasoline/diesel – are large enough to compensate for their incrementally higher capital costs. This is only the case when driving intensities are higher, however; the opposite is the case for lower driving intensities.

Scenario Homog_LimBeh remedies this situation by adding disutility costs to the capital costs of all vehicle technologies, but doing so in a rather generic way by retaining the single representative consumer implementation. Yet, even without a detailed representation of heterogeneity, one sees an enormous difference in the model results, particularly from 2050 onward (Table 5 and Figure 3). (Note that none of the scenarios sees particularly large AFV deployment prior to 2050. This has to do with the moderate stringency of the assumed climate policy and the fact that near-to-medium term mitigation can be more cost-effectively carried out in other sectors of the energy system.) In particular, electric vehicles become far less attractive as a mitigation option, owing to the monetization of range anxiety concerns and those related to technology risk and limited model availability. ICEs running on gasoline/diesel, biofuels, and fossil synfuels (from coal or natural gas synthesis with carbon capture and storage) fill the gap left by the large reduction in BEV deployment. This happens because the disutility costs associated with these vehicle types are all assumed to be quite low, given widespread consumer familiarity at present with liquid fuels, namely gasoline/diesel, and their ubiquitous refueling infrastructure.

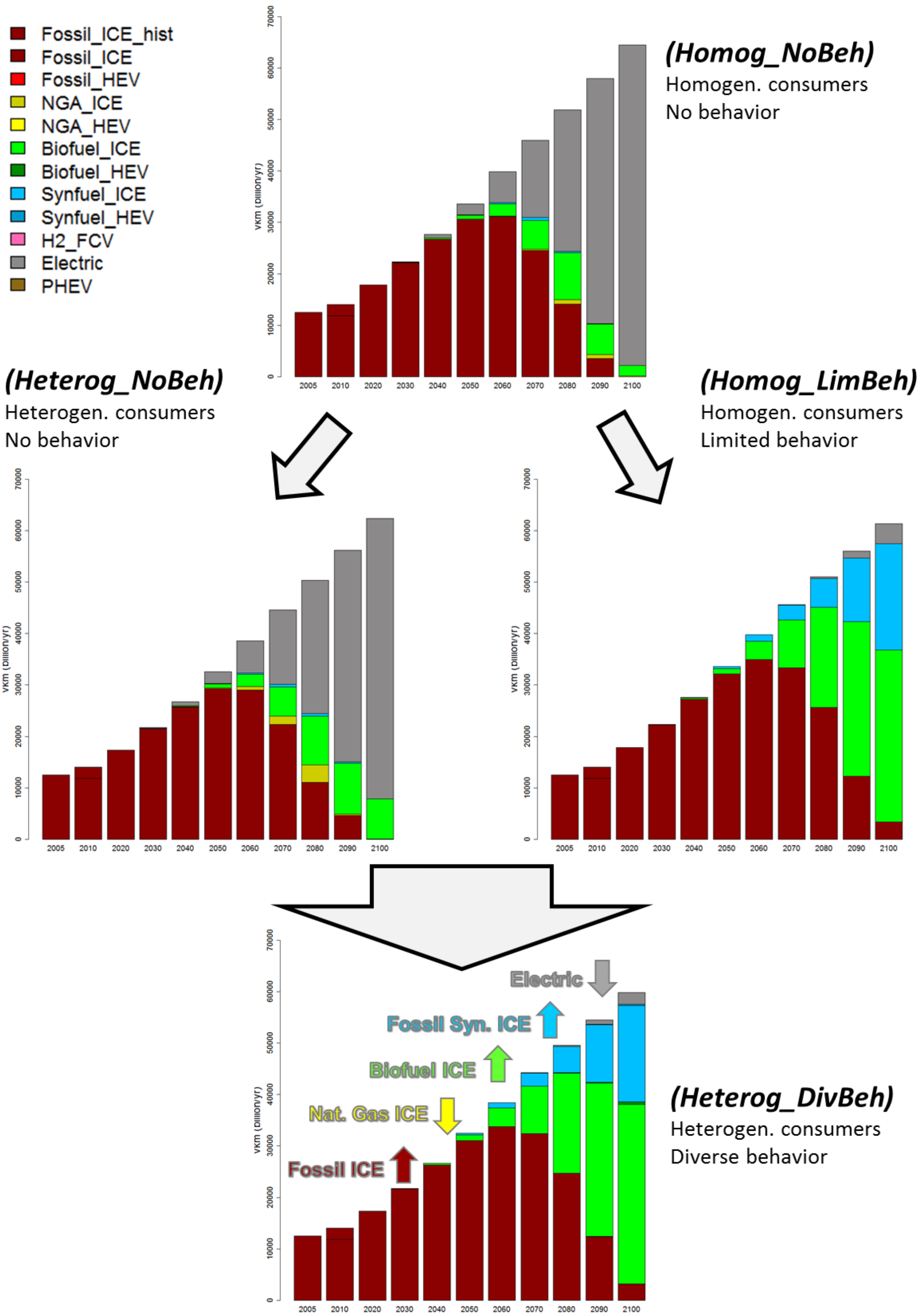

FIGURE 3. LIGHT-DUTY VEHICLE DEPLOYMENT FROM 2005 TO 2100, BY TECHNOLOGY, IN EACH OF THE FOUR SCENARIOS. GLOBAL RESULTS SHOWN: VEHICLE-KM/YR.

Scenario Heterog_DivBeh aggregates the combined, inter-related dynamics evident in scenarios Heterog_NoBeh and Homog_LimBeh, and for this reason it is the scenario with the lowest levels of electric vehicle deployment over the century. More specifically, compared to scenario Homog_NoBeh, the timing of BEV penetration is delayed by several decades, and combined sales of BEVs and PHEVs by 2100 are an order of magnitude smaller, as summarized in Table 5. Meanwhile, cumulative hydrogen and natural gas use by 2100, while not terribly large (or even zero) to begin with, drops even further. Increased numbers of fossil (gasoline/diesel and synfuels) and biofuel ICEs make up for the bulk of the shortfall in the low-carbon vehicle alternatives. As a result of these dynamics, and more generally because mitigating LDV CO_2 emissions becomes marginally more expensive from the perspective of the model, this scenario combining heterogeneity and behavioral considerations (Heterog_DivBeh) sees a much greater quantity of cumulative (direct) CO_2 emissions from LDVs than in scenario Homog_NoBeh. (The upscaling of low-carbon biofuels partly compensates for the drop in the other low-carbon fuels, but not entirely, due to the lower efficiencies of combustion engines relative to electric drivetrains.)

Underlying the aggregate results shown in Figure 3 are heterogeneous consumers having different preferences for vehicles. Figure 4 illustrates this by showing LDV deployment in scenario Heterog_DivBeh along alternative consumer group dimensions. Furthermore, the vehicle adoption decisions are found to vary quite markedly by world region, due, at least partly, to differences in non-monetary preferences for consumers in different countries (as evidenced by the empirical base and implemented in the modeling through the regionally differentiated disutility costs). This is shown in the SM for two regions with quite different characteristics: North America and South Asia.

Note that when viewed from the aggregate level, the differences between scenarios Homog_LimBeh and Heterog_DivBeh do not immediately appear to be great. However, at higher carbon prices, which further induce electric and hydrogen vehicles into the vehicle mix, more divergent behavior is observed, particularly between the consumer groups, and this leads to bigger differences between the scenarios that either do or do not include heterogeneity explicitly. To illustrate this point, the SM presents detailed consumer group results for a modified version of scenario Heterog_DivBeh that assumes higher carbon prices; these can be directly compared to the results shown in Figure 4. Furthermore, the similarities seen in Figure 3 between scenarios Homog_LimBeh and Heterog_DivBeh are partly driven by our experimental design, in particular the choice to illustrate our proof-of-concept methodology using disutility costs that are held constant at today's levels throughout the time horizon of the model. Were these costs to approach zero over time in response to increased AFV market share and refueling/recharging infrastructure availability, the differences brought about by including heterogeneity would be considerably more pronounced. This is because the disutility costs would vary in magnitude and decline rates across consumer groups. To illustrate this point, the SM also presents results for modified versions of scenarios Homog_LimBeh and Heterog_DivBeh that assume non-frozen disutility costs.

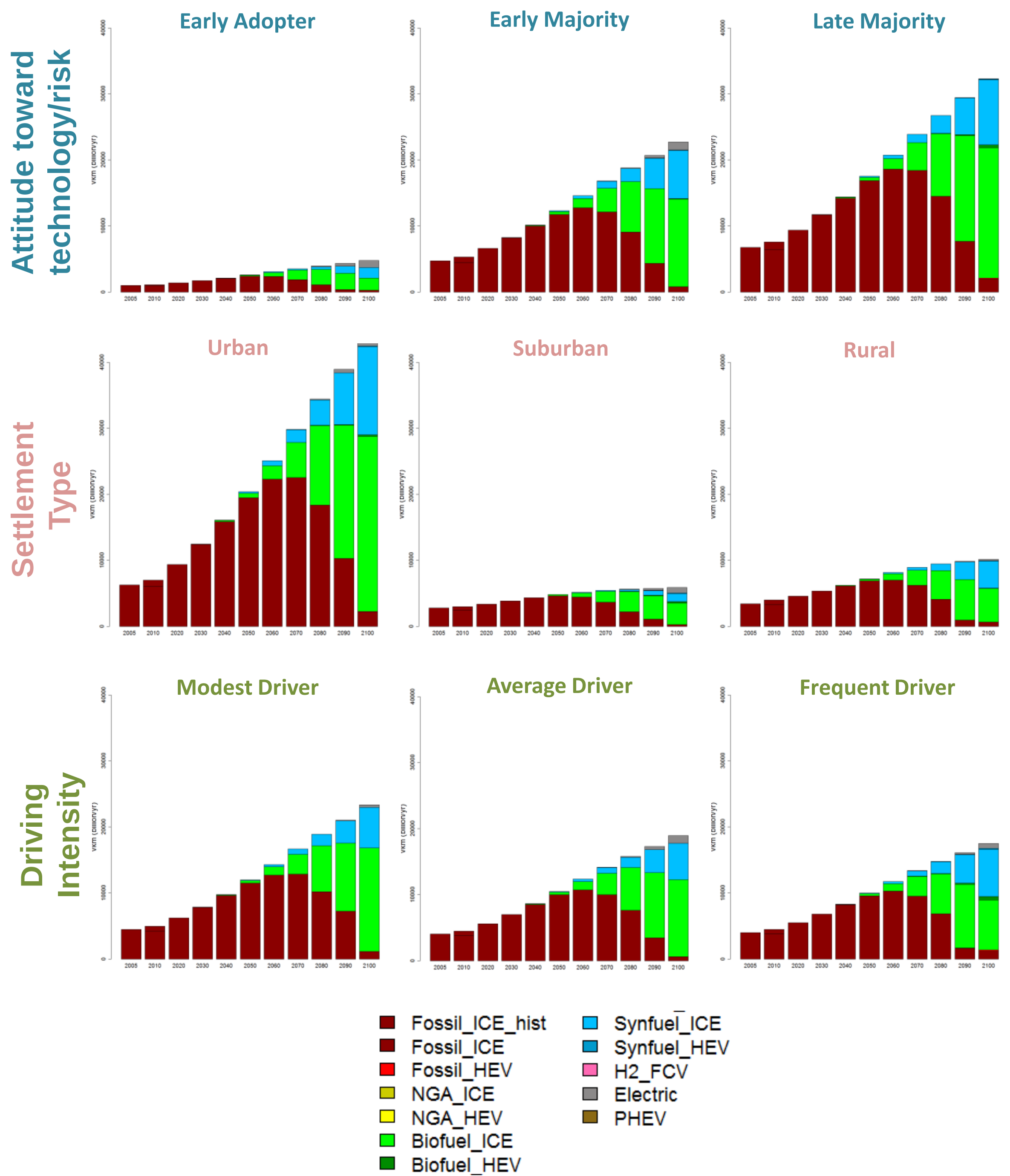

Figure 4. Light-duty vehicle deployment from 2005 to 2100, by technology and along alternative consumer group dimensions (sum across each dimension equals the total vehicle market). Global results shown: vehicle-km/yr.

4.2 System-wide impacts

The added value of capturing heterogeneity and non-monetary preferences of light-duty vehicle adoption (or any other energy end-use decisions) in an IAM, on top of an enhanced ability to generate more realistic scenario results, is that impacts can be assessed across the different parts of the inter-connected energy system. Multiple sectors compete, in a sense, for constrained energy supplies, or they may respond differently to changes in fuel prices. Similarly, because energy resources are not evenly distributed throughout the world, fuels must be traded, meaning that fuel-technology decisions in one place can have an effect elsewhere. While highlighting every system-wide impact brought about by our improved behavioral realism of vehicle adoption in MESSAGE-Transport is beyond the scope of this paper, a couple illustrative examples are highlighted below.

As presented in the SM, in scenario Heterog_DivBeh BEVs make inroads in the North American context post-2050 but 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. Part of this can be explained by differences in driving intensity levels between the regions (see SM for further elaboration). Another part can be explained by differences in electricity prices, and this is where system-wide considerations become important. Although not shown here, electricity prices in scenario Heterog_DivBeh are calculated (endogenously by MESSAGE-Transport) to be considerably higher in South Asia than in North America over the coming decades, which makes BEVs much less attractive in the former region. If MESSAGE-Transport were to not also have a detailed representation of upstream processes like electricity generation within its framework, then systemic effects of this type would not be possible to identify. In the same vein, the ability to simultaneously account for supply- and demand-side dynamics explains why biofuels deployment is found to be relatively small in South Asia (see SM): because of strict supply-side constraints on sustainable biomass feedstock availability in the region.

Another example of a systemic impact we are able to capture in MESSAGE-Transport relates to the estimation of climate policy costs. The inclusion of heterogeneous disutility costs into the cost accounting of the model leads to higher total costs for low-carbon mitigation options in the light-duty vehicle sub-sector. The corollary is that LDV CO_2 abatement becomes more expensive in the aggregate, shifting some of the mitigation burden to other sectors of the energy system where it can be more cost-effectively achieved. It also means a given carbon price has a lower impact on spurring LDV-related emissions reductions (direct emissions), relative to the single representative consumer implementation with no regard for non-monetary preferences. Table 5 already highlighted this insight for a single carbon price trajectory; Figure 5 goes further by presenting results for a range of carbon price trajectories across two distinct scenario groups. This allows for the estimation of two separate marginal abatement cost (MAC) curves for CO_2 mitigation in the LDV sub-sector globally: one for the highly homogeneous model formulation with limited behavioral realism (in the same family as scenario Homog_NoBeh) and another for the highly heterogeneous implementation including non-monetary preferences (in the same family as scenario Heterog_DivBeh). Emissions reductions are cumulative (2010-2100) and relative to the single representative consumer formulation. The individual points on the curves represent scenarios with different climate policy assumptions (i.e., alternative carbon price trajectories, in all cases rising at 5%/yr interest). Comparison of the curves reveals, for a given carbon price, systematically lower LDV CO_2 abatement in the scenarios capturing non-monetary preferences, as characterized by the leftward shift of the MAC curve exhibited in Figure 5. Put another way – viewing this effect as an upward shift of the MAC curve – when incorporating heterogeneity and behavior into the model, a higher carbon price is needed to achieve a similar level of CO_2 abatement. Such a finding has obvious implications for real-world policy making: namely that climate policies geared toward mitigation in the LDV sub-sector are likely to require stronger price-based policy incentives than has previously been suggested by integrated assessment and energy-economic model-derived scenarios, or alternatively that non-price-based policies in the LDV sub-sector (on both the vehicle and fuels side) will need to complement price-based regulations.

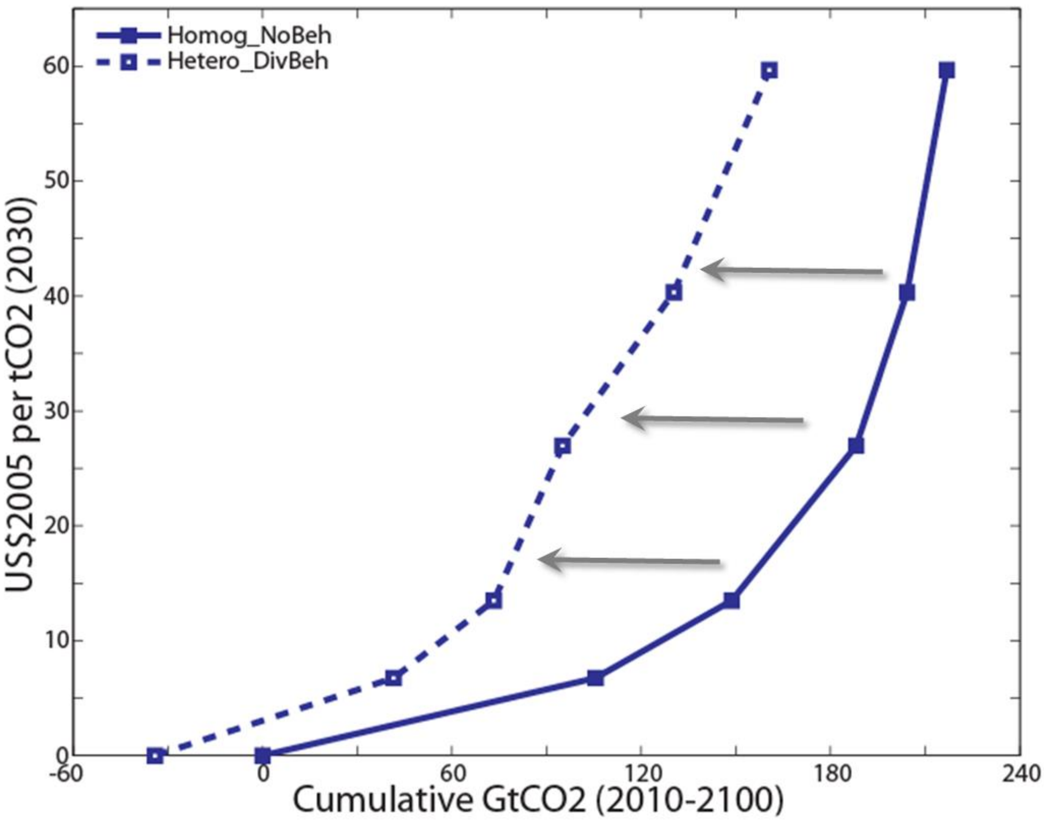

Figure 5. Marginal abatement cost (MAC) curves for CO_2 mitigation in the light-duty vehicle sub-sector globally. Two separate curves denote contrasting model formulations for representing consumer heterogeneity and non-monetary preferences. Individual points on curves represent scenarios with different climate policy assumptions. CO_2 reductions are cumulative (2010-2100) and relative to the single representative consumer formulation with limited behavioral realism (Homog_NoBeh). This explains the "negative abatement" (i.e., increased emissions) seen at zero carbon prices in the Hetero_DivBeh scenario. Carbon prices in the year 2030 are shown in US$2005. See text for further details.

5 CONCLUSIONS

Global integrated assessment models (IAMs) are widely used to evaluate the costs, potentials, and consequences of different greenhouse gas emission trajectories over the medium-to-long term. Representations of the social, technological and physical systems in IAMs are necessarily stylized and simplified. Yet, IAMs are increasingly being designed to be more 'realistic' by incorporating features observed in the real world. An improved representation of human behavior is at the frontier of research for IAMs, particularly in the area of non-monetary preferences of heterogeneous energy consumers and technology adopters. Capturing these behavioral features increases the usefulness of IAMs to policy makers by allowing the models to (more realistically) assess a wider range of policy measures. This paper demonstrates the value of incorporating behavioral features relevant to vehicle choice in the MESSAGE-Transport IAM framework. The model formulation developed is flexible and simple enough to be applied to a diverse array of IAMs, yet is detailed enough to capture the most influential behavioral features that have previously been identified in the empirical evidence base.

Several insights emerge from the scenarios that employ our new approach for capturing non-monetary considerations in the transport sector. We find representing heterogeneity and behavior significantly alters the model-estimated portfolio of light-duty vehicles deployed over the coming decades to meet climate mitigation targets: the timing of electric vehicle penetration is delayed by up to several decades, and hydrogen and natural gas use decrease significantly. Because mitigating LDV CO_2 emissions becomes marginally more expensive from the perspective of the model, the scenarios combining heterogeneity and behavioral considerations see a much greater quantity of cumulative (direct) CO_2 emissions from LDVs out to 2100 (i.e., less CO_2 abatement), for a given carbon price.

More generally, compared to what has been previously suggested by IAM-derived scenario analyses focusing on passenger transport, our findings indicate that:

- For climate change mitigation efforts driven solely by price-based incentives, a higher carbon price would be needed for achieving a specified level of LDV emissions abatement.
- In the absence of more stringent price-based incentives for low-carbon LDVs, emissions abatement in other transport sub-sectors (e.g., aviation, rail, freight trucks, shipping) and other energy sectors (electricity generation, industry, buildings) would have to increase for a given overall emissions budget.
- Non-price-based policies targeting the deployment hurdles for AFVs could counteract the reduced effectiveness of price-based incentives, particularly in the early-market phase of AFVs. Examples include vehicle or fuel emissions standards, mandates and subsidies, and refueling/recharging infrastructure support.

These insights highlight the unique value of bringing heterogeneity and non-monetary preferences into IAMs (for any energy end-use sector, but particularly transport), given that the strength of such models lies in their ability to capture systemic effects related to, for example, resource consumption, fuel prices, and emissions abatement across different sectors and regions. Moreover, IAMs with improved behavioral realism are able to assess a much wider suite of policies than before (i.e., not only price-based instruments), which will likely be crucial for future climate policy analyses utilizing these models. Specifically, IAMs could eventually weigh in on the debate over the effectiveness of price- vs. non-price-based policy instruments to incentivize transformational change in the transport sector (Mock and Yang, 2014, Creutzig et al., 2011, Heinrichs et al., 2014). This is particularly important in light of the fact that real-world climate policies are often implemented via instruments other than carbon pricing; in fact, many make use of a mix of instruments (Bertram et al., 2015, Jenkins, 2014).

We do, however, recognize certain limitations of our current approach to modeling heterogeneity and non-monetary preferences. For instance, we make exogenous assumptions for the disutility costs in the scenarios where they are active and in this paper have opted to hold the disutility costs constant at today's levels throughout the time horizon of the model. Future work (either with MESSAGE-Transport or other models) could explore scenarios where the disutility costs approach zero over time (i.e., converging to the levels of conventional gasoline/diesel vehicles), as AFVs become more commonplace and their requisite refueling/recharging availability expands. Such 'endogenous behavioral change' (EBC) would be akin to the commonly applied modeling technique of 'endogenous technological learning' (ETL) for energy supply and demand devices. The trade-off with endogenization is that it might require more complex model algorithms and greater computational requirements. Whether such implementations are justified, in terms of improved model insights, remains an open question. Additionally, or perhaps as an alternative, soft-linking stylized IAMs (without behavioral realism) to detailed, sector-specific models (with behavioral realism) could offer a promising path forward in this space. This would have the side-benefit of permitting an even deeper diver into the considerable technological and consumer heterogeneity characterizing the light-duty vehicle sector specifically, and the transportation sector more generally. For instance, an improved representation of different LDV size classes (e.g., sports car, small/midsize/large car, small/large SUV, minivan, pickup truck) could be useful for capturing consumer preferences for interior/cargo space and acceleration, attributes that may be more tied to age, gender, and family size than the consumer characteristics we represent in this study. What is more, the current paradigm of private vehicle ownership could eventually shift toward a more shared, public vehicle culture (perhaps utilizing autonomous, self-driving vehicles). This could affect consumer perceptions towards alternative fuel vehicles in major ways, as the disutility costs would be borne, at least in part, by the vehicle providers, who would benefit from economies of scale.

Whichever direction is pursued, a recognized bottleneck for behavioral modeling is the lack of existing empirical data packaged in a form that is amenable to global analysis. The empirical research community – in particular the social sciences – has an important role to play here. Through advances in both theoretical and applied research, the major behavioral features driving future energy consumption patterns can be better understood (IRGC, 2015).

Acknowledgements

The authors acknowledge funding provided by the ADVANCE project (FP7/2007–2013, grant agreement No. 308329) of the European Commission. K. Ramea was supported by the US National Academy of Sciences during her time at IIASA. Both she and C.B. separately developed the MESSAGE-Transport model while participating in IIASA's Young Scientists Summer Program. Z.L. was funded by the US Department of Energy Vehicle Technologies Office for his technical support on the use of MA^{3}T. We also recognize Peter Kolp and Manfred Strubegger of IIASA for their assistance with model code development. The comments of the editor and anonymous reviewers helped to substantially improve this paper.

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