Energy demand futures by global models

Projections of a complex system

Oreane Y. Edelenbosch

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Energy demand futures by global models

Projections of a complex system

Toekomstige energievraag volgens mondiale modellen

Projecties van een complex systeem

(met een samenvatting in het Nederlands)

Proefschrift

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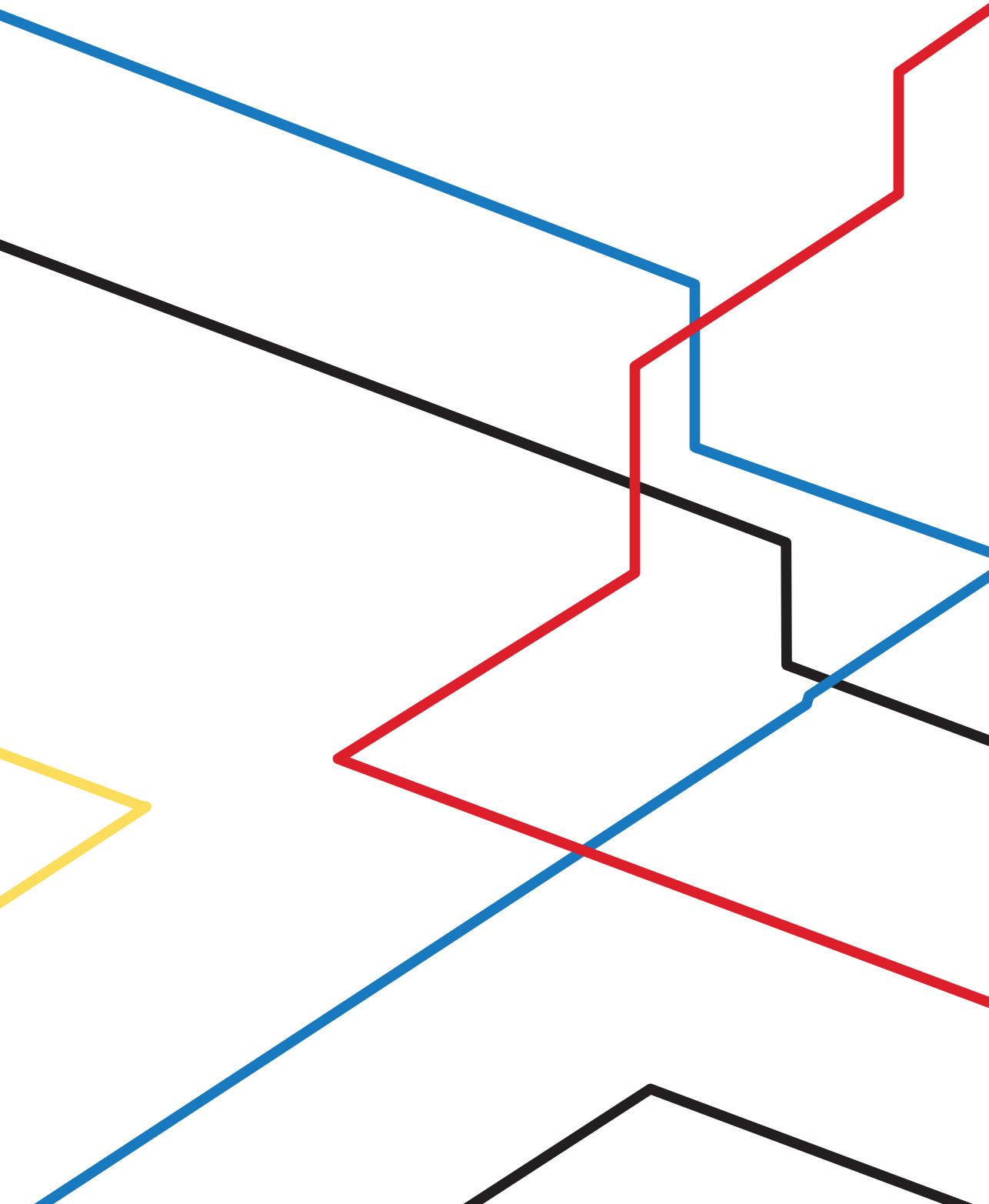
Units and Abbreviations

C °	degree Celsius
/cap	per capita
/yr	per annum
2W&3W	Two wheels and three wheels
AEEI	Autonomous energy efficiency improvement
AF	Alternative Fuel
AFOLU	Agriculture, Forestry, and Other Land Use
AFV	Alternative Fuelled Vehicle
AIM/CGE	Asia-Pacific Integrated Model – Computable General Equilibrium
BAU	Business as usual
BEV	Battery Electric Vehicle
CCS	Carbon, Capture and Storage
CES	Constant Elasticity of Substitution
CGE	Computable General Equilibrium
COP	Conference of the Parties
CO2	Carbon dioxide
CO2eq	Carbon dioxide equivalent
CTL	Coal to gas
CTG	Coal to liquid
DNE-21+	Dynamic New Earth 21 plus
EA	Early Adopter
EM	Early Majority
EJ	Exajoules (1 EJ = 1018 Joules)
EV	Electric Vehicle
FE	Final Energy
FCV	Fuel Cell Vehicle
g	gram
GCAM	Global Change Assessment Model
GEA	Global Energy Assessment
GEM-E3	General Equilibrium Model for Energy-Economy-Environment interactions
GEO-3	Third Global Environment Outlook
GE	General Equilibrium
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GLOBIOM	GLobal BIOsphere Management
Gt	Gigatonne (1 Gt = 109 tonne)
IAM	Integrated Assessment Model
ICE	Internal Combustion Engine
IEA	International Energy Agency
IMAGE	Integrated Model to Assess the Global Environment
IPCC	Intergovernmental Panel on Climate Change
IVA	Industry Value Added
kg	kilogram
kWh	kiloWatthour
km	kilometre
LDV	Light Duty Vehicle
LG	Laggards
LM	Late Majority
LR	Learning rate
MAGPIE	Model of Agricultural Production and its Impact on the Environment

MER	Market Exchange Rate
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact
MJ	Megajoules (1 MJ = 106 Joules)
MNL	Multinomial logit
O&M	Operation and Maintenance
OECD	Organisation for Economic Co-operation and Development
PE	Partial Equilibrium
PIEEI	Price induced energy efficiency improvement
Pkm	Passenger kilometre
PHEV	Plug-in Electric Vehicle
POLES	Prospective Outlook on Long-term Energy Systems
PPP	Purchasing Power Parity
REMIND	Regional Model of Investments and Development
R&D	Research and Development
SSP	Shared Socioeconomic Pathways
TIAM-UCL	The Integrated Assessment Model – University College London
Tkm	Tonne kilometre
TMB	Travel Money Budget
TPES	Total Primary Energy Supply
TTB	Travel Time Budget
UNEP	United Nations Environment Programme
Vkm	Vehicle kilometre
WEO	World Energy Outlook
WITCH	World Induced Technical Change Hybrid
WTP	Willingness to pay
W/m2	Radiative forcing in watts per square meter



Chapter 1

Introduction

1.1 Climate Change and Energy

Anthropogenic greenhouse gas emissions (GHG) have increased to a level that is the highest in history. As a result, the atmospheric concentration of greenhouse gases has reached 441[1] parts per million carbon dioxide equivalent (ppm CO_2eq) in 2014 . This is 56 ppm CO_2 eq. more than the value around the first Conference of Parties (COP) of the Climate Convention (UNFCCC) in 1995 (UN 1997) (EEA 2016). The Intergovernmental Panel on Climate Change (IPCC) has concluded that continued emissions of greenhouse gases at these levels will cause warming and long-lasting changes in all components of the climate system, increasing the likelihood of severe and irreversible impacts for ecosystems and people across the world (IPCC 2014a). Fossil fuel combustion and industrial processes currently account for roughly for two-thirds of global GHG emissions and have in fact contributed to almost 80% of the total GHG emission increase between 1970-2011 (IEA 2015a; IPCC 2014b). Clearly, an effective GHG mitigation strategy will require major change of the current energy sector (Riahi et al. 2007; van Vuuren 2007)

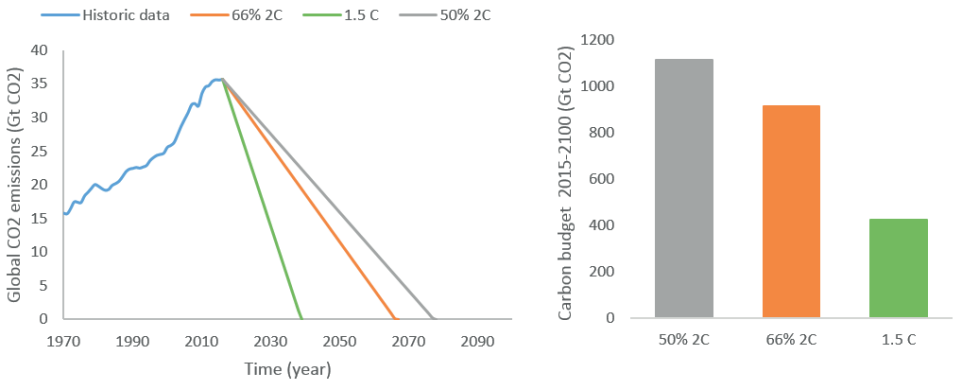


Figure 1-1. Indicative global CO_2 emissions pathways constrained to different carbon budgets corresponding to temperature rise limits. Historic data contains the CO_2 emissions fossil fuel combustion and industrial processes. Source: J.G.J. Olivier (2017); Janssens-Maenhout (2017); Rogelj et al. (2016b).

The Paris climate agreement's central aim is to keep the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C (UNFCCC 2015). Due to uncertainties in the carbon cycle and the climate response, it is not possible to calculate the *exact* level of cumulative GHG emissions corresponding to global mean temperature to stay below 1.5 °C or 2 °C (Meinshausen et al. 2009). Instead, limiting climate change is generally discussed in terms of

1 All greenhouse gases including aerosols

probabilities to stay below a specified level of temperature rise. The near-linear relationship of *cumulative* CO_2 emissions, following their dominance in total GHG emissions and their long-lived nature, and average global temperature rise implies that to remain within a long-term climate stabilization goal, *annual CO_2 emissions eventually will need to drop to zero* (Matthews and Caldeira 2008; Meinshausen et al. 2009). Based on this relationship the concept of remaining "CO_2 budgets"[2] is defined, i.e. the cumulative amount of CO_2 emissions left over a given time frame. A total CO_2 budget of 590-1240 Gt CO_2 between 2015 and 2100 is estimated to correspond with a more than 66% probability of staying beyond 2 °C (Rogelj et al. 2016b), while a budget between 990 and 1240 Gt CO_2 corresponds to a 50-66% likelihood. To remain within 1.5 °C with a 50-66% probability, this budget will need to be around 400-450 Gt CO_2 (IEA 2016c)[3]. In a recent publication, Millar et al. (2017) suggests that the carbon budgets could be higher, as a result of rescaling climate models to observed temperature change. However, a low estimate of current temperature increase was used and therefore these results have been criticized. As current global carbon emissions are around 41 Gt CO_2, of which 5 Gt originate from land use change and 36 Gt from fossil fuel combustion and industrial processes (Le Quéré et al. 2016), the remaining time for the required energy system changes to reduce emissions has become very limited (see Figure 1-1).

1.2 The energy system

Although there are many possible intersections of the energy system, a common approach is to divide the energy system into the energy supply sector and the energy demand sector. In the energy supply sector primary energy, i.e. the energy stored in natural resources, is transformed to secondary energy by cleaning (natural gas), refining (crude oil to oil products) or by conversion to electricity or heat. The total energy supply sector comprises the processes of energy extraction, conversion and energy transport, storage and distribution of energy to its final use (IPCC 2014a). From this point it is called final energy and the sectors the energy is delivered to fulfil final energy services are the so called energy demand sectors. An energy service (also referred to by *energy end use* or *useful energy*) is defined as human activity obtained through the use of energy and to satisfy a human need (Blok and Nieuwlaar 2016), such as for mobility, lighting, heating, cooking, agricultural

2 This is the threshold avoidance budget (TAB), which is defined by (Rogelj et al. 2016b) as "Amount of cumulative carbon emissions over a given time period of a multi-gas emission scenario that limits global-mean temperature increase to below a specific threshold with a given probability. This budget thus takes into account the impact of non-CO_2 warming at peak global-mean warming, which is approximately the time global CO_2 emissions become zero and global-mean temperature is stabilized." The concept of cumulative emission budgets relating to temperature rise have been quantified only for carbon emissions as emission budgets are only relevant for long-lived gases.

3 This range is from a different source. Therefore the underlying uncertainties of this range might not be one on one comparable to the 2 °C ranges.

production, and powering appliances and heavy machinery.

If GHG emission are allocated to the sectors where they physically occur, in 2010 49 % of the energy system global GHG emissions are emitted by the energy supply sector (IPCC 2014d). The remaining 51% share is emitted directly in the energy demand sector, for example while driving a conventional internal combustion engine car. Direct emissions do not provide the full representation of the importance of the energy demand sectors though. The energy demand sectors indirectly also impact the GHG emissions originating from the energy supply sector, determining the amount of primary energy used and converted to secondary energy such as electricity, heat or steam. In the GHG protocol these emissions are referred to as the demand sectors' scope 2 indirect emissions, shown for carbon emissions in 2014 in Figure 1-2. Scope 3 of the GHG protocol goes even a step further where all indirect emissions are included, i.e., emissions that are associated with the extraction and production of purchased materials, fuels, and services, outsourced activities and waste disposal (WBCSD/WRI 2001). In this thesis indirect emissions refers to scope 2 emissions.

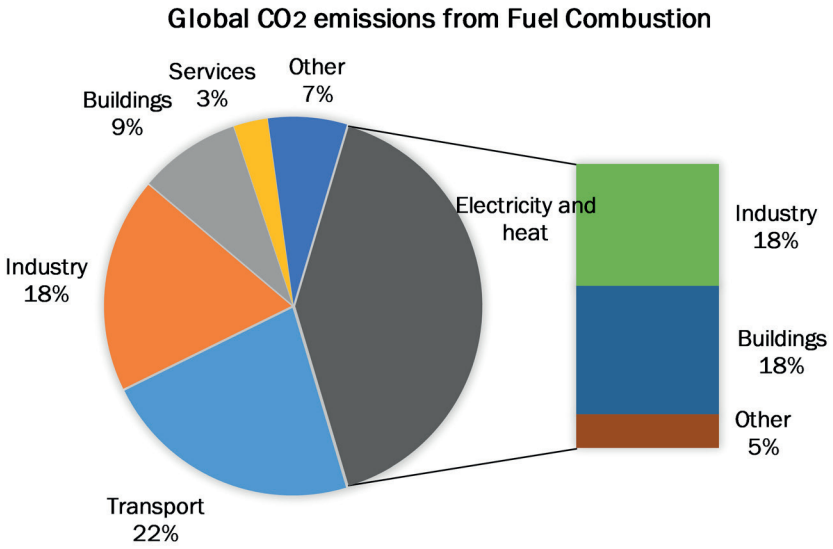


Figure 1-2. Global CO_2 emissions from Fuel Combustion in 2014. Source: (IEA 2016a)

The energy demand sectors thus directly and indirectly play a central role in the energy systems GHG emissions. Often energy demand analysis concentrates on the transport, industry and buildings sector as they are the most energy intensive sectors. In terms of energy use transport, industry and buildings, had a respectively 27%, 38%[4] and 31% of global total primary energy use (TPES) energy consumption in 2016 (IEA 2016c). The demand sectors have different characteristics and experienced different developments over the last year. The transport sector direct GHG emissions grew from 2.8 $GtCO_2eq$ in 1970 to 7.0 $GtCO_2eq$ in 2010, increasing faster than any other energy end-use sector (IPCC 2014f). Important factors contributing to this growth are increasing transport demand, urban development and sprawl, relatively low oil prices, lack of infrastructure for less energy intensive cycling or public transport in certain regions and consumers continuous desire to travel by faster modes (IPCC 2014c; Schäfer 2009). The transport sector is for 94% fuelled by oil, 2% biofuels, 1% electricity and 3% natural gas and other fuels. Currently the indirect emissions are thus very small (0.1 Gt $GtCO_2eq$).

The direct and indirect GHG emissions from global industry and water/wastewater amounted 15.4 $GtCO_2eq$ in 2010 (30% of total global GHG emissions), making the industry sector the largest emitting end use sector. More than half of the direct industry emissions are emitted in the Asia region[5], where emissions have also grown the fastest in the 2005-2010 period (7% average annual growth) (IPCC 2014f). About 2.6 Gt CO_2eq of the reported industrial emissions are process related emissions, not released during fuel combustion but for example during cement grinding or lime production. The buildings sector, including residential, commercial and public sector buildings, is the largest energy consuming end-use sector. It, however, has a smaller contribution to direct GHG emissions than industry and transport, emitting 3.2 Gt CO_2eq in 2010. This can be explained by the sectors large electricity share. Therefore, also being responsible for an additional 6.0 $GtCO_2eq$ of indirect emissions. While global direct emissions originating from buildings have stagnated over the last years, indirect emissions continue to grow.

1.3 Integrated assessment

While so far historic energy system developments affecting global GHG emissions have been discussed, a key question when analysing climate change is: How will global emissions develop in the future? Addressing this question requires knowledge on the development of human societies in terms of demography, economic development and change, technology, energy systems and land use (Nakicenovic et al. 2000). Integrated

4 Excluding feedstock use and transformation losses e.g. in blast furnaces.
5 This refers to the definition of the Asia region as used by the Intergovernmental Panel on Climate Change fifth assessment report which is the Non-OECD Asia.

assessment has been developed as a method to look into the long-term development of key societal and environmental trends. The methods aim to *integrate* different systems and types of knowledge in order to *assess* possible future trends. This means that integrated assessment goes beyond isolated studies of the various parts of the problem (Dowlatabadi 1995), but has a holistic and comparative view. To create such a more comprehensive overview, integrated assessment thus relies upon the expertise and knowledge from other scientific disciplines (Rotmans and Van Asselt 1996). At the same time in order for this overview to be comprehensive, a balance needs to be found between too detailed and too simplified representation of related processes (Rotmans and Van Asselt 1996). Both adding and removing detail can improve or decrease its credibility, depending on the question addressed. The added value of integrated assessment is having an overall picture of the system in question and identifying key relationships and reliance's between sectors or subsystems that are robust, and which were difficult to recognize when focusing on individual issues.

1.3.1 Integrated Assessment models

In order to analyse the complex interactions of different system components, scientific models have been developed that are referred to as integrated assessment models (IAMs). The models built upon a larger tradition of modelling to look into energy-related sustainability problems. Energy and economic models started to emerge on a larger scale in the 1970s. Around the same time climate change came to be recognized as a serious issue, and therefore the models that had been used for energy-economic analysis were modified to project greenhouse gas emissions and possible policy responses. While the energy-economic models were extended to consider the physical dimensions of the climate system in an aggregated manner, models that had previously focused on the physical climate system were extended to represent processes leading to greenhouse gas emissions (Peace and Weyant 2008). From here IAMs started to develop that since then continued to evolve, becoming more sophisticated and further widening their scope (Krey 2014). There are other integrated assessment methods as well, such as expert judgements, participatory, heuristic methods, or policy exercises, but IAMs have become the dominant method used for integrated assessment (Rotmans and Van Asselt 1996).

In the broadest definition IAMs describe the key processes in the interaction of human development and the natural environment to gain a better understanding of global environmental problems. Combining the known relationships in a model enables us to analyse the dynamic behaviour of complex systems, show interrelations and feedbacks between subsystems, develop end-to-end strategies. Therefore IAMs are particularly useful to signify policy challenges and frame relevant issues (Rotmans and Van Asselt

1996). Although integrated assessment models can be used for analysis of various global environmental change issues, integrated assessment models have been – until now – primarily used to address climate change issues. Especially in the last two decades they have become common tools of climate change analysis and the amount of scenarios has increased hugely (Krey 2014). They address policy issues such as the mitigation measures needed to reach certain climate targets and cost-effective emissions reduction pathways.

IAMs are not a homogenous group of analysis tools but evolving from different model classes, they can differ in terms of their system boundaries, the amount of detail in representing the various system parts and their solution method (Krey 2014). Some models are characterized by relatively detailed biophysical processes and a wide range of environmental indicators, such as the IMAGE (Integrated model to assess the Global Environment) model that is utilized extensively in this thesis; in contrast, other models have more details in their representation of economics and policy instruments (Stehfest et al. 2014). As such the models have different strengths and weaknesses. Results depend on their own set of assumptions, definitions, structure and data choices, differing per model. Model output in that sense can be as important as input (Peace and Weyant 2008). Key categories of assumptions that inputs for instance include are demographic and economic development, lifestyle change, natural source availability, technology development and policy and government. For modellers this might be clear, but also as they have been growingly become more complex, critical assumptions might not always apparent to the outsider.

Along that same line, it has been stressed often that IAMs are used for insights but not exact numbers (Huntington et al. 1982). They cannot – and are not intended to – predict future events or to produce precise projections. Prediction is possible is when all variables and relationships in a system are known and the system can be observed in controlled and reproducible situations. Environmental problems are however characterized by complex relationship and a high level of uncertainty (van Vuuren et al. 2012). The longer the time horizon, the larger the uncertainty. Using IAMs to assess climate change therefore should be seen as particularly useful to explore possible trends in relation to uncertain development of driving forces.

For that purpose, scenario analysis and multi-model comparison are very important. Scenario analysis does not aim to show the most likely development, but assesses different pathways under key assumptions to distil robust insights and evaluate uncertainties (Van Asselt et al. 1995; van Vuuren et al. 2012). They provide plausible descriptions of socioeconomic, technological and environmental futures (Moss et al. 2010). Similarly, multi model comparison builds on the diversity of models (in terms of their structural and

parametric assumptions) to distinguish the robust insights across models. If more models are applied to the same question, it can on the one hand lead to higher relevance of the results, but also the range of solutions – e.g., climate futures - across the models gives an indication of the uncertainty and the implication of different approaches to mitigation. In recent years for that reason more attention has gone to multi model comparisons as well as scenario development, such as the scenario framework the Shared Socio Economic Pathways (Kriegler et al. 2015b; O'Neill et al. 2014) (see box Emission scenarios).

Box 1. Emission scenarios

IAMs are used to develop different types of scenarios. These scenario types correspond to different research questions.

- Baseline emission scenarios (often called "counterfactuals") of IAMs show futures where no explicit measures to reduce GHG emissions are taken. The baseline scenarios can still correspond to very different sets of assumptions. Often storylines are introduced to ensure a consistent set of assumptions (e.g. for population, income and technology development).
- Mitigation scenarios are developed to look into the impact of policies. Such scenario can just start from existing policy formulation, but also explore the question how to reach certain policy outcomes (e.g., normative targets for reducing emissions) (Morita et al. 2000).

Other characterization of scenario types can also be made, such as descriptive versus normative scenarios. Where it could justifiably be argued that all scenarios are normative as they contain interpretations of developments, descriptive scenario have as purpose to explore different future pathways while normative scenarios intend to describe the probable futures, also in some cases referred to as the reference scenario (Van Notten et al. 2003).

An example of descriptive scenarios is the recently published Shared Socioeconomic Pathways (SSPs) that are developed to cover the range of plausible future developments affecting climate change at a comprehensible (i.e. limited number of scenarios) and at a comprehensive manner (i.e. covering the space of plausible futures sufficiently). More specifically they intend to explore the consequences of socioeconomic developments on anthropogenic climate change and available response options through mitigation and adaptation (Kriegler et al. 2010). The scenario framework consists of a set of five qualitative pathways of future changes in demographics, human development, economy, lifestyle, policies and institutions, technology and environment and natural resources (O'Neill et al. 2014). In Chapter 7 of this thesis the demand side development of the SSP scenarios is explored.

1.3.2 Supply-side vs. demand side focus

IAMs tend to focus analyses more on mitigation of energy supply side emissions, while relatively less attention has gone to the use of energy and the role of energy reduction in a global setting to achieve climate targets. Generally, the energy supply sector is also represented with more detail in IAMs and energy system models than the energy demand sectors.

There are several key reasons for this:

- Energy demand sectors are highly diverse, with many sub-sectors, different functions for which energy is used, technologies and users making these sectors more difficult to describe by models. These different users moreover vary in their preferences and needs.
- There is a faster turnover of capital stock and innovation cycles in the energy demand sector than in the energy supply sector, which adds to the sectors complexity.
- The rules affecting future energy demand change are less defined, as actors use many more criteria in making decisions than the "rational" cost-optimization to investment decisions that are typically used in the energy supply sector (Krey 2014).

Therefore, models, in contrast, often use a more a very aggregated description to represent energy demand, relating demand directly to aggregated economic and demographic scenario drivers, based on historical trends, and a stylized representations of efficiency change. Recently, however, more details, especially in the transport sector, have been added (Sugiyama et al. 2014). Within the global decadal scope of IAMs including more details does not necessarily improve accuracy, as over the long-term uncertainties increase (see box Level of integration).

Box 2. Level of integration

A key characteristic of a model is its system boundaries, which defines the scope of the analysis. The models' scope can include a part of the energy system such as the transport sector on itself or the electricity sector, or the whole energy system. The scope of analysis also refers to the temporal (time-horizon) and spatial (regional scope) dimensions. Krey (2014) refers to this dimension as the "level of integration". While the level of integration is not a quality criterion on itself, it does indicate which questions it can suitably address.

The inertia of the climate system and its cross border nature, and emission sources from sectors beyond the energy system have driven IAMs to widen their scope to the global, coming century and covering natural and human systems. From a modelling perspective the challenge lies in modelling clear and simple relations, that capture the complexity but do not over constrain it. Specificity does not imply greater accuracy as within longer time horizons and scope uncertainties increase (Dowlatabadi 1995). This is partly due to the practical issues associated with buildings, maintaining and applying models – in particular to maintain the required expertise to assure quality for this level of detail. Perhaps equally as important, is when modelling long-term, global trends more detailed representations can be harmful as it increases the number of uncertain assumptions made. However, representing sectoral, regional or temporal heterogeneity can improve the model and capturing system dynamics too. Therefore, there is a balance that must be struck between the level of detail and the level of integration.

The focus on aggregated regions and sectors can limit the models' ability to represent short term policies, or existing policies at the national or sub-national level, making the results less tangible for policy makers. However recently several research efforts to bridge the gap between global long-term models and regional short term policy are made (Rogelj et al. 2016a; Tavoni et al. 2015). Combining information streams of models with different levels of integration is important and ensures to make use strengths of models with different characteristics (Krey 2014).

Still, within the more aggregated representation energy demand sector changes play a very important role to meet stringent climate targets. There are a number of key strategies to reduce demand side sector emissions: 1) reducing energy service demand, 2) increasing energy efficiency, 3) switching to low carbon fuels and 4) increasing the electricity share combined with decarbonisation of electricity generation. The Global Energy Assessment (GEA) explores three distinct pathways to meet a range of sustainability objectives[6], by using the integrated assessment models IMAGE (Stehfest et al. 2014) and MESSAGE (Riahi et al. 2007), which demonstrates the importance of demand sector changes:

1) the GEA efficiency: Pathway emphasizing demand-side and efficiency improvements;
2) the GEA mix: energy demand follows an intermediate level of between GEA-Efficiency. This pathway also emphasizing regional diversity;
3) the GEA supply: emphasizing the supply-side transformation at relatively high energy demand (Riahi et al. 2012);

A key message of this extensive assessment is that the radical improvements in energy efficiency in the GEA-Efficiency scenario throughout the energy system, but in particular in the energy demand sectors, are the most important options to achieve the energy system transformation toward a more sustainable future, i.e. scoring high on all sustainability objectives. This is in line with many other studies that have stressed the direct environmental, cost and security benefits of energy efficiency (Lovins 2005). In this scenario in addition the transformation is less dependent on energy supply side technologies that might be restricted in their application such as nuclear or carbon capture and storage. However, also in pathway 2 and 3, that focus more on energy supply decarbonisation, demand sector changes are required. In GEA efficiency scenario energy efficiency and energy service reduction (the first two strategies discussed) are more important while in GEA mix and GEA supply fuel switching and electrification (the last two strategies) are more pronounced (Johansson et al. 2012; Riahi et al. 2012).

Also other methods than IAM models are used to look possible trends in future energy demand and mitigation opportunities. An important method is assessing technology options in a bottom up fashion. These typically focus more on the at the sectoral or local level and more short term potentials. Opportunities to improve energy efficiency in the buildings sector lie in thermal characteristics of insulation in walls, roofs, and windows (Ürge-Vorsatz

6 Specific sustainability objectives addressed in this study are: 1) providing almost universal access to affordable clean cooking and electricity for the poor; 2) limiting air pollution and health damages from energy use; 3) improving energy security throughout the world; and 4) limiting climate change.

et al. 2007). While paying attention to energy efficiency when designing a building can save time and money compared to retrofitting existing buildings, without retrofitting the speed of an efficiency transition in this sector will be strongly slowed down given the long lifetime of buildings (Nejat et al. 2015). Besides many energy efficiency options in the transport sector for cars, trucks and planes (Lovins 2015), switching to electricity can be effective in reducing demand side emissions, if electricity is generated by low carbon fuels. While switching to electric cars could be an attractive strategy to reduce GHG emissions, electrification of air transport and freight are less obvious choices due to battery requirements and costs (van Vuuren et al. 2017a). Urban transport experts, in contrast, emphasize the importance of compact urban development, rapid bus transit, bicycle highways and telecommuting to mitigate transport emissions the so called avoid and shift strategies (Creutzig et al. 2015). Besides adopting more efficient technologies, in the industry sector there are a broad set of additional mitigation options. Examples are changing material use efficiency, material recycling and re-use of materials and products, product service efficiency (e.g. longer life for products) or activity reduction (e.g. less product demand) (Allwood 2011; IPCC 2014e). These various strategies across sectors show that suitable climate policy in energy demand sectors depend on sector specific details that differ per sub-sector (e.g. cars or airplanes) and also vary per region and over time (e.g. the affected by the electricity mix portfolio).

The consequence of the aggregated representation of energy demand developments in IAMs is first of all that the comparison between demand sector changes anticipated by the models and tangible mitigation measures such as discussed in the previous paragraph is not straightforward. Secondly, although significant potential of behaviour change to reduce energy demand is identified (Dietz et al. 2009; van Sluisveld et al. 2016), the stylized modelling approach has resulted in this component not well understood (Krey 2014; McCollum et al. 2017). This knowledge gap motivates the aim of this thesis and the research questions addressed.

1.4 Aim of this thesis

In the previous sections, we identified that a key purpose for the use of IAMs is the development of mitigation scenarios to advise policy-makers on different mitigation strategies. At the same time, the demand side sector of the energy system is relatively difficult to represent in these models because of the 1) complexity of different sectors in terms of the number of technologies and processes, 2) the heterogeneity of users, 3) the short stock turnover and innovation cycles and 4) the role of consumer behaviour. In this thesis, we aim to contribute to a better understanding of the role of energy demand changes in the context of global climate change mitigation scenarios as well as a better

representation of energy demand dynamics in IAMs. In order to do so in this thesis, the following main question is addressed:

How can the representation of energy demand side dynamics be improved in global models assessing long-term climate change?

To answer this question, we focus on the following sub questions:

- How do IAMs represent energy demand and what do they project?
- How do energy demand sectors in IAMs respond to climate policy?
- How do IAMs perform in their energy demand representation?
- How can complicated demand processes such as technology transitions be represented in global models?

1.5 Thesis Outline

Following the questions posed the thesis can be divided into three sections:

- Comparison of demand sector projections and model evaluation
- IAM representation of a demand side technology transition
- Cross demand sector and scenario analysis

The first section explores the first three questions, the second the fourth questions and the third section finally takes a birds eye view, comparing different demand sectors representation in several models as well as scenarios.

Comparison of demand sector projections and model evaluation

To set the stage in the *first section* the modelling of sectorial energy demand in integrated assessment models are discussed in detail and projections are compared. There are many different types of integrated assessment models, with a wide variation in energy demand representation. This section gives an overview of the state of the art of the models. Projected energy demand pathways are discussed in detail, the "between model" uncertainty better understood by clarifying the differences between models and possible improvements are identified. Novel model comparison methods are used to gain more insight in the model dynamics and as a model evaluation exercise by comparing future demand trends to historic data (Schwanitz 2013).

Chapter 2 assesses industrial energy demand and greenhouse gas emissions of several

IAMs. The chapter compares model output to input and structure assumptions to better understand model behaviour. To examine industrial sub sector representation a specific section looks at the projected global emissions, material and energy consumption of the cement sector. **Chapter 3** compares global transport passenger futures by quantifying the contribution of the sectors' activity growth, modal structure, energy intensity and fuel mix to the projected emissions pathways. In order to do so the Laspeyres index decomposition method is used. Results are compared across models, scenarios with and without climate policy and against historical transport trends.

Economic growth and fuel price pathways are key determinants of projections made by integrated assessment models. To quantify the dynamic model response to fuel price in the transport sector, in **Chapter 4** the baseline fuel prices is shocked in various scenarios. By doing so, price effects on energy demand are isolated and a transparent environment is created to compare transport demand to fuel price elasticities. In addition, through a similar analysis transport demand to income elasticities are calculated and compared across models and to historic data.

IAM representation of a demand side technology transition

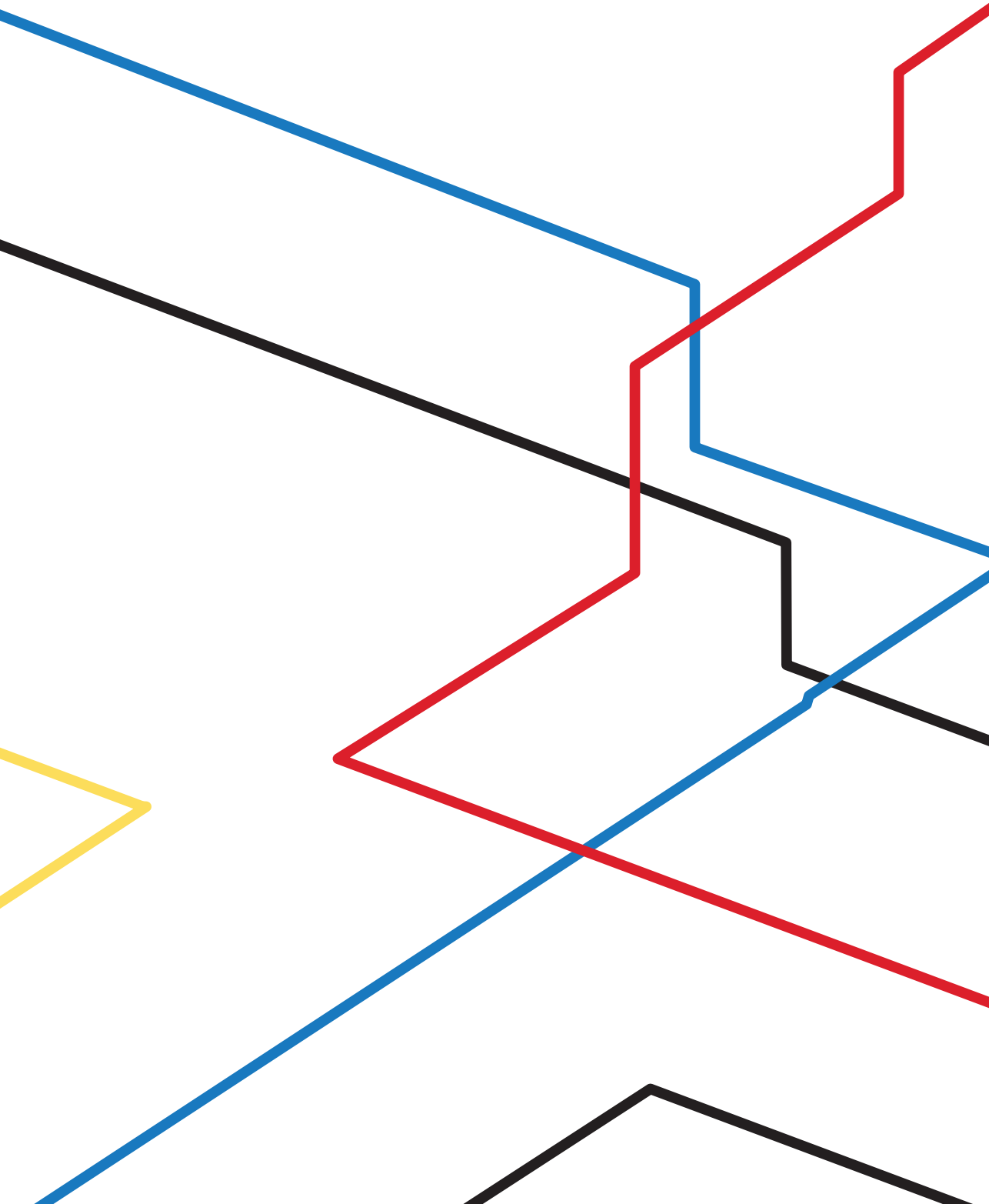
The *second section* of the thesis addresses the scope of technology change and the level of integration topic by specifically looking at the Light Duty Vehicle (LDV) sector. Specifically the LDV sector is analysed since 1) IAMs show that reducing greenhouse gas emissions in the transport sector is more challenging than in other end-use sectors (Kriegler et al. 2014) 2) 72% of total transport GHG emissions originate from road transport (IPCC 2014f) and 3) transitioning to alternative vehicles, such as electric cars, could represent a promising approach to reduce the currently rapid growing transport GHG emissions. Whether this technology transition takes place depends on vehicle choice, influenced by technology developments as well as consumer preferences. This section looks at modelling the opportunities and barriers (i.e. technological potential and behavioural change) of such a transition within the global integrated modelling framework IMAGE.

More specifically **Chapter 5** examines the sensitivity of model results to technology development assumptions. Over the last years the costs of electric vehicle batteries have dropped faster than expected, which spurred a dramatic rise in sales, with two million electric cars on the road worldwide in 2016. How battery costs will continue to develop is an ongoing debate. A more interesting question is perhaps, how does this impact future transport electrification. This study examines how, based on recent battery costs developments, possible future battery cost pathways affect LDV transport projections. Besides technology development vehicle choice decisions are also influenced by non-financial behavioural

factors. **Chapter 6** analyses how technological learning and social learning relate and can interact during a technology transition, affected by the heterogeneity of transport users. The chapter reflects on the appropriate resolution for representing complex demand side dynamics in IAMs.

Cross demand sector and scenario analysis

Finally in **Chapter 7,** which forms *the third section*, compares industry, transport and buildings demand futures in detail. Through index decompostion analysis the future changes in demand sector emission pathways are distributed over population change, final energy per capita, electrification and fuel switching. This detail enables to compare the demand sectors to each other and with sector specific technical assessments. Not only are different models compared but also the effect of the different SSP baselines on demand sector developments and the required avoided emissions to meet stringent mitigation targets.



Chapter 2

Comparing projections of industrial energy demand and greenhouse gas emissions in long-term energy models

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"Comparing projections of industrial energy demand and greenhouse gas emissions in long-term energy models." Energy 122 (2017): 701-710.

Abstract

The industry sector consumes 37% of the global final energy use and currently emits more GHG emissions than any other end-use sector. Effective mitigation strategies needed to reach a climate target will require a significant reduction of industrial emissions. In long-term energy models, which are used to identify strategies to mitigate emissions, the industry sector representation thus plays a crucial role. To improve our understanding of the variation in the projected industrial pathways, in this study, a comparison of the models key input and structure assumptions in relation to the modelled sectors' mitigation potential is performed. All models show similar trends in a reference scenario (i.e., absent emissions mitigation policies), with strong decoupling of final energy use to GDP growth in Non-OECD countries and the sector remaining mostly (>50%) reliant on fossil energy through 2100. Even so, industrial final energy demand spans a wide range (between 203-451 EJ/yr) across the models. There is significant divergence in the projected ability to switch to alternative fuels to mitigate GHG emissions. Among the set analysed here, the more technologically detailed models tend to have less capacity for switching from fossil fuels to electricity. This highlights the importance of understanding of economy-wide mitigation responses and costs as an area for future improvement. Analysing industry subsector material and energy use details can improve the ability to interpret results, and provide insight in feasibility emission reduction measures.

Keywords

Industry, model comparison, integrated assessment, energy efficiency, climate change mitigation

2.1 Introduction

In 2010, 37% of global final energy consumption was used by industrial activities (IEA 2012a). Moreover, annual industrial greenhouse gas (GHG) and waste/wastewater emissions increased from 13.0 to 15.4 $GtCO_2eq$ between 2005 and 2010, emitting more GHGs than any other end-use sector[7] (IPCC 2014e). While global industrial energy intensity decreased within the past years due to the adoption of energy and material efficiency measures and due to efficient capacity increases in developing countries, the increasing demand for industrial products and the shift towards more energy intensive industrial products (structural changes) have resulted in an increase in global industrial energy use (UNIDO 2011). The International Energy Agency (IEA) projects that if current trends continue, the industrial energy use could more than double from 126 EJ[8] in 2009 to 250-270 EJ in 2050 (IEA 2012b). For the same period, the associated GHG emissions are projected to increase by 45 to 56%. Effective climate change policies will thus need to be adopted in the industry sector to reach stringent climate targets (IPCC 2014e).

Integrated Assessment Models (IAMs) have been frequently used to analyse the potentials for reaching climate targets by identifying strategies of emission reduction and associated investment costs. The strength of IAMs lies in analysing trade-offs and synergies in mitigation across different sectors (IPCC 2014a), projecting future anthropogenic emissions of energy production, energy conversion, energy consumption and land use change. Following the identification of the industrial sector as a large energy consumer and GHG emitter, it is clear that industry representation plays an important role in these models scenarios.

Including sector specifics at the global level running over the coming decades, which is the scope in which many IAMs operate, is a modelling challenge however (Krey 2014). End-use sectors are highly diverse, characterized by different energy functions and a large variety in technologies affecting the demand for energy (Sugiyama et al. 2014). This is particularly true for the industrial sector, where energy is used in many different industrial processes to manufacture a wide variety of products[9] (Liu and Ang 2007; OECD 2011). Where traditionally end-use sectors in most IAMs were represented in a stylized manner, over the last years, many models have started to include more sector details.

7 The total energy demand is usually broken down into four end-use sectors: industry, transport, buildings and agriculture, forestry and other land use (AFOLU).
8 This figure includes energy use as a feedstock, energy use in blast furnaces and coke ovens (own energy use and transformation energy) and excludes energy use in refineries.
9 In this paper the term industry is used for all activities contributing to the production of goods and construction of building and infrastructure. Main industrial products are iron & steel, non-metallic minerals, chemicals & petrochemicals, pulp & paper, non-ferrous metals and other products.

The IPCC Fifth Assessment report shows that there is a broad range in the estimated development of industrial emissions over the century, across the different integrated studies (IPCC 2014a). To design effective mitigation policies, accurate estimations on emission reduction potentials and the associated investments are needed. Therefore, understanding the origins of the variation in model outcomes, by identifying the robust and uncertain features in the projected pathways, is of great importance (Kriegler et al. 2015b). Over the last few years, many model comparison studies have been published which looked at the behaviour of IAMs. A few studies focussed on the energy and land-use systems as a whole, such as (van der Zwaan et al. 2013) comparing technology diffusion, (Kriegler et al. 2014) on the role of low carbon technologies for energy transformation; (Calvin et al. 2012) comparing regional projections; and (Rosen and Guenther 2015) exploring mitigation costs, while others have targeted a specific sector (such as the transport sector (Girod et al. 2013)) or specific forms of renewable energy (such as bio-energy (Calvin et al. 2013)).

A limited number of studies however, have specifically dealt with the modelling of the industrial sector. Zhang et al. (2015), investigated the advantages and weaknesses in the methods used for modelling the Chinese industry in nineteen energy models; including bottom-up, top-down, hybrid, global vs national and industrial level models. They identify key issues to be the modelling technology options, change, cost, and diffusion, emphasize that modelling technological change is vital for realistic industrial energy projections. Moreover, non-linearities such as in market saturation effects as well structural change and synergies between energy use climate change and air pollution mitigation pose large challenges to industrial modelling. Sathaye (2011) performed a review of the technology representation in seven energy models that specifically model the cement industry and highlighted the importance of the inclusion of bottom-up details for more accurate cost estimations.

Recognizing the industrial sector complexities and the importance of understanding "between model" uncertainties, we conduct a detailed comparison of the industrial sector representation within models that use an *integrated* strategy to reach a global GHG reduction target. Model output is compared to model input and structure assumptions to better understand the similarities and differences in model behaviour. In addition, we take a detailed look into one major industrial subsector - the cement industry - in terms of global energy consumption and emission generation to assess the more detailed sub-sector representation of some models.

The article is structured as follows. In Section 2.2, the method applied to compare the industry model assumptions and outputs is discussed. In the following Section (Section 2.3)

we provide an overview of the industry sector representation in models. Then, in Section 2.4 the model projections for two scenarios are presented, i.e. i) a "baseline scenario" where current trends continue and significant improvements beyond business-as-usual in energy intensity are not considered and ii) a mitigation scenario, where CO_2 emissions are mitigated and concentration levels stay below 450 ppm ("450 ppm scenario"). In Section 2.4, specific attention is given to the modelling of the cement industry. Finally, Sections 2.5 presents the discussion and conclusions paragraphs.

2.2 Methods

Long-term energy models The models included in the study can be classified as IAMs and energy system models which together will be called long-term energy models. IAMs describe the interaction between the human system and the natural environment, i.e. climate change, energy use and land-use. Energy system models are models that focus on the energy system, from the extraction of primary energy to its use in the final end use sectors.

2.2.1 Model structure and assumption comparison

To better understand how the industrial sector is modelled, a descriptive questionnaire that addresses the assumptions made in the models structure, system boundaries, energy and material demand drivers, technology change and policy measures has been constructed and filled in by all participating models. The questionnaire results are discussed in Section 2.3 and presented in more detail in the Appendix.

2.2.2 Scenario description

To compare the industrial sector projections of the models, key industrial model outputs of *two scenarios* were collected:

- one scenario without new climate policies ("baseline scenario") and,
- one scenario aiming at a stabilization level at 450 ppm CO_2-eq ("mitigation scenario").

The modelling results were collected under the EU-FP7 ADVANCE project. For some models, MESSAGE, GCAM and Imaclim-R, that did not provide modelling results under the EU-FP7 ADVANCE, the results from another study under the Energy Modeling Forum (Kriegler et al. 2014) were used.

Models were asked to provide a medium-growth baseline but no attempt was made to harmonize assumptions – thus taking different demographic and economy growth rates as part of the overall uncertainty (see Section 2.3.2). The baseline scenario is compared to

the *current policy scenario* of the IEA's World Energy Outlook (WEO), that takes into account those policies and measures affecting energy markets and were formally enacted as of mid-2013. The mitigation scenario is compared to the WEO *450 scenario*, which stabilizes at around 450 ppm CO_2-eq in 2100 as well (IEA 2013b).

The model drivers, global population and GDP are depicted in Figure 2-1. For reference, the WEO scenario is shown as well. In the WEO scenario global GDP (expressed in real purchasing power parity [PPP] terms) is projected to continue to grow between 2011 and 2035 at an average annual rate of 3.6%, doubling in size over this period. Population, a fundamental driver of energy demand, grows from 7.0 billion in 2011 to 8.5 billion in 2035 (IEA 2013b). Most models scenario drivers stay relatively close to these assumptions in the coming decades, and start to diverge after 2035.

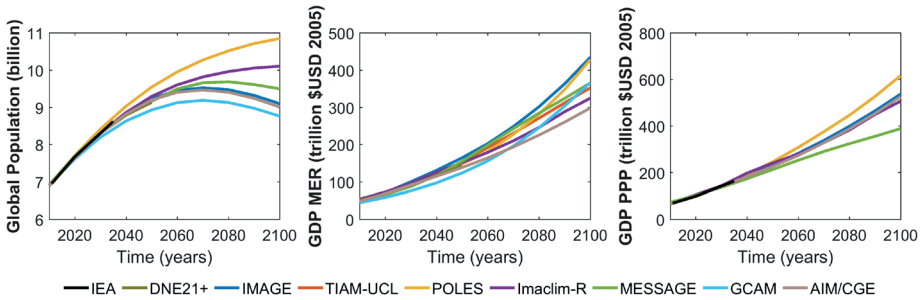

Figure 2-1: Scenario drivers: a) Global Population; b) GDP expressed in Market Exchange Rates; c) GDP expressed in real purchasing power terms.

2.3 Description of the industry sector in global energy system models

2.3.1 Model characteristics

Eight models[10] participated in this study, that are widely used in IPCC assessment reports, namely: AIM-CGE, DNE21+, GCAM, Imaclim-R, IMAGE, MESSAGE, POLES and TIAM-UCL. The models are briefly introduced in Table 2-1 in terms of their general characteristics.

10 All models presented here are part of the European Union Seventh Framework Programme FP7/2007-2013 ADVANCE project

Table 2-1: General characteristics of the models studied.

	AIM-CGE	DNE-21+	GCAM	Ima-clim-R	IMAGE	MESSAGE	POLES	TIAM-UCL
Type of model	CGE	Energy system model	Hybrid/ IAM	CGE frame-work with bottom-up modules for every sector	Hybrid/ IAM	IAM based on bottom-up energy model	Energy system model	IAM based on bottom-up energy model
Solution type	Simula-tion	Optimiza-tion	Simula-tion	Simula-tion	Simula-tion	Optimiza-tion	Simula-tion	Optimi-zation
Number of regions	17	54	14	12	24	11	57	16

Although the distinction is not always clear, energy models are commonly categorized based on their disaggregation level into top-down and bottom-up models. Bottom-up models have a relatively high amount of technological detail. Most of the 'bottom-up' models are energy-system models focusing on the behaviour of the energy system. Top-down models, with less technological details model the economy by taking into account interactions between the various sectors (e.g. the interaction between the energy sector and the rest of the economy). Most top-down models are Computable Generic Equilibrium (CGE) models, representing the sectoral economic activities by production functions (Löschel 2002). Another key difference across the models is the solution type used. This study includes optimization models, i.e. an algorithm is used to optimize a distinct target (depending on model type mostly maximizing consumption or minimize energy system costs) across a period of time, as well as simulation models, that run based on a set of rules that determine the decisions made in every single time-period based on the information from the previous time step. The diverse set of models included in this study give a good representation of the broad range of type of long-term energy models.

2.3.2 Industry sector model characteristics

The main differences in industry representation between the models assessed in this study can be found in the breakdown of industrial subsectors, explicit representation of material demand, drivers used to project final energy demand, explicit modelling of technologies and energy efficiency change, as descibed in Table 2-2[11].

11 A more in depth description of the models in general and more specific details on their representation of the industrial sector can be found in the Appendix.

Economic and demographic drivers are either directly related to industrial energy demand or to the demand for materials and industrial products, based on historical relations observed. By including material demand projections, various material production technologies and material recycling opportunities can explicitly be accounted for, which impact energy use per industrial product (Allwood 2011; IPCC 2014e). In CGE models, the projection of economic activity is the outcome of the production function, and energy intensity or material intensity improvements are typically represented by the substitution between capital, material, labour and energy inputs.

Some models include a diversifed set of current and future industry subsector specific technologies, characterized by their costs and efficiency. Technology deployment is modelled on the basis of relative costs, leading to more efficient technologies deployed when fuel prices increase. Other models do not account for technologies explicitly, but technology development is driven by either exogenous assumptions or for example learning-by-doing based functions.

Finally, an important difference in modelling are system boundary assumptions. Key differences among models are the inclusion or not of the energy use for feedstock purposes (also known as non-energy use of fuels) and the energy use in coke ovens and blast furnaces in the iron and steel industry. The energy use in refineries, agriculture and forestry is not included in the reported models industry data.

Table 2-2. Main industry model characteristics. Information acquired primarily from the FP7 EU ADVANCE industry models stock taking.

IAM	Industry sector drivers	Industrial subsector breakdown	Techno-logy	Efficiency improve-ments	Policy measures	Policy impact	Material trade (indu-strial goods)	Stock turn-over	Re-cy-cling	Energy use as feeds-tock	Energy use in coke oven and blast furnaces [3]	Process emissi-ons[4]
AIM-CGE	CES production function with the energy nested with value-added	Iron and steel[8], chemicals[8], non-metal-lic minerals[8], food proces-sing, pulp and paper[8], constructi-on, others (7)	No	CES nesting structure determines the technological energy efficiency and fuel use	Carbon tax or emission constraint with carbon tax	Price me-chanisms	Yes	No	No	Only iron & steel	Only blast furnaces	From cement
DNE-21+	Material demand is related to production, consumpti-on, import, export, population and GDP	Iron and steel[1], cement[1], pulp and paper[1], aluminium, some chemicals[1] (ethylene, propylene and ammonia) (7)	Yes	Exogenous per technology. More efficient technologies get a larger market share in response to higher fuel prices.	Carbon pricing, efficiency standards, and sectoral intensity targets.	Implemen-tation rates of tech-nologies and price mechanism	Yes (exo-genous scenario)	Yes	Yes	Yes	In steel sector: Yes, other sectors: No	From cement, iron, etc.

Table 2-2. Main industry model characteristics. Information acquired primarily from the FP7 EU ADVANCE industry models stock taking. *(cont)inued)*

IAM	Industry sector drivers	Industrial subsector breakdown	Techno-logy	Efficiency improve-ments	Policy measures	Policy impact	Material trade (indu-strial goods)	Stock turn-over	Re-cy-cling	Energy use as feeds-tock	Energy use in coke oven and blast furnaces [3]	Process emissi-ons[4]
GCAM	Endogen-ously from land use model (for fertilizer), and total GDP (for the remaining industry)	Cement[1], nitrogenous fertilizers[1], others (3)	No, only for CCS	Technology improvement rates take into account the opportunities for improved energy efficiency, and are a scenario input assumption	Carbon taxes, emission constraints,	Modi-fied fuel choices, production technolo-gies and demands for industri-al goods.	No	No	No	Yes	Yes	From cement
Imaclim-R	Endo-genously from the equilibrium point bet-ween the supply and demand of industrial goods	None	No, only for CCS in cement and fertilizer	Autonomous, and fuel price induced energy efficiency	Carbon/ energy taxes (or energy subsidies), emissions permits	Price me-chanisms	Yes	Yes	Yes, but not expli-citly	No	No	No

Table 2-2. Main industry model characteristics. Information acquired primarily from the FP7 EU ADVANCE industry models stock taking.*(cont)inued)*

IAM	Industry sector drivers	Industrial subsector breakdown	Techno-logy	Efficiency improve-ments	Policy measures	Policy impact	Material trade (indu-strial goods)	Stock turn-over	Re-cy-cling	Energy use as feeds-tock	Energy use in coke oven and blast furnaces [3]	Process emissi-ons[4]
IMAGE	Material demand is related to economic activity and material intensity for steel and cement; energy intensity for other sectors	Steel[1], cement[1], other (3)	Steel, cement	Exogenous per technology more efficient technologies get a larger market share in response to higher fuel prices.	Carbon tax, prescribing certain efficient technolo-gies	A dynamic response to changed technology costs (incl. fuel price) or prescribed technology mix	Yes, only for cement and steel	Yes	Yes	Yes	Yes	From cement
MESSAGE	Total energy demand is related to GDP and population, based on historical energy intensity trends	Thermal and electric demand of total industry, non-energy use, cement process emissions	No, only CCS for process CO2 emis-sions explicit-ly repre-sented	Improvement of energy intensity depends on long-term price deve-lopment. Fuel switching im-plies efficien-cy changes. No explicit representati-on of energy efficiency technologies.	GHG and energy pricing, GHG emission cap, permits trading, fuel subsidies, capacity, production and share target regulations[4]	Price me-chanisms and model constraints	No	No	No	Yes	In steel sector: yes, other sectors: no	From cement

Table 2-2. Main industry model characteristics. Information acquired primarily from the FP7 EU ADVANCE industry models stock taking. *(cont)inued)*

IAM	Industry sector drivers	Industrial subsector breakdown	Techno-logy	Efficiency improve-ments	Policy measures	Policy impact	Material trade (indu-strial goods)	Stock turn-over	Re-cy-cling	Energy use as feeds-tock	Energy use in coke oven and blast furnaces [3]	Process emissi-ons[4]
POLES	Energy demand in industry depends on energy costs (short and long term effects) and an activity variable that is sub-sector dependent	Iron and steel[1], chemicals and petro-chemicals[2], non-metal-lic minerals[2], others (4)	Boilers are de-scribed with a fixed cost, an efficien-cy and a life-time	Improvement of energy intensity depends on long-term pri-ce elasticities. No explicit representati-on of energy efficiency technologies.	Taxation policy on energy fuels, which includes carbon pricing.	Price me-chanism	Yes	(only for boilers)	No	Yes	Only own energy use in blast furnaces	From cement
TIAM-UCL	GDP and other economic activity to derive energy demand or material demand	Pulp and paper[1], chemicals[2], iron and steel[1], non-metallic minerals[1], others (5)	Yes	Exogenous per technology more efficient technologies get a larger market share in response to higher fuel prices	Carbon tax/ cap, permit trading, technology subsidy, efficiency require-ment	Price me-chanisms and model constraints	Yes, but not explicitly model-led	Yes	No recy-cling	Yes	Yes	No

[1] Modelling physical production and energy demand of the subsector; [2] Modelling energy demand of the subsector ;[3] transformation and own energy use; [4] The process emission that can be assigned to a specific sub sector

2.4 Global Industrial model projections

2.4.1 Baseline scenario projections

Final Energy Demand

The baseline industrial final energy demand projected by each model (with and without feedstock use), are compared to the IEA WEO current policy scenario in Figure 2-2. In the short-term (next 20-30 years), all models project a steady increase of industrial final energy use, similar to the IEA projections. In the long-term, however there are clear differences in the projected trends, though these differences are not directly related to the different model assumption described in Section 2.3. MESSAGE and GCAM project a continuous high growth of energy demand, DNE21+ (running until 2050), AIM/CGE, TIAM-UCL, and IMAGE show moderate growth and saturation of energy demand at the end of the century while POLES and Imaclim-R show reduction of energy demand in the second half of the century. In 2100, this results in a range of more than a factor 2 between the highest and the lowest projection. The ratio of final energy demand in 2100 compared to 2010 (2010=1) is between 3.4 and 1.4, which is very comparable to final energy range of the much larger (120 BAU scenario) set of industry sector scenarios shown by the IPCC over the 21st century (IPCC 2014a).

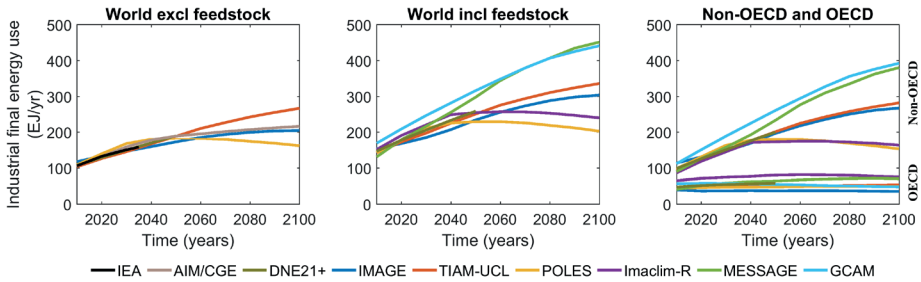

Figure 2-2: Baseline final energy demand projections in the industry sector up to 2100: a) Global excl. feedstock, b) Global incl. feedstock and c) Non OECD and OECD countries incl. feedstock..

Disaggregating the results between regions, shows that the final energy consumption pathways in Non-OECD countries is crucial in understanding these global trends (Figure 2-2c). All models project annual industrial final energy use in OECD countries to remain more or less constant compared to current values, while in Non-OECD countries industrial energy use is projected to grow significantly. How long this growth continues is a key uncertainty across models.

Energy intensity trends

Reduced energy intensity (E/$ GDP) can be the result of economic structural change (slower growth of industry sector activities than the overall economy), shifts towards higher-value goods produced by the industrial sector, and improved energy efficiency within an industrial sub-sector. Between 1995 to 2010, the reduction in energy intensity (w.r.t. industrial value added (IVA)) has been higher in OECD countries than in non OECD countries, but starting from a much higher level (17 MJ/$IVA in Non OECD 1995 as opposed to 9.5 MJ/$IVA in OECD) (IEA 2015b). Literature suggests that a key factor in the energy intensity decline in developing countries has been technological change while in developed countries shift towards high tech industry has had a larger impact on energy intensity reduction (Olivier 2013; UNIDO 2011). Moreover, the share of IVA in GDP has decreased in OECD countries which decreased the energy intensity compared to GDP even further, as can be seen in Figure 2-3.

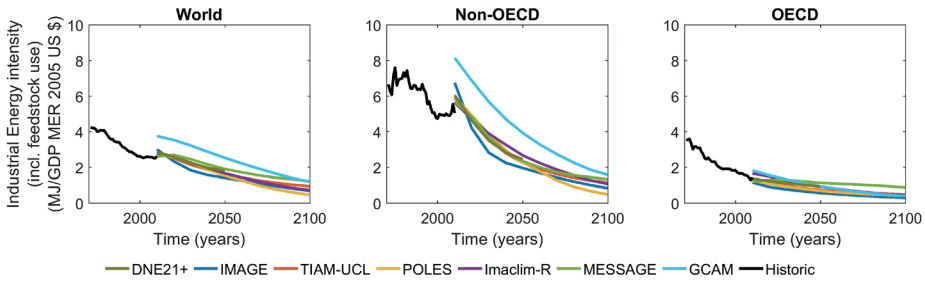

Figure 2-3: Industrial energy intensity expressed in final energy use/GDP MER (in USD $2005) for different regions: a) global, b) Non-OECD countries and c) OECD countries. From 1970-2005 historic energy intensity values (IEA 2015b) are shown in black.

The historical energy intensity trends are compared to the modelled energy intensity futures. The models project energy intensity of Non-OECD countries in the coming century to decline with annual reduction rates ranging from 1.8-2.2%. This relative reduction significantly larger than the average 0.6% measured empirically between 1970 and 2010. In OECD countries energy intensity continues, but with lower annual reduction rates varying between 0.3 and 1.65%, compared to the historic average of 2.7%. As mentioned this historical reduction in OECD countries is largely the result of reducing IVA share in GDP. A key uncertainty for future industrial final demand is whether energy intensity in non-OECD countries converges to projected OECD levels.

Energy consumption by fuel type

In Figure 2-4 the projected industrial final energy per fuel type is shown for the year 2010, 2030, 2050 and 2100. AIM/CGE and IEA results do not include industrial feedstock use. Interestingly, there is a reasonably large agreement across the modelled fuel shares, remaining close to current shares. Fossil fuels are projected by all models to take up more than 50% of the industrial fuel use in 2100. Most models, except Imaclim-R and TIAM-UCL project a slight increase in electricity use and a decrease in fossil fuel use, both between 10-20% change. The electricity and gas shares in the models are relatively low compared to IEA scenarios, projecting respectively 31 and 21 % in 2030.

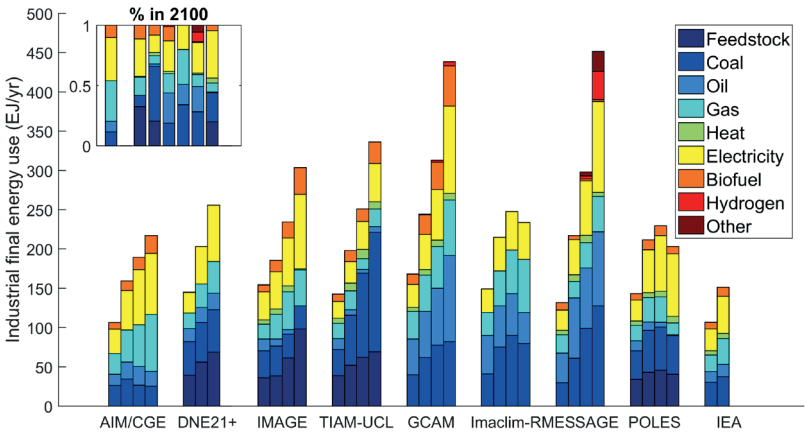

Figure 2-4: Baseline final energy demand of the industry per energy carrier in 2010, 2030, 2050 and 2100. The reported values include feedstock use for MESSAGE, GCAM and IMACLIM, which in 2010 is mainly oil use in the chemicals and petrochemicals sectors, and cokes in the iron and steel sector. In the top left the fuel shares in 2100 are shown.

2.4.2 Mitigation scenario projections

In the stringent climate policy scenario all models show a decrease in final energy demand compared to the baseline (Figure 2-5 left panel). The range of industrial final energy use in 2100 drops from 203-451 EJ to 115-306 EJ, i.e. which is compared to baseline a reduction of 10%-50%. The IEA project a reduction of 18% in 2035. TIAM-UCL, GCAM and MESSAGE project a more or less constant reduction in time, while IMAGE, POLES, AIM-CGE and Imaclim-R show a high reduction in the first 50 years and continue with a steady percentage. Interestingly, the models with low industrial energy demand (with the exception of TIAM-UCL) in the baseline find that there is potential to decrease the industrial energy intensity

even further to reach a climate target, and this decrease occurs in those models more rapidly in the coming decades than in the other models.

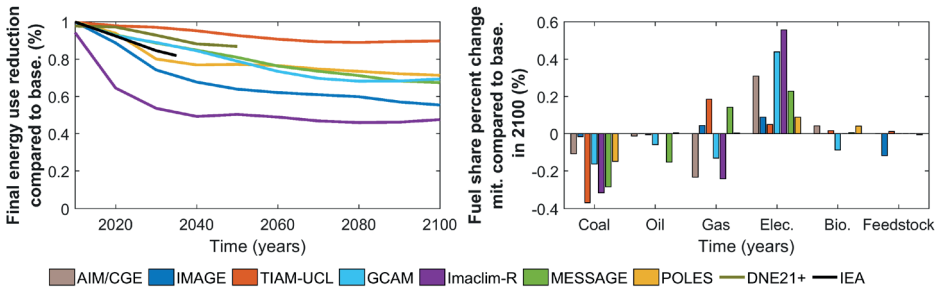

Figure 2-5: a) Mitigation scenario final energy demand as a portion of the baseline scenario final energy demand and b) Percent change in fuel share mitigation scenario compared to baseline.

The fuel mix changes significantly in the mitigation scenario which can be seen in Figure 2-5b, showing the percentage change in fuels shares in 2100 between a mitigation scenario to a baseline scenario (indicating how flexible the model is to switch to different fuels as a response to higher fossil fuel prices). All models except IMAGE show a significantly lower use of fossil fuels in the mitigation scenario. The general trend is a decrease in coal use and an increase in the use of electricity to reduce industrial emissions. This transition takes place steadily over time. TIAM-UCL and MESSAGE also show a switch from coal to gas.

Oil and biomass shares do not change severely in all models. Although IEA scenarios show a significant contribution of biomass to CO_2 emission reduction (IEA 2010; IEA 2012b), in this set of long term energy models deploying biofuels as a mitigation measure is less attractive than switching to electricity to decrease emissions. The apparent shift towards electricity is significantly larger for AIM/CGE, GCAM, Imaclim-R and MESSAGE than other models. It should be noted though that these models do not model industrial manufacturing processes explicitly, which could explain a higher flexibility in fuel switching. In technology-rich models the additional information on preferred fuels for different processes and/or the lack of more advanced technologies in the model's representation could constrain fuel switching.

This divergent behaviour highlights a broader issue that is relevant for modelling future industrial energy use: that is, the appropriate level of detail at which to model the products manufactured, and the specific of the manufacturing technologies used. In this exercise,

the more aggregate models tend to represent many industrial subsectors together with generic production technologies in which all fuels are substitutes, which may be unrealistic for many industrial processes. However, process-based, technologically detailed models may not have the capacity for future fuel-switching, simply because the technologies that would enable future fuel-switching do not currently exist. In the past few decades however, electric arc furnaces in the steel industry and mechanical separation technologies in the chemicals industry have led to increasing shares of electricity in both of these industries.

The different approaches to reduce these industrial emissions are summarized in Table 2-3. Variation across models lie in the extent and rapidness of energy intensity reduction, and flexibility to switch fuels as discussed in the previous paragraphs. In models where both approaches have a limited application (e.g. TIAM-UCL, MESSAGE), other sector's emission budget will be more constrained.

Table 2-3. Annual reduction with respect to 2010 of energy intensity, CO_2 intensity and CO_2 emissions in the models mitigation scenario. The relative high value are marked bold.

	Energy intensity (MJ/$)		**CO2 intensity (g/MJ)**		**CO2 emissions**	
	2050	*2100*	*2050*	*2100*	*2050*	*2100*
DNE21+	1,45		1,23		0,12	
IMAGE	**2,95**	**2,25**	1,60	1,55	1,66	1,45
TIAM-UCL	1,53	1,30	0,85	0,91	-0,38	0,08
POLES	**2,09**	**2,31**	1,54	1,78	1,01	1,77
Imaclim-R	**2,79**	**2,20**	1,93	1,78	**2,21**	**2,03**
MESSAGE	1,30	1,26	1,93	1,78	0,43	0,86
GCAM	1,56	1,66	**1,84**	**6,91**	0,89	**6,29**

2.5 The cement industry – subsector model comparison

To get a better impression of how the industrial sub-sectors are represented in the models, in this section we take a closer look into the projected material production and energy use for the cement industry of the IMAGE, DNE21+, AIM/CGE, POLES, GCAM and TIAM-UCL models for the baseline scenario (only for these models data was available). For comparison, also the IEA projection for the 6°C scenario (6DS) is shown (IEA 2012b).

The reason to focus on the cement industry is that it represents a considerable share of global industrial energy consumption and GHG emissions. In 2009, the global cement industry consumed 11 EJ, which is 11% of global industrial energy consumption (excl. feedstock use) and emitted 2.3 $GtCO_2$ which is 26% of global industrial GHG emissions of

which more than half were process emissions from calcination (IEA 2011). Several studies have identified technologies/measures that can limit the energy use and GHGs, and improve material efficiency in this sector (JRC/IPTS 2010; WBCSD/CSI-ECRA 2009; Worrell 2013). Another reason to focus on this sector is that compared to the other major energy intensive industries, the cement industry is less complex. Cement is almost entirely used by the construction industry. Cement plants globally use the same three process steps i) raw material preparation, ii) clinker calcination, and iii) final material preparation. In addition, trade between the different countries is limited as cement transportation is very costly. In 2009, only 4.5% of cement consumption was traded (Harder 2008), meaning that for most countries, and certainly the large regions covered in models, cement production is equal to cement consumption.

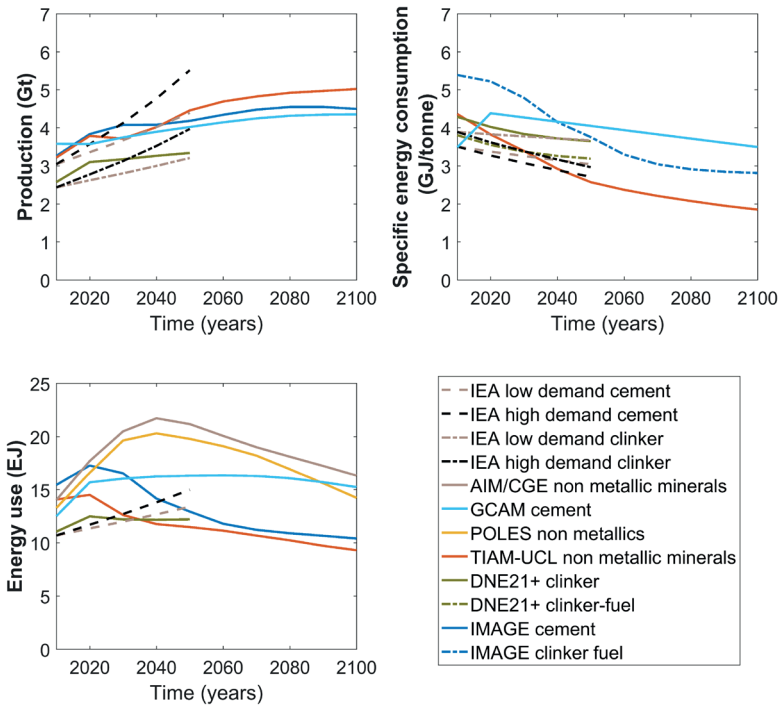

Figure 2-6: a) Projected material production in the non-metallics/cement industry b) energy use c) specific energy consumption for cement and clinker making in different long-term energy models under the baseline scenario in different long-term energy models in comparison with the IEA projections

Figure 2-6a shows the projected production of cement in GCAM and IMAGE, the production of non-metallic minerals in TIAM-UCL and the production of clinker in DNE21+, that model material use explicitly. The global cement production in 2010 was 3.2 Gt (USGS 2013) and the global estimated clinker production was 2.4 Gt (based on a clinker to cement ratio of 76%)[12] (WBCSD/CSI 2012). In IEA, clinker production increases from 2.4 Gt in 2009 to 3.2 and 4.0 Gt in 2050 under the low demand and the high demand scenarios, respectively. Compared to the IEA projections, the three models forecasts are on the low side of the projections (IMAGE is calibrated to 2005). This is due to lower growth rates and different calibration years. In addition, all long-term energy models show a saturation of demand, while the IEA projects steady growth.

The projected energy demand for the non-metallics/cement industry by IMAGE, GCAM, TIAM-UCL and DNE21+ peaks relatively early and then levels off or even declines (Figure 2-6b). AIM/CGE and POLES project the energy demand to peak at a much later year (2040) after which also a decline is observed. The IEA projections show continues growth rates, in line with the earlier observation on material production rates. The models show again show difference in base year data. All models project that the cement sector share in total industrial final energy use decreases.

Figure 2-6c shows the development of specific energy consumption (GJ/tonne product) for cement and clinker making in the various energy models. This is projected to decline in all models driven by technology development (with exception of the GCAM results for the first 20 years of the projection). In IEA, the 2009 energy use for cement making, 3.5 GJ/tonne cement, is forecasted to drop to 3.1 and 2.7 GJ/tonne by 2050 under the low and high demand scenarios, respectively. In clinker making, the energy use (mainly fuel) is projected to decline from 3.9 GJ/tonne clinker in 2009 to 3.7 and 3.0 GJ/tonne clinker in 2050 in the low and high demand scenarios, respectively (IEA 2012b). That is an annual decrease in the specific energy consumption of clinker calcination of 0.14 or 0.66%.

The annual decline rates of the specific energy consumption during the 2010-2050 period, for clinker/cement/non-metallics production are about 0.40%, 0.42% and 1.31% for DNE21+, IMAGE and TIAM-UCL respectively, compared to the IEA range of 0.56-0.85% for cement making. Literature suggests that the energy use for clinker making can drop to 2.9 GJ/tonne clinker (JRC/IPTS 2010) and when improved equipment for cement making and lower clinker to cement ratios are used the energy use could drop to 2.1-2.7 GJ/tonne

12 Although there is data available on cement production, data on clinker production is not. Therefore, clinker production is usually estimated based on information concerning the clinker to cement ratios. The clinker to cement ratio reported by the WBCSD/CSI (2012) is lower from the clinker/cement ratio of 80% reported in IEA (2012b). For an 80% clinker/cement ratio, the 2010 clinker production would be 2.56 Gt.

cement (IEA 2012b; Kermeli et al. 2014). This means that considerable improvement of the energy intensity would still be possible in the mitigation scenarios.[13]

The detailed focus on the cement sector here shows that understanding how total industrial projections relate to subsector material, energy demand and technology deployment improves the ability to interpret the scenario results.

2.6 Discussion and conclusion

2.6.1 Discussion

Comparing the industrial sector representation in long-term energy models has revealed some striking similarities in the projected energy use pathways. Energy intensity (w.r.t GDP) in Non-OECD regions is projected to decrease more rapidly over the coming century than the one observed in recent decades with annual reduction rates varying between 1.8-2.2%, compared to average annual reduction of 0.6% between 1970 and 2010, which is a clear trend break. OECD countries final energy use remains close to current energy use ranging between 36 and 71 EJ/yr in 2100 across the models. Similarly, industrial fuel shares remain close to current values, with electricity use increasing slightly and fossil fuel use decreasing, both between 10-20% change.

Still, projected industrial carbon emission pathways cover a broad range across the models (between 7.5 and 24 Gt/yr in 2100). This can be explained by already different base year assumptions in fuel shares, energy consumption and accompanying emissions, as well as diverging trends of final energy consumption in Non-OECD countries in the second half of the century. These differences could be significantly larger if for example Non-OECD countries would not decouple so strongly from GDP as seen in current projections, or if there is a higher shift to electricity.

To assist the result comparison, describing in detail how the industrial module works and thereby increasing transparency in each model is of great importance. The base year final energy data differs per model and in order to make a credible comparison, reporting the industry boundaries is important. Feedstock use accounts for 17% of industrial energy consumption and it should be clear whether it is accounted for. The same holds for the energy use in coke ovens and blast furnaces and in refineries. In the cement/non-metallic comparison the same effect is visible but by specifying which production processes are accounted for, the variation can be clarified.

13 The IMAGE energy intensity values are relatively high as they are the energy use for cement making divided by the tonnes of clinker production.

The industry data comparison has shown that the models project different appropriate measures to mitigate emissions. Some models show that to mitigate GHG emissions a significant reduction of final energy demand needs to take place in the coming decades, while other models remain close to their baseline final energy levels and rely more on fuel shifting. Comparing long-term energy models at the sub-sector level, such as done in this analysis for the cement sector, can improve our understanding of differences and similarities underlying the model projections. Moreover, comparing bottom-up model details to sector-specific case studies could improve projections, and increase the ability to assess sector specific mitigation policies– at least in the short term. For example, comparing the projected SEC of cement production to state of the art knowledge shows that energy intensity for cement making could reduce further than currently assumed in the models.

Using energy intensities of specific countries/regions, in combination with projected material demand to model industrial future energy, could help to understand the role of recycling, material efficiency, and technology efficiency in mitigating emissions. This can help to clarify what levels of energy intensity improvements are reasonable to achieve, which share of the energy use can be replaced by less carbon intensive fuels, and how fast both processes could take place. For example, by improving the material efficiency in cement making, by using higher amounts of supplementary cementitious materials at different stages of cement production. On the long term constraining industrial technology change to what is currently known on the other hand might be detrimental, as unknown technology options are not accounted for.

Accounting for material demand at sub-sectorial level has as additional advantage that, in the integrated structure that global system models operate, it provides the opportunity to relate the material demand to activities that require material, which are also represented in the model. An example would be to relate cement demand to construct future infrastructure and building requirements, which could give more guidance in better projections of material demand saturation.

2.6.2 Main conclusions

In the reference baseline scenario, the projected behaviour across the models is comparable in the coming decades: the industry sector is relatively energy intensive and remains reliant on fossil fuel (>50%)– but in the second half of the century energy use models project either continuous growth or saturation. This leads to more than a factor of two difference between the highest and the lowest industrial energy demand projection in 2100, ranging between 203 and 451 EJ/yr. Saturation of industrial energy demand depends strongly on whether Non OECD countries are projected to reach similar energy intensity levels as achieved in

OECD countries, which is a key uncertainty across models.

Models show different responses to mitigate CO_2 emissions, where uncertainties are the potential of fuel switching or energy intensity improvements. The reduction of final energy use in 2100 compared to the baseline scenario span a range of 10%-50%. The models show a switch from coal to electricity use as a measure to reduce industrial emissions. Explicitly modelling industrial technologies can constrain the flexibility to use different fuel types and this is recognized in the mitigation scenario results, as models with rich technology representation tend to project less variability in to switch fuels as a measure to mitigate GHG emissions. This divergence highlights that understanding of economy-wide mitigation responses and costs is an area for future improvement in the models.

In line with Sathaye (2011) using industry subsector material and energy use details to support the projected mitigation potential can provide insight in feasibility of how emissions reduction can be achieved. More information at a subsector level could improve the understanding of what realistic energy intensity improvements as a result of material usage and technology efficiency changes are in the short term, along with the potential to use less carbon intensive fuels. Moreover, this would create the opportunity to relate material demand to non-economic drivers, such as infrastructure growth and building stock turnover to improve the understanding of demand saturation and assess the role of subsector specific climate policies to mitigate emissions.

Acknowledgements

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Appendix: Overview of participating models

Asia-Pacific Integrated Model – Computable General Equilibrium (AIM/CGE).

The AIM/CGE model, developed by the National Institute for Environmental Studies in Japan, has been widely used for the assessment of climate mitigation and impact (e.g.,(Fujimori et al. 2014b; Hasegawa et al. 2014; Hasegawa et al. 2015)). The AIM/CGE model is a one year step recursive-type dynamic general equilibrium model that covers all regions of the world. AIM/CGE has an option to be used as country mode (Thepkhun et al. 2013).

The industrial sectors are assumed to maximize profits subject to each input price. The production function is multi-nested Constant Elasticity Substitution (CES) functions. The production structure starts from fixed coefficient (Leontief) with two inputs; namely energy-value added and intermediate inputs. The energy-value added bundle is further nested by CES which has a price elasticity of 0.4. The energy inputs are again nested by CES of each energy carrier and the elasticity is 1.0. The value added is aggregated by labour and capital inputs where elasticity is 1.0. The capital is distinguished by newly installed and already existing one

Instead of using typical CES function, there is an option to couple very detailed technological information for energy end-use sectors (more than 300 kinds of technologies) adopted in AIM/Enduse which is bottom-up type model (Fujimori et al. 2014c). To assess bioenergy and land use competition appropriately, agricultural sectors and land use categories are also highly disaggregated (Fujimori et al. 2014a).

Dynamic New Earth 21 plus (DNE-21+).

DNE21+ is an energy-related CO_2 emission assessment model developed by the Research Institute of Innovative Technology for the Earth (RITE) in Japan. The model is the key assessment model of RITE's integrated assessment framework, and an optimization type of bottom-up linear programming model, highly technologically detailed, where the global costs are minimized when policies such as carbon tax, emission cap, and energy standard are applied (Akimoto 2010; Akimoto 2008) . The salient features of the model include (1) analysis of regional differences with fine regional segregation (The world is divided into 54 regions.), (2) a detailed evaluation of global warming measures by modelling around 300 specific technologies that can be used to counter global warming, and (3) explicit considerations on facility transition for the specific technologies over the entire time period. Historical capital stocks by energy efficiency levels of the specific technologies are assumed considering regional current differences in energy efficiency (Oda 2012).

In DNE21+, the industrial sector is broken down into the iron and steel, cement, pulp and paper, aluminium, some chemicals (ethylene, propylene, and ammonia) and the others sub-sectors. All sub-sectors are modelled following a bottom-up approach except for the others subsector which is modelled in a top-down way (Oda 2007). The future material demand is estimated based on historical relationships between production, consumption, imports, exports and GDP and population levels. Furthermore, availability of steel scrap is also considered for developing future crude steel scenario (Oda 2013).

Global Change Assessment Model (GCAM).

GCAM, previously known as MiniCAM, is an integrated assessment model developed by the Joint Global Change Research Institute (JGCRI 2014), at the Pacific Northwest National Laboratory. It links the world's economy, energy, agriculture, land use and technology systems together with a climate model to assess a variety of climate change policies (EPA 2013; GCAM 2015). It has been used in a number of climate change assessment and modelling activities such as the Energy Modeling Forum (EMF), the U.S. Climate Change Technology Program, and the U.S. Climate Change Science Program and IPCC assessment reports. GCAM is freely available as a community model (JGCRI 2014).

In GCAM, the energy demand in the industrial sector is derived from a constant elasticity equation where energy demand is indexed to GDP change (Brenkert A. 2003). The demand for cement is driven by GDP and the demand for fertilizers is determined by the land use module. For the remaining industrial sectors, GCAM models a single homogeneous industrial good.

Imaclim-R.

The Imaclim-R model (Waisman et al. 2012) is a multi-region and multi-sector model of the world economy. It combines a Computable General Equilibrium (CGE) framework with bottom-up sectoral modules in a hybrid and recursive dynamic architecture. It is developed by the Centre International de Recherche sur l'Environnement et le Développement (CIRED). Imaclim-R studies the relationships between energy systems and the economy, and can be used to assess the feasibility of climate change strategies and the transition options towards a global low-carbon future (ADVANCE 2015). In Imaclim-R, industrial energy use is not modelled with disaggregated technologies. The energy intensity of the industry sector decreases over time due to price-induced energy efficiency improvements and due to new installed capacities characterized by higher efficiencies. In the industrial sector, structural change (a decrease in the activity of the heavy industries as compared to the manufacturing industries) leads to an additional decrease in energy intensity. To represent saturation of

industrial goods consumption, the income elasticities of consumption of industrial and agricultural goods are assumed to decline with increasing per-capita income (Waisman et al. 2012).

Integrated Model to Assess the Global Environment (IMAGE).

The Integrated Model to Assess the Greenhouse Effect (IMAGE), was developed by PBL Netherlands Environment Assessment Agency. The IMAGE model, is an IAM that simulates the environmental consequences of human activities in industry, housing, transportation, agriculture and forestry worldwide. It represents large scale and long term interactions between human development and natural systems to gain insight into the processes of global environmental change, assesses options for mitigation and adaptation, and identifying levels of uncertainty. A great number of global studies, such as the IPCC Special Report on Emissions Scenarios (SRES), the UNEP Third Global Environment Outlook (GEO-3) and the Millennium Ecosystem Assessment (MA) have used the simulated results from IMAGE (Stehfest et al. 2014) (Bouwman 2006).

In the industrial module of IMAGE, the final energy demand is modelled as a function of changes in population, economic activity and energy efficiency. The change in energy-intensity (i.e. energy units per monetary unit) is assumed to be a bell-shaped function of the level of per capita activity (i.e. sectoral value added or GDP). The industrial energy intensity can decrease due to autonomous energy efficiency improvements but also due to increased energy prices. To model the decrease in industrial energy intensity two multipliers are used; 1) an Autonomous Energy Efficiency Increase (AEEI) multiplier which is linked to the economic growth rate, representing energy efficiency improvements that occur as a result of technology improvement independent of energy prices, and 2) The Price-Induced Energy Efficiency Improvement (PIEEI) multiplier which is used to describe the effect of (rising) energy costs on energy intensity. The PIEEI multiplier is calculated with the use of a sectoral energy conservation supply cost curve and end-use energy costs.

The material demand (in tonnes of product) and production technologies for two industrial sub-sectors; the iron and steel and the cement industrial sub-sectors are explicitly modelled. The material demand is a function of the economic activity and material intensity. Once the consumption level has been determined, a material production model simulates how to fulfil the demand for steel and cement, taking into account trade, stock turnover, recycling, and competition between different steel and cement production technologies The material production is met by different steel and cement producing technologies, which are characterized by investment cost, fuel costs and energy requirements. For all the remaining industrial sub-sectors, the energy demand is modelled based on activity data,

structural change, and the AEEI and PIEEI, as described above.

Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE).

The MESSAGE IAM, is a technology detailed hybrid model (energy engineering partial equilibrium model linked to general equilibrium model), developed by the International Institute for Supplied Systems Analysis (IIASA) for energy scenario construction and energy policy analysis (ADVANCE 2015). Its results have been used in major international assessments such as the Intergovernmental Panel of Climate Change (IPCC) and the Global Energy Assessment (GEA)(IIASA 2012).

The industrial sector in MESSAGE is not disaggregated into the various industrial sub-sectors. The total industrial energy demand is generated using regression analysis with the use of historical GDP/capita and final energy use data as well as GDP and population projection data (ADVANCE 2015).

Prospective Outlook on Long-term Energy Systems (POLES).

The POLES model is an econometric, technology detailed, partial-equilibrium model initially developed by the Institute of Energy and Policy and Economics (IEPE, now known as LEPII-EPE), Enerdata and the Institute for Prospective Technological Studies (IPTS) (JRC/IPTS 2010). POLES is primarily used for energy demand and supply projections, analysing greenhouse gas emission reduction pathways, and assessing the impacts of technological change. It has been used for policy evaluation purposes by the EU-DG research, DG Environment, DG TREN, the French Ministry of Ecology and the Ministry of Industry (Criqui 2009).

The industrial sector is disaggregated into the iron and steel, non-metallic minerals (cement and glass), chemical (including feedstock use) and the rest of the industry sub-sectors (including non-energy use) (Criqui 2009; JRC/IPTS 2010) and it entails detailed technological modules for the sub-sectors iron and steel, aluminium and cement (Russ et al. 2007). The industrial final energy demand depends on energy costs, either income or sub sector specific national value added, and autonomous technological trends (Criqui 2009; JRC/IPTS 2010). Improvements in energy intensity depend as well on long-term price elasticities.

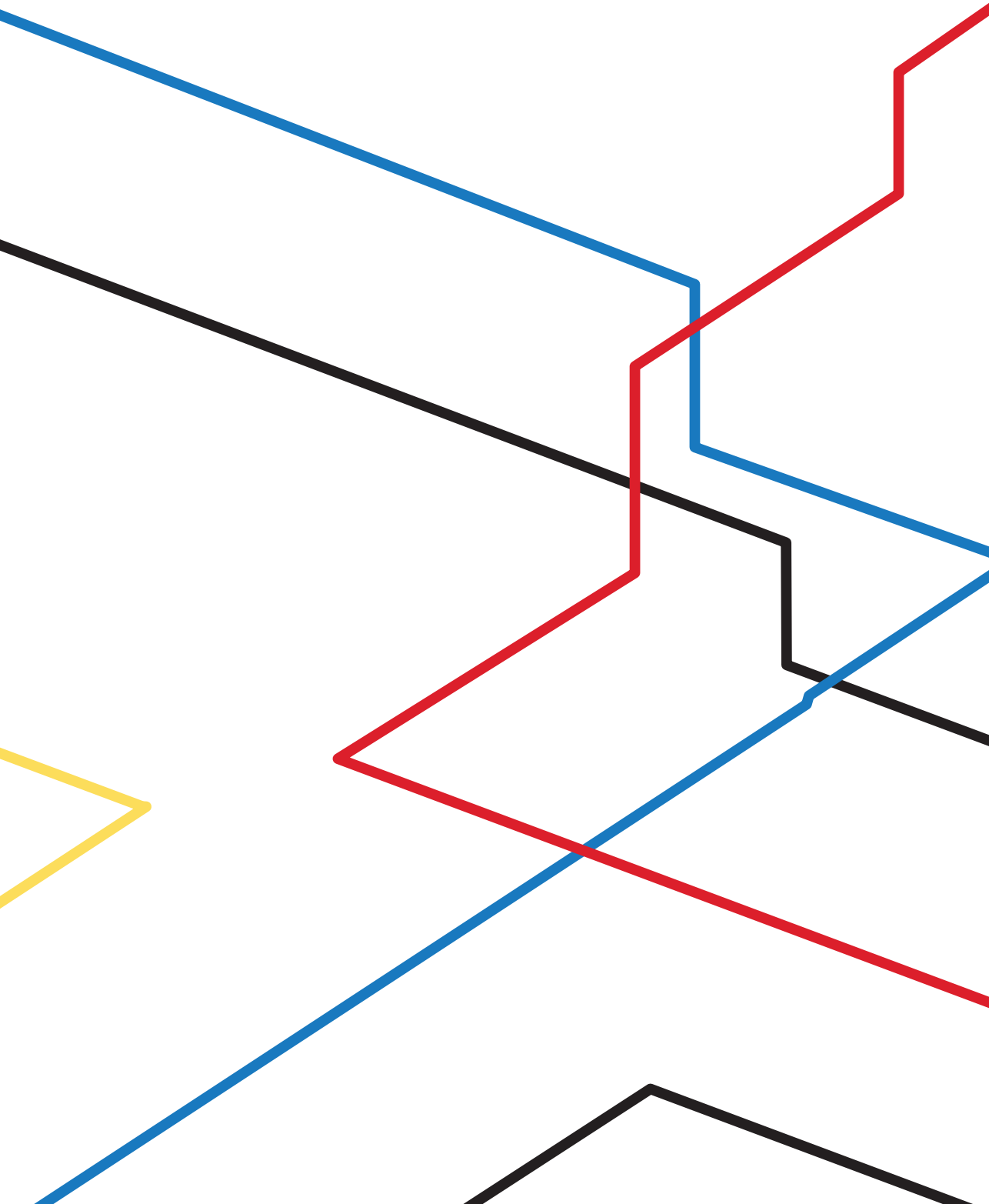
TIMES Integrated Assessment Model – University College London (TIAM-UCL).

TIAM was developed by the Energy Technology Systems Analysis Programme (ETSAP). The ETSAP-TIAM model has been used for the analysis of different climate change mitigation policies (Anandarajah et al. 2011). The TIAM-UCL energy systems model is a global

optimization model that investigates decarbonisation of the global energy-environment-economy system.

Industrial energy services modelled in TIAM-UCL are chemicals, iron and steel, non-ferrous metals, non-metals, pulp and paper and other industries. The material demand is modelled for iron and steel, pulp and paper and non-metals, while in the remaining industrial sub-sectors the total energy demand is related directly to economic activity. The development of industrial sectoral growth rates are geared to GDP. A shift in the GDP composition towards the service sector is implied, so that agriculture and industry will become less important for the whole economy in the future. Demand drivers (population, GDP, etc.) are obtained externally, via other models or from other sources (Anandarajah et al. 2011)

TIAM-UCL models a large number of technologies in the industrial sector to meet the energy-service demands (divided into steam, process heat, machine drive, electro-chemical processes and other). To satisfy every energy-service of each industry, the existing technologies, characterized by an efficiency, an annual utilization factor, a lifetime, operation costs, and six seasonal share coefficients are represented in the model for the base year. New technologies progressively replace the existing ones. Regional specific hurdle rates are applied to new technologies varying from 10% for developed countries to 20% for developing countries.



Chapter 3

Decomposing passenger transport futures: comparing results of global integrated assessment models

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Abstract

The transport sector is growing fast in terms of energy use and accompanying greenhouse gas emissions. Integrated assessment models (IAMs) are used widely to analyse energy system transitions over a decadal time frame to help inform and evaluating international climate policy. As part of this, IAMs also explore pathways of decarbonizing the transport sector. This study quantifies the contribution of changes in activity growth, modal structure, energy intensity and fuel mix to the projected passenger transport carbon emission pathways. The Laspeyres index decomposition method is used to compare results across models and scenarios, and against historical transport trends. Broadly-speaking the models show similar trends, projecting continuous transport activity growth, reduced energy intensity and in some cases modal shift to carbon-intensive modes - similar to those observed historically in a business-as-usual scenario. In policy-induced mitigation scenarios further enhancements of energy efficiency and fuel switching is seen, showing a clear break with historical trends. Reduced activity growth and modal shift (towards less carbon-intensive modes) only have a limited contribution to emission reduction. Measures that could induce such changes could possibly complement the aggressive, technology switch required in the current scenarios to reach internationally agreed climate targets.

Keywords

passenger transportation, energy modelling, model comparison, low emission scenarios

3.1 Introduction

The increased use of motor vehicles and airplanes has led to a higher mobility, flexibility and accessibility of the current population. At the same time, this has also resulted in social and environmental impacts at both the international/national and local scales (GEA 2012). At the local scale, transport activities cause urban air pollution, noise, congestion, water and soil degradation, asthma, obesity, road deaths and social and urban fragmentation (GEA 2012). At the international/national scale, mobility contributes to greenhouse gas emissions, trans-boundary air pollution, and the depletion of oil resources. Global greenhouse gas emissions from transport doubled over the 1970–2010 period to 7.0 $GtCO_2$-eq, increasing at a faster rate than any other end-use sector (IPCC 2014f). Strategies to decrease transport energy use, or even demand growth, can clearly lead to many co-benefits (Woodcock et al. 2009).

Integrated assessment models (IAMs) are commonly used to explore energy system transitions over the long term to meet global climate targets. Their strength lies in analysing trade-offs and synergies across economic sectors, and providing insights in the costs and benefits of different policies (IPCC 2014a). Due to the importance of the transport sector as a final energy consumer, most of these models also include a relatively detailed representation of developments in this sector and its potential to contribute to mitigating GHG emissions. Girod et al. (2013) and Pietzcker et al. (2014) have performed comparison studies of transport sector representation in energy system models, including IAMs. Both studies show that, in these models transport CO_2 emission reduction potential depends highly technological change and changing fuel composition, which would breakthrough in the second half of the century. However, there is a large difference across models regarding the relative potential of the sector to mitigate.

There are different possible interventions to reduce the impact of transport: 1) lower transport demand, 2) shift towards low carbon-intensity modes, 3) reduce the energy intensity of technologies and 4) reduce the emissions intensity of fuels. Creutzig et al. (2015) argue that limiting demand growth by shifting to low carbon intensity modes and reducing the distance travelled has limited application in global IAM scenarios and emissions could be further reduced than currently suggested. Local studies often show that behavioural and infrastructure policy interventions impacting modal shift, distance travelled as well as technological change could be effective measures to decrease emissions (Creutzig 2016). Moreover these measures can already impact transport emissions in the short term and can in fact potentially avoid infrastructure path dependency (Banister et al. 2011; Creutzig et al. 2015).

In this study we look at a large set of IAM transport model projections and determine the relative contribution of intervention strategies through decomposition analysis. This allows us to improve the understanding of these scenarios and to compare the application of the models in a transparent manner, by relating model structure to scenario results. Moreover, the disaggregation can provide further insight into how specific projected components compare against historical transport trends and, by extension, can potentially improve translation into and comparison with local measures, such as those highlighted by Creutzig et al. (2015). Secondly, input data on technology costs are compared in an attempt to further understand uncertainties underlying model differences in projections of vehicle and fuel choice.

The article is structured as follows: Section 3.2 discusses the method applied. The subsequent Section 3.3 discusses the results of a GHG mitigation scenario that is evaluated against a common baseline, focusing on specific GHG mitigation interventions. In Section 3.4, specific attention is given to technology input data representation in the USA affecting light-duty vehicle (LDV) choice. In Section 3.5, the results and identified key transport model developments are discussed, and in Section 3.6 we come to our conclusions.

3.2 Methods

3.2.1 Description of the IAM models

Eleven IAMs were included in this study, namely AIM/CGE, DNE21+, GCAM, GEM-E3, Imaclim-R, IMAGE, POLES, MESSAGE, REMIND, TIAM-UCL and WITCH. A qualitative questionnaire was sent to the modelling teams to take stock of their transport sector representations. This section discusses the concept and solution method of these models, along with the transport modes accounted for. In addition, the Appendix provide a summary of the responses. Several papers that are published in the same special issue that this paper is part of include more detailed presentations of the transport modelling in GEM-E3 (Karkatsoulis et al. 2017), MESSAGE (McCollum et al. 2017), AIM/CGE (Dai 2016), Imaclim-R (Ó Broin and Guivarch 2017) and WITCH (Carrara and Longden 2017).

IAMs differ in the way they represent the transport sector. The ones with greater transport detail (i.e., compared to the ones described herein) use a hybrid approach to model the transport demand and use of energy in the transport sector. In the hybrid approach a top-down demand formulation, relating demand to population and economic growth, is combined with the explicit modelling of modes and technology options per mode. Clearly, the degree of detail determines how well models are able to represent the key dynamics of the various transport sub-sectors and the different ways to mitigate emissions.

Transport demand in AIM-CGE is derived using a top-down method, where energy demand is input to a production function driven by gross domestic product (GDP) growth. In WITCH, the service demand of the explicitly modelled LDV mode is related to GDP and population, while the rest of the transport sector is indirectly comprised in the more general non-electric sector which is an input to a nested constant elasticity of substitution (CES) production function. Also the REMIND transport projections are based on a nested CES production function, but includes a second step in which three different technology options for the LDV mode and one generic end-use technology representation for the other modes. In POLES, DNE21+ and TIAM-UCL, GDP per capita drives modal service demand through income elasticities, while being sensitive to fuel prices. GEM-E3 transport demand depends on bilateral trade flows and on consumer preferences and budgets.

To capture modal shift dynamics and the transition between modes as countries develop (i.e., wealthier individuals use higher-speed modes (Schäfer 1998)), a few models relate the demand per mode to mode speed and cost, MESSAGE and IMAGE both use travel money budget (TMB) and travel time budget (TTB) as top-down elements to constrain per capita person kilometres per mode in combination with the price and speed of the modes to project transport service demand per mode (Girod et al. 2012). GCAM uses a similar approach, where the speed of the transport mode and vehicle operating cost affect the service price, which is related to income levels to determine the energy service demand. Imaclim-R travel demand and modal split are calculated endogenously from household utility maximization under constraint of revenues and time spent, assuming that mode speed is affected by utility of infrastructure. Girod et al. (2013) previously found that income-induced shifts to faster modes are more pronounced in the models that consider travel time.

Most IAMs are able to meet the overall service demand with different transport modes (see Table 3-1, e.g. cars, buses, air planes and trains), with the number of discrete modes in passenger transport ranging from one to seven modes. In several models, including DNE 21+, AIM-CGE and TIAM-UCL, the share of each mode is set exogenously. IMAGE, MESSAGE, Imaclim-R, POLES, REMIND, GEM-E3 and GCAM calculate the modal shares endogenously based on cost and, in some models, time and saturation constraints. WITCH features LDVs only.

Within any mode, vehicle technologies compete on the basis of cost, either through a logit distribution (GEM-E3, GCAM, POLES, IMAGE and Imaclim-R) or least-cost optimization (MESSAGE, REMIND, TIAM-UCL, WITCH and DNE21+). AIM/CGE does not explicitly model technologies. POLES takes exogenous assumptions on infrastructure development into account as a constraint to vehicle choice. The parameters used to describe the costs of

transport technologies as well as their future development differ per model. REMIND, GEM-E3 and WITCH, for example, assume that the investment costs for currently immature technologies (battery-electric vehicles (BEV), plug-in hybrid vehicles (PHEV), fuel cell vehicles (FCV)) decrease endogenously as a function of deployment, following a global learning rate. In Imaclim-R, technology learning rates are applied to all technologies. In other models, the costs of some or all technologies decrease exogenously over time.

Table 3-1: Model description and passenger mode represented in the IAMs.

	AIM/CGE[1]	**DNE21+[2]**	**GCAM[3]**	**GEM-E3[4]**	**IMACLIM-R[5]**
Model concept	General equilibrium	Partial equilibrium	Partial equilibrium	General equilibrium	General equilibrium
Solution method	Mixed complementarity	Intertemporal optimization	Recursive simulation	Recursive dynamic model solved with mixed non-linear complementarity	Recursive dynamics
Passenger modes	Train, aviation, bus, LDV	LDV, bus	LDV, bus, 2W&3W, aviation, train	LDV, aviation, train, bus, ship	Aviation, bus & rail, cycling & walking, LDV
IMAGE[6]	**POLES[7]**	**MESSAGE[8]**	**REMIND[9]**	**TIAM-UCL[10]**	**WITCH[11]**
Partial equilibrium	Partial equilibrium	Partial equilibrium model soft-linked to general equilibrium mode	Hybrid model that couples an economic growth model with a detailed energy system model	Partial equilibrium	Hybrid model that couples an economic growth model with a detailed energy system model
Recursive dynamic	Recursive simulation	Linear optimization	Inter-temporal optimization	Linear optimization	Non-linear inter-temporal optimization and game theoretic setup
LDV, bus, train, aviation, cycling and walking	LDV, bus aviation, train	LDV, bus, 2W, aviation, train	LDV, rail, aviation and bus	LDV, bus, 2W&3W, train, aviation	LDV

1)Fujimori et al. (2014c), 2)Sano et al. (2015), 3)Kyle and Kim (2011), 4)Karkatsoulis et al. (2014), 5)Waisman et al. (2013) 6)Girod et al. (2012), 7)Girod et al. (2013), 8)Riahi et al. (2012), 9)Luderer et al. (2012), 10)Anandarajah et al. (2011) 11)Bosetti and Longden (2013) and Longden (2014), 1:11ADVANCE (2015)

3.2.2 Transport model scenarios

Two scenarios have been used to examine the main passenger transport model outputs (freight transport projections are not compared for the purposes of this paper):

- a baseline scenario (no explicit climate policies beyond those already in place);
- a mitigation scenario (aiming to stabilize atmospheric concentrations of GHGs at 450 ppm CO_2-eq in 2100, compatible with the long-term target of achieving a 2°C increase in global temperature at the end of the century with respect to pre-industrial levels);

The baseline is the standard run scenario of the IAMs that represents a business-as-usual state where no explicit climate policy is assumed but current policy trends (e.g. efficiency) are in some cases extrapolated. Most model teams[14] are currently using or have harmonized their drivers to the population and income projections of the "middle of the road" shared socioeconomic pathway (SSP2) scenario, which assumes that economic and social trends continue in the future following the current patterns (O'Neill et al. 2014). Projected GDP and population are shown in Figure 3-1; in some models these are scenario drivers while in others they are model outputs. There are some differences in GDP/capita visible already in the base year but in particular in the long term. Population projections are very similar, with the exception of POLES after 2030.

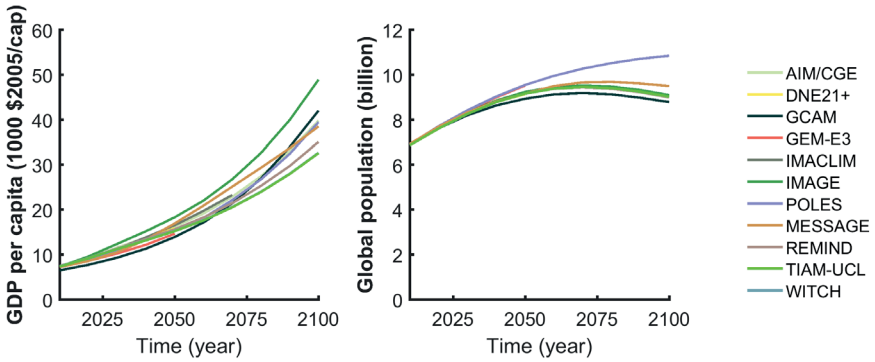

Figure 3-1 Left panel) global population Right panel) global GDP (MER) per capita.

3.2.3 Data analysis

The Laspeyres index decomposition method is used to quantify the contribution of the changes in components (corresponding to the above mentioned potential intervention strategies) to the aggregate emissions in the IAM transport model projections. This method has been used in energy research in recent decades to understand historical trends. There

14 Models not harmonized to the SSP drivers are POLES, using UN projections of demographic drivers, and MESSAGE which is based on a Global Energy Assessment (GEA)-Mix storyline for population and GDP growth. GEM-E3 drivers are not fully harmonized but close to SSP2 projections.

are different decomposition methods and the advantages and disadvantages have been discussed extensively in the literature (Ang 2004) (Ang and Zhang 2000). Even though there are more sophisticated decomposition methods with factor and time reversal properties, the Laspeyres index is easy to interpret which, in this large multi-model comparison study, is an advantage. Moreover this method has been used in several studies to analyse historical transport sector developments across global regions and for a straight forward comparison the same method is applied (Millard-Ball and Schipper 2011; Schipper et al. 1992; Scholl et al. 1996). We use the following variant of the IPAT formula (Ang 2004) to compute the index:

$$Transport\ CO_2\ emissions = \sum_{i,j} population(P) * activity(A) * modal\ share\ (S)_i * energy\ intensity\ (I)_i * fuel\ mix\ (F)_{i,j}$$

(Eq. 1)

The formula shows a disaggregation of total CO_2 emissions from the transport sector into a combination of:

i. population in capita;
ii. the average per capita distance travelled in passenger km/capita (activity);
iii. the share of the different transport modes in fulfilling this travel demand in passenger-km/passenger-km (modal share of each mode i);
iv. the energy used per passenger km travelled for each mode in MJ/passenger-km (energy intensity of each mode i);
v. the CO_2 emissions per unit of energy consumed in g/MJ (fuel mix of each fuel j used per mode i).

Combining the last two components, the CO_2 emissions per passenger kilometre can be derived, which represents the CO_2 intensity per mode. Changes in these components are not necessarily independent from each other; for example, an increase in fuel prices can lead to a change in modal share as well as a decrease in travel activity. It does however give a measure of the relative importance of the change in each of the components in the development of CO_2 emissions.

The Laspeyres index indicates the contribution of the annual change in a single component to the projected CO_2 emissions, holding the others at their base year levels (in this analysis 2010, 2030 or 2050). For example activity growth affecting CO_2 emissions is calculated as:

$$CO_{2t}^{A} = \frac{A_t}{A_{t0}}$$

(Eq. 2)

where A_t is the total passenger kilometres in year t and A_0 is the total activity in the base year. The Laspeyres index represents the annual average change δ^A in the period between

the year t and t0:

$$\delta_{a,b}^{A} = exp\left[\frac{logCO_{2t}^{A} - logCO_{2t0}^{A}}{t-t0}\right] - 1$$

(Eq. 3)

The index calculation shown in Equation 3 has been used 1992 by Scholl et al. (Scholl et al. 1996) to compare developments in energy use and CO_2 emissions in – amongst others – the USA, Japan, France, former West Germany, Italy, the UK, Denmark, Norway and Sweden over the 1973–1992 period. The study found that activity growth is the main contributor to the increase in CO_2 emissions in these regions. In the countries that are part of the Organization for Economic Co-operation and Development (OECD), passenger kilometres per capita grew by 37% on average in the 1973–1992 period. In most countries the modal structure shifted from bus and rail to automobiles and airplanes. The increase in car ownership, driven by growth in income, expanding suburbs, and greater female participation in the workforce, led to an increase in activity. Higher income along with a decrease in the cost of flying led to a larger share of air travel.

The change in CO_2 emissions as a result of the modal shifts was however relatively small compared to the contribution made by activity growth. Scholl et al. found that shifting modes in some countries led to unexpected effects and that the impact on total CO_2 emissions can be time dependent (Scholl et al. 1996). In Japan, for example, the CO_2 intensity of air travel dropped from the most intensive mode to just below the value of cars in 1992. Shifting to air transport therefore would result in a decrease in total CO_2 emissions, while in earlier years it had the opposite effect (Scholl et al. 1996).

A more recent study running up to 2008 showed that the combination of slower activity growth and decline in energy intensity has led to stable or even declining transport GHG emissions in some OECD countries in recent years (Millard-Ball and Schipper 2011). These examples illustrate the relevancy and type of analysis that can be performed through the decomposition method, that can improve understanding of developments contributing to GHG emissions.

3.3 Global trends in IAM transport projections

3.3.1 Transport carbon emission pathways

Figure 3-2 shows the direct and indirect passenger transport emissions[15] projected by the eleven IAMs in the baseline and GHG mitigation scenarios at the global level. All models,

15 The passenger projections of REMIND and WITCH only account for LDV transportation. GEM-E3, POLES and TIAM-UCL emissions include total aviation, and not specific aviation for passenger transport purposes. DNE21+ and Imaclim-R do not account for rail transport explicitly (see Table 3-1). DNE21+ and GEM-E3 projections run to 2050 and Imaclim-R to 2070.

show an increase in direct emissions between 2010 and 2050 in the baseline, although the size of this increase clearly differs. In 2100, the projected emissions range (between 4 and 12 Gt/year) is further amplified. The models follow different baseline emission pathways, either continuous increase until 2100, saturation, or even peak-and-decline. In the mitigation scenario, all models show a significant decrease in transport emissions compared to the baseline; this is necessary to achieve the stringent, long-term climate target. However, whereas direct emissions are less than one Gt in some models, in others they are comparable to base year values.

The lower panel of Figure 3-2 shows the indirect emissions from electricity and hydrogen use in the transport sector, calculated by using the average emission intensities of the models of electricity and hydrogen production[16] to enable straight-forward comparison across the models. Zero carbon emissions are assumed for biofuels, thus the indirect emission figure indicated the degree of electrification. Transport electrification takes place in all models, especially between 2050 and 2100. Whether electrification of transport will actually lead to lower emissions will depend on the fuel production process.

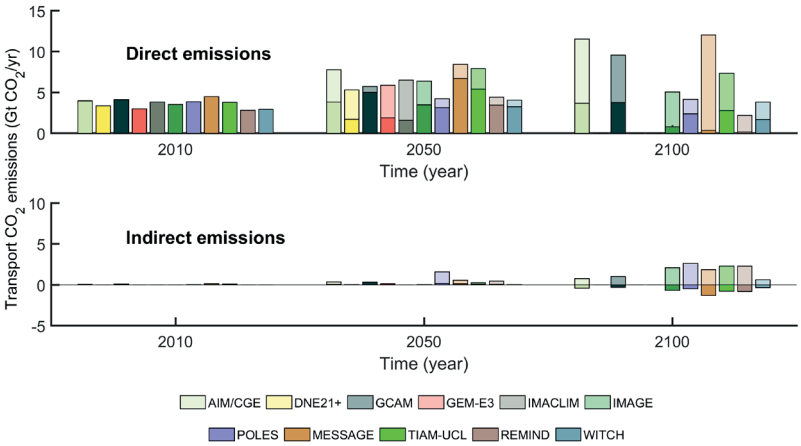

Figure 3-2: Passenger transport direct (top) and indirect (bottom) CO_2 emissions projected by IAMs in baseline (transparent colour) and mitigation (solid colour) scenarios. Average CO_2 intensity factors for hydrogen and electricity production across models are used for the indirect emissions calculation. REMIND and WITCH results only include LDV emissions.

16 In the mitigation scenario the average electricity emission factor across models is negative (this is not the case for all models) at the end of the century due to biofuel use combined with carbon capture and storage use for electricity production.

3.3.2 Laspeyres index scenario decomposition

To untangle the underlying dynamics that lead to the models projected pathways, the Laspeyres indices are calculated for several components (Table 3-2): *activity* (pkm), *structure, energy intensity* (MJ/pkm) and *fuel mix* (g/MJ). The analysis focuses on direct emissions. The Laspeyres index is calculated for three time periods, namely 2010–2030, 2030–2050 and 2050–2100. As REMIND and WITCH only model LDV explicitly as a passenger mode, structural change – which refers to mode shifting – does not play a role in these models projections. The results of eleven IAMs are compared to Millard-Ball and Schipper (2011) for a selection of OECD countries in the 1973–2007 period, which is summary of data collected by Scholl et al. (1996) and Schipper (1994) over a long time frame.

Activity growth makes a large contribution to the total CO_2 emissions pathways; in some models, it increases by a factor five between 2010 and 2100. In the baseline scenario, all models except REMIND and WITCH show a deceleration in activity growth in the second half of the century. The average annual activity change between 2010 and 2100 varies across models and ranges from -0.1% to 1.1%. Between 1973 and 2007, activity growth ranged from 1.0% to 3.1% per year in the six OECD countries studied. Activity growth reduced over time ranging from -0.8% to 1.8% between 2000 and 2007 (Millard-Ball and Schipper 2011). This small set of countries shows a large variation in activity across the regions studied. Although the models' activity growth projections are well within that range, the variation in global activity increase across models over the century has a significant impact on total CO_2 emissions. Moreover, activity level differences between models within a single scenario are more pronounced than for a single model between the two scenarios. In other words: activity reduction in the mitigation scenario compared to the baseline scenario as a measure to decrease emissions has a limited effect according to the models.

Energy intensity increased over time in some of the OECD regions evaluated by Millard-Ball and Schipper (2011) but decreased in others, ranging from -0.6% to 0.3% between 1973 and 2007, and from -1.2% to 0.8% in more recent years (2000-2007). All models project that the global average energy intensity of motorized passenger transportation will decrease in the baseline, even though historically this has not always been the trend. Several models project that the energy intensity will drop more strongly in the first half of the century than in the second half in the baseline. REMIND, AIM/CGE and TIAM-UCL show the opposite effect over time and Imaclim-R and GEM-E3 show a constant decrease. In all models energy intensity reduces further in the mitigation scenario; it still remains within the range of reduction rates measured across OECD regions historically, although at the high end.

Table 3-2: Laspeyres index decomposition of activity, structure, energy intensity and fuel mix contributing to direct CO_2 emissions in IAM passenger transport model projections. The index value indicates the annual rate of change in emissions with respect to the base year if only that component changes while the other components remain constant. WITCH and REMIND show results at the LDV level. Annual change rates higher than 1% are highlighted in bold.

		Activity	**Structure**	**Energy intensity**	**Fuel mix**				
		BAU	450	BAU	450	BAU	450	BAU	450
AIM/CGE	2010-2030	**1.1%**	**1.0%**	-0.2%	-0.2%	-0.2%	-0.5%	0.0%	-0.2%
	2030-2050	0.6%	0.6%	0.0%	-0.1%	-0.4%	**-1.2%**	0.0%	-0.2%
	2050-2100	0.9%	0.8%	0.0%	0.0%	-0.4%	-0.6%	0.0%	-0.2%
DNE21+	2010-2030	0.5%	0.5%	0.1%	0.1%	-0.3%	-0.3%	0.0%	-0.2%
	2030-2050	0.2%	0.2%	0.0%	0.0%	-0.1%	**-1.2%**	-0.1%	**-1.2%**
GCAM	2010-2030	0.5%	0.5%	0.2%	0.1%	-0.5%	-0.5%	-0.1%	-0.1%
	2030-2050	0.3%	0.3%	0.2%	0.2%	-0.3%	-0.3%	-0.2%	-0.4%
	2050-2100	0.4%	0.2%	0.4%	0.3%	-0.1%	-0.2%	-0.1%	-0.6%
GEM-E3	2010-2030	0.8%	0.7%	0.0%	0.0%	-0.5%	-0.7%	0.0%	-0.1%
	2030-2050	0.9%	0.7%	0.1%	0.1%	-0.5%	**-1.0%**	0.0%	**-1.5%**
IMACLIM	2010-2030	0.9%	0.2%	0.0%	0.1%	-0.3%	-0.3%	-0.1%	-0.1%
	2030-2050	0.6%	-0.1%	0.0%	0.0%	-0.3%	**-1.0%**	-0.2%	-1.3%
IMAGE	2010-2030	0.8%	0.7%	0.1%	0.0%	-0.5%	-0.9%	0.0%	-0.1%
	2030-2050	0.5%	0.4%	0.2%	0.1%	-0.1%	-0.5%	-0.1%	-0.3%
	2050-2100	0.5%	0.5%	0.0%	0.0%	-0.4%	-0.7%	-0.6%	**-1.6%**
POLES ADVANCE	2010-2030	0.8%	0.7%	0.0%	0.0%	-0.6%	-0.7%	-0.4%	-0.4%
	2030-2050	0.6%	0.6%	0.0%	0.0%	-0.5%	-0.7%	-0.7%	-0.9%
	2050-2100	0.5%	0.5%	0.1%	0.1%	-0.2%	-0.3%	-0.6%	-0.7%

		Activity	Structure	Energy intensity	Fuel mix				
MESSAGE[17]	2010-2030	0.8%	0.8%	0.0%	0.0%	-0.8%	-0.8%	0.0%	0.0%
	2030-2050	0.7%	0.6%	0.1%	0.1%	-0.1%	-0.2%	-0.1%	-0.3%
	2050-2100	0.6%	0.5%	0.1%	0.0%	-0.2%	-0.4%	-0.2%	**-2.3%**
REMIND	2010-2030	0.7%	0.6%			-0.2%	-0.2%	-0.1%	-0.1%
	2030-2050	0.4%	0.3%			-0.3%	-0.2%	-0.2%	-0.6%
	2050-2100	0.6%	0.8%			-0.6%	**-1.0%**	-0.8%	**-3.1%**
TIAM-UCL	2010-2030	**1.1%**	**1.1%**	0.1%	0.1%	-0.5%	-0.6%	0.0%	0.1%
	2030-2050	0.8%	0.8%	0.1%	0.0%	-0.6%	**-1.1%**	-0.1%	-0.4%
	2050-2100	0.9%	0.9%	0.0%	0.0%	-0.7%	-0.4%	-0.3%	-0.9%
WITCH	2010-2030	0.7%	0.7%			-0.6%	-0.6%	0.0%	0.0%
	2030-2050	0.5%	0.5%			-0.5%	-0.6%	-0.1%	-0.5%
	2050-2100	0.7%	0.7%			-0.3%	-0.6%	-0.4%	-0.8%
OECD[18]	*1973-2007*	*1.0 to 3.1%*	*0.0 to 0.8%*	*-0.6 to 0.3%,*					
	2000-2007	*-0.8 to 1.8%.*	*-0.3 to 0.2%*	*-1.2 to 0.8%*					

17 The MESSAGE transport module used in this study is a simpler version than used in other papers of the special issue (e.g.. McCollum et al., 2017). Specifically, this version is MESSAGE-Transport V.5; yet, for the purposes of this paper, the model did not make any explicit assumptions about heterogeneous behavioural features among consumers

18 The historical OECD Laspeyres decomposition index values are based on the analysis performed by Millard-Ball et al., 2011.

Fuel mix has not been reported Millard-Ball and Schipper (2011) as historically shifting to alternative fuels has had limited application. 94 % of transport final energy is currently fuelled by oil (IPCC 2014f). Even in the baseline all models move away from this trend with changing fuel mix impacting the projected transport CO_2 emissions. This impact is more pronounced in IMAGE, POLES, WITCH and TIAM-UCL towards the end of the century. This effect is even larger in the mitigation scenario where the majority of the models show a high reduction in direct CO_2 emissions as a result of changing fuel mix, especially in the second half of the century. This could be related to electrification or increased shares of less CO_2 intensive fuels such as biofuels or natural gas.

Modal shift contribution might be underestimated as a result of using the Laspeyres method where all other factors remain at their base year level. The reason for this is that aviation, rail and LDV have similar base year energy intensity and CO_2 intensity levels. Table 3-2 indeed shows that modal shift plays a limited role in emission changes. Consistent with historical trends, modal shift leads to increasing emissions in the baseline projections with the exception of AIM/CGE. In the mitigation scenario this trend is not reversed and is hardly applied as a mitigation measure in the policy scenario.

Looking across the different models, we see that TIAM-UCL, AIM/CGE and MESSAGE – with high activity growth assumption – project high emissions. GCAM includes a structural shift towards carbon intensive modes, which explains why even with relatively low activity growth the projected emissions are at the higher end of the model range. Similarly, activity and structural change lead to increasing emissions in IMAGE and POLES, but a strong decrease in CO_2 intensity – as a result of energy intensity and fuel mix change – resulting in lower total CO_2 emissions: the decline in CO_2 intensity of transport strongly offsets the increase in transport service demand. The models are comparable in their behaviour in the sense that they show activity growth and reduced CO_2 per passenger kilometre, which further declines as measures to meet the climate target are set. Even though the direction of change is the same, the differences in extent – which is especially pronounced in fuel mix change, but it also true for energy intensity or activity change – leads to large differences in projected CO_2 pathways over the century. Figure 3-3 further illustrates this, depicting the increase in CO_2 emission development resulting from change in a component following Equation 2. IMAGE and MESSAGE for example project that CO_2 intensity developments will reduce emissions by a factor as high as 21–22, if all other components remain at their base year value, and REMIND (only accounting for LDV) even goes as far as a factor -74, reaching full decarbonisation of transport fuels.

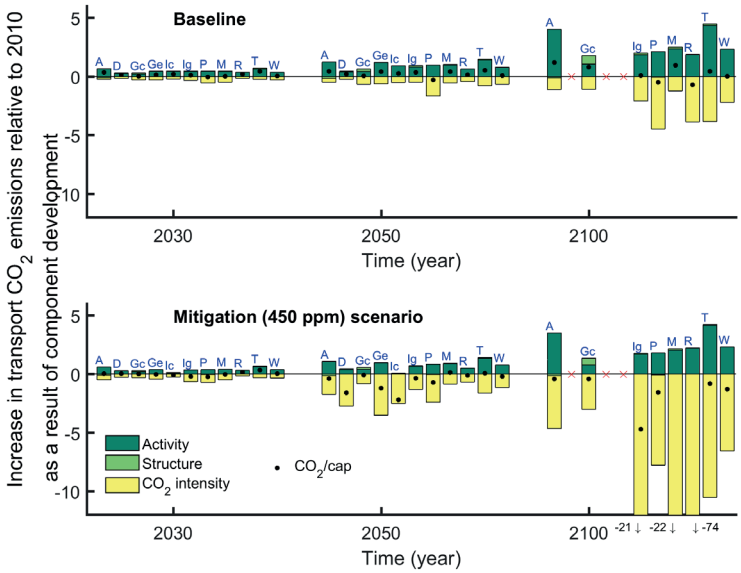

Figure 3-3: Passenger transport direct CO_2 emission increase relative to 2010 due to activity, structure or CO_2 intensity development, in accordance with Equations 1 and 2 for baseline (top) and mitigation (bottom) scenarios in AIM/CGE (A), DNE21+ (D), GCAM (G), GEM-E3 (Ge), Imaclim-R (Ic), IMAGE (Ig), POLES (P), MESSAGE (M), REMIND (R), TIAM-UCL (T) and WITCH (W). WITCH and REMIND show results at the LDV level.

3.3.3 Individual components: activity growth, structure, energy intensity and fuel mix

The projection of structural change due to modal shift can be seen in Figure 3-4, which shows the modal shares in 2010, 2050 and 2100. The figure shows some common elements:

- LDVs dominates passenger travel, both currently and far into the future in most models.
- Most models show an increasing share of aviation at similar rates. At the level of individual models, MESSAGE, IMAGE, GCAM and Imaclim-R consider speed to be a determinant of modal choice, leading to a shift towards aviation. TIAM-UCL and POLES also show increased aviation shares. Train and bus shares remain similar to the base year in most models, although MESSAGE and GCAM show a significant decrease in bus usage and IMAGE a significant decrease in train usage. POLES and Imaclim-R, which consider infrastructure constraints, show a reduction in LDV share over time.
- There are quite clear base year differences across the models, which contribute to inter-model differences in the future.
- In most models, policy induced emission mitigation does not lead to a significant

change in the modal split of transport modes compared to baseline, reflecting its limited role in decreasing emissions in the models. AIM/CGE, DNE21+ and TIAM-UCL modal shares are exogenously set and therefore not responsive to a climate target. Imaclim-R projects more cycling and walking and MESSAGE, GCAM and IMAGE project reduced air travel compared to the baseline scenario.

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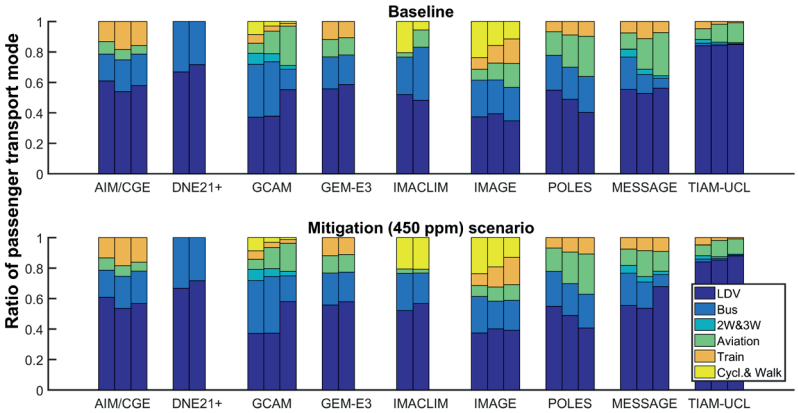


Figure 3-4: Passenger modal shares (structure component) in 2010, 2050 and 2100 for baseline (top) and mitigation scenario (bottom)[19].

The impact of component development on total CO_2 projections is further specified in Figure 3-5, which shows the global CO_2 emissions per capita (indicated by the isolines), due to activity growth plotted against CO_2 intensity, again for the baseline and mitigation scenarios[20]. The activity growth projected by the models is offset by the CO_2 intensity reduction in the baseline and most models remain at 0.6 kg CO_2/cap annually at a global level over the course of time. GCAM, MESSAGE and AIM/CGE are the exception with higher CO_2 per capita values in the second half of the century. The models move away from 0.6 CO_2 kg/cap in the mitigation scenario, mainly due to CO_2 intensity reduction, with some models reaching values lower than 0.2 CO_2 kg/cap.

19 The Bus component for Imaclim-R also includes rail travel while the LDV component includes 2W & 3W.
20 Only direct transport emissions are accounted for, and biofuels are treated as zero-carbon fuels

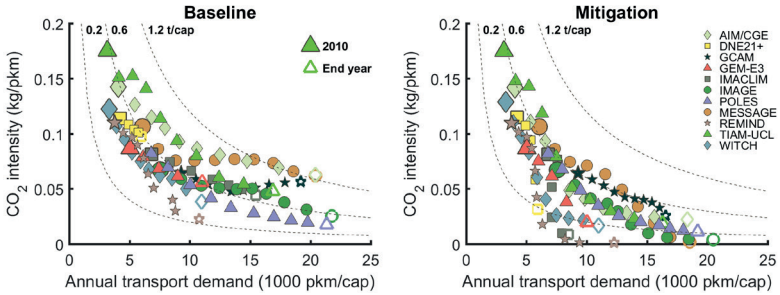


Figure 3-5: Global passenger transport activity per capita (x-axis) compared to CO_2 intensity (y-axis) development over time. The CO_2 emissions per capita are indicated by the plotted isolines. The left panel shows baseline and right mitigation scenario. DNE21+ and GEM-E3 model projections run to 2050, Imaclim-R to 2070 and the rest until 2100.

Figure 3-6 shows the carbon intensity impact of fuel mix and energy efficiency on CO_2 per passenger kilometre. For both scenarios, this is compared to the fuel mix of hydrogen/electricity, biofuels and fossil-based fuels. In the baseline scenario, in most models the reduction in CO_2 intensity is the result of energy efficiency increases, although IMAGE, REMIND, WITCH, TIAM-UCL and POLES also show fuel intensity reduction between 2050 and 2100, due to switching to a mix of hydrogen, electricity and biofuel use. This is in agreement with the Laspeyres index results in Table 3-2. Most models project that average global energy efficiency will decrease to 0.5–1 MJ/pkm in 2100. This is a significant decrease (46–72%) compared to 2010 values, but in line with current estimations for drivetrain fuel consumption reduction potential. Already in 2030 gasoline ICE fuel consumption could reduce with 30-50%, while switching to alternative driving mechanisms could reduce fuel consumption even further.

The higher CO_2 intensity reduction in the mitigation scenario (see also Table 3-2) is highly dependent on fuel switching in all models, but also on further energy efficiency improvements. IMAGE, MESSAGE (from 2090), REMIND (from 2080), and Imaclim-R (from 2060) project that more than 80% of global passenger transport fuel use will be non-fossil in a scenario stabilizing at 450 ppm CO_2eq. These models justifiably project relatively low emissions in the mitigation scenario. Both electric and hydrogen fuelled vehicles, as well as biofuel use, are attractive alternative options in this scenario[21]. REMIND, Imaclim-R, IMAGE and WITCH show the trend of switching to biofuels in the first half of the century and then switching to hydrogen/electric, as found by Pietzcker et al. (2014), but other models do not follow this pathway. AIM-CGE and GCAM are more than 40% fuelled by fossil fuels, which

21 WITCH does not take into account hydrogen

also explains their higher transport CO_2 emissions (Figure 3-2). DNE21+ is the only model that does not shift towards electricity/hydrogen.

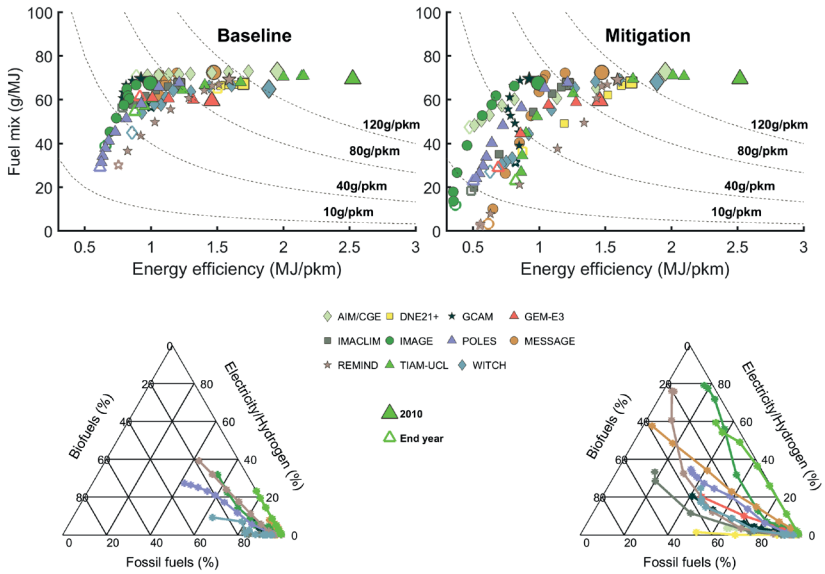


Figure 3-6: Global passenger transport energy intensity (x-axis) compared to fuel mix (y-axis) development in top figures. The isolines indicate emissions per passenger kilometre. The bottom panel shows passenger transport fuel shares over time, for baseline (left) and mitigation scenario (right). DNE21+ and GEM-E3 model projections run to 2050, Imaclim-R to 2070 and the rest until 2100[22].

3.4 Comparing model inputs to outputs for the USA: a focus on light-duty vehicles

So far, fuel switching – either to electricity/hydrogen or biofuels –, has proven to be an essential measure in IAMs to mitigate emissions from the transport sector. Models that project that the transport sector will remain relatively dependent on fossil fuels are at the high end of transport sector CO_2 emissions projections in the mitigation scenario. Similarly, models that show fuel switching in the baseline scenario are at the low end of the baseline emission range.

22 The tenary figures at the bottom show fuel mix of LDV for REMIND and WITCH.

In an attempt to improve our understanding of differences in fuel mix projections, in this section we look specifically at LDV choice dynamics in the models. To standardize and simplify the comparison, we focus on the results for the USA region in each model. As mentioned in Section 3.2.1, vehicle choice in the models depends on cost of travel, which includes capital costs of the technology, efficiency, fuel prices and in some cases non-operating costs. Capital costs are related to deployment in REMIND, GEM-E3 and Imaclim-R and to R&D investments in WITCH, while in other models they are fixed in time. The distribution between vehicles is determined by either a logit or cost-optimizing algorithm.

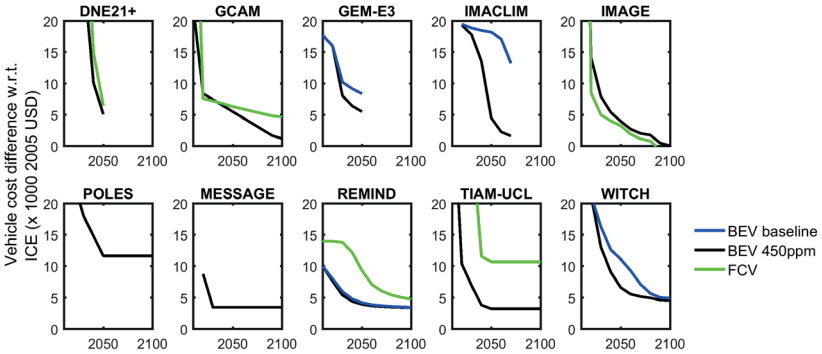


Figure 3-7: Difference in USA LDV fuel cell vehicle (FCV) and battery electric vehicle (BEV) investment costs compared to conventional vehicles (ICE) in the mitigation scenario. POLES and MESSAGE FCV investment cost remain to be more than 20.000 2005 USD more expenisve than conventional vehicles, i.e. outside the displayed range.

Figure 3-7 shows the *differences* in capital costs of alternative vehicles compared to conventional (ICE) vehicles. AIM/CGE does not consider vehicle cost. BEV prices are currently substantially higher than conventional vehicle prices, although they have decreased rapidly in recent years (Nykvist and Nilsson 2015). All models show a steep decline in BEV costs in the coming decades. POLES, MESSAGE TIAM-UCL, REMIND and WITCH reach a fairly constant value in the second half of the century for both BEV and for FCV, where FCV remaining significantly more expensive than BEV., DNE 21+, GCAM, GEM-E3, IMAGE and Imaclim-R on the other hand show a continuous decrease in alternative vehicle costs, some ultimately reaching comparable levels to conventional vehicle costs, which would lead to fuel prices combined with vehicle efficiency being more dominant in determining vehicle cost.

Comparing the techno-economic assumptions underlying the vehicle choice outcome represented by the fuel split shown in Figure 3-7, we see that different vehicle capital cost

development assumptions do not necessarily explain different fuel distribution outcomes. For instance, GCAM with low electric vehicle cost projections also shows low-to-medium electric vehicle deployment compared with the other models. Uncertainty in the cost development of BEVs and FCVs can be seen in the variety of the model cost projections, but does not in itself explain differences in model outcomes. Consideration of non-economic factors such as behavioural considerations limiting alternative vehicle deployment in the models, optimizing vehicle choice, as well as interaction with other sectors that for example affect fuel prices, can also potentially play an important factor.

3.5 Discussion

In this paper, IAM passenger transport CO_2 emission scenarios from eleven global models have been compared by decomposing them into transport activity, modal structure, energy intensity and fuel mix development. The decomposition method untangles the complex model dynamics in to reduced form representation of the models, enabling us to compare the models to each other, as well as comparing them to historic trends. Some discussion on the applied method is provided.

Suitability of the decomposition method

Model comparison studies can show key model uncertainties by comparing the output of different models to their underlying model assumptions (Kriegler et al. 2015b). A decomposition method can be applied to identify structural changes contributing to energy consumption trends. This can also be used to validate the model baseline results by historic comparison, as shown by Marcucci and Fragkos (2015) at the regional level. Although more sophisticated methods exist, the Laspeyres decomposition analysis is an appropriate method to distinguish model dynamics underlying the projected futures. The advantages and disadvantages of the Laspeyres method index method have been discussed in literature (Ang 2004) and include the fact that the method has no time and factor reversal properties, and the residual term can become large. However, the method is relatively easy to implement and interpret, which is an advantage in the large multi model study. Moreover the use of this method allows easy comparison with several studies on historical transport sector developments across global regions over a longer time (Millard-Ball and Schipper 2011; Schipper et al. 1992; Scholl et al. 1996).

It should be noted that also other indicators can be calculated to compare models, both across a larger set of models or with historic data, such as the intrinsic income and price elasticities (Schäfer et al. 2016), also discussed in Chapter 4. Where price and income elasticities verify demand response to economic indicators, which are often the models key

drivers, the decomposition method here focuses on the development of physical indicators such as service demand and technology change.

Discussion of the key outcomes

Interestingly, the model results presented here show a relatively small range in annual travel activity growth. Empirical activity growth data for example passenger-km/capita, spans a much wider range than that observed across the model scenarios. Still, the rates should be compared to long-term averages and relatively small differences in annual rates of change can lead to large spreads in passenger kilometre demand projections over the century. As a result, activity increases by a factor of five in some models, and in others by a factor of two. This has a large effect on the projected transport emissions pathways, and is thus a key uncertainty.

One key observation is that activity growth and modal shift hardly contribute to mitigation in the IAM transport scenarios. Earlier research has compared low carbon transport scenarios of IAMs to those of transport sector specific models and place-based research, focusing on local transport, and indicate that different scientific communities have a different perspective and find different solutions to mitigate transport emissions. Where models (IAM and transport sector models) put higher emphasize on efficiency and fuel switch potential, place-based research often show that behavioural and infrastructure policy interventions, especially in urban areas, impacting modal shift, distance travelled and technological change, can cut transport energy use and CO_2 emissions significantly (Creutzig 2016). These policy measures, that currently find limited application in IAM scenarios, could complement the drastic technology changes that are needed to reduce emissions (IEA 2012b). Another example on modal split, is Fulton and Eads (2014) who concluded that a high shift scenario with far greater urban passenger travel by low-carbon public transport and non-motorized modes could lead to a 1.7 Gt reduction in transport emissions globally by 2050 (a 40% reduction in urban transport emissions). Further research to quantify the impact of travel reduction and modal shift either by dynamic response or scenario design in IAM transport models would be an important next step. This could improve current IAM transport scenarios and make them less reliant on technology transition, which is uncertain.

The high dependence of transport emission mitigation in the IAM scenarios on technology change (alternative vehicle adoption as well as improved efficiency) concur with previous IAM transport comparison studies (Girod et al. 2013; Pietzcker et al. 2014). Diffusion of advanced vehicle technologies, however, will depend on technology development impacting costs and efficiency, as well as behavioural considerations. These processes are highly uncertain and this is reflected in the models results, which show a large range in

annual fuel mix change. A comparison between the projected capital cost assumptions of LDV alternative propulsion mechanisms and the vehicle choice outcome represented by the LDV fuel split, shows that different capital cost assumptions do not necessarily explain different fuel distribution outcomes. Behaviour or non-monetary considerations are often accounted for indirectly in the models by for example using a logit distribution, inertia assumptions or implicit discount rates. When taking in to account behavioural consideration a transition to advanced vehicles to mitigate GHG emissions can be more difficult (McCollum et al. 2017). A better understanding of technology diffusion dynamics is important and, moreover, could provide the opportunity to explicitly analyse policies related to the transition to new technologies by removing these barriers to market adoption (e.g., cities installing EV chargers in urban areas).

3.6 Conclusions

Based on the results and the discussion, the study leads to the following conclusions.
The IAM models show similar trends in the baseline scenarios for the different factors contributing to emission changes in the transport sector: 1) continuing activity growth, 2) reduced energy intensity, 3) a limited impact of structural change to CO_2 intensive modes and 4) a fuel switch towards alternative fuels. For most factors, changes in these factors are within the historical range. However, fuel switch forms an exception. As, the transport sector has historically been dominated by oil, fuel switching did not play a role. In the future, models expect fuel mix moves away from oil in response to increasing oil prices in several models, thus pushing the impact of carbon intensity on future emissions far beyond historical rates.

In mitigation scenarios, reductions are mostly achieved through fuel switching and further enhancements in energy efficiency. In some models, activity reduction and some modal shifting also contribute to emission reduction (e.g. Imaclim-R), but energy intensity improvement and fuel switching are nevertheless much more important. The enhancement of technology efficiency as an intervention strategy for emission reduction pushes the annual efficiency change rate to the maximum of what has historically been measured in OECD regions between 1973 and 2007 by Millard-Ball and Schipper (2011). Fuel switching towards electricity, hydrogen and biofuels goes significantly beyond historical rates of change and the scenarios would imply a clear break with historical trends.

Model comparison studies allow a better understanding of future transport system behaviour. At the same time, further model development is needed. The models show different pathways of technology transition, with different fuel types being deployed and

different rates of deployment. Technology transition in the models is found to depend on travel cost, which is uncertain, reflected also in the range of vehicle capital cost projections in the models. Other important aspects such as fuel price and non-economic factors, (e.g. anxiety for new technologies) that are represented in various ways in the models but are not harmonized or explored in this study may also be important in projecting future shares of alternative-fuelled vehicles. To improve transport modelling, further enhancement is required in the modelling of technology transition and behavioural considerations. Moreover, an analysis of scenarios addressing the mitigation options that result from modal shift and from policies that impact behaviour and infrastructure, especially in urban areas, could complement current results.

Acknowledgements

*The research leading to these results has received funding from the European Union's Seventh Programme FP7/2007-2013 under grant agreement n° 308329 (ADVANCE).

Appendix: Overview of the transport models based on the ADVANCE survey.

Table A2.1: Drivers of energy demand in the transport sector of eleven IAMs.

	TIAM-UCL[1]	IMAGE[2]	Imaclim-R[3]	MESSAGE[4]*	POLES[5]
System boundaries	The fuel mix is determined endogenously. Indirect fuel use from manufacturing, upstream energy and emissions are calculated but not tied to transport.	The model determines the fuel use, which is linked to the TIMER model, hence all emissions from fuels are considered. Embodied emissions of vehicles are included in the industry sector.	As a CGE model all GHG-emitting and energy producing/ consuming sectors are included. This implies that indirect energy use and emissions from fuel production and vehicle manufacture are included, but in the energy transformation and industry sectors.	All GHG-emitting and energy producing/ consuming sectors are included. This implies that indirect energy use and emissions from fuel production and vehicle manufacture are included, but the latter is not represented by a direct linkage.	The transportation sector covers the transport of goods and passengers. Transport of energy and associated losses, which are accounted for in the own energy uses of the energy sector.
Relationship drivers and demand	GDP, population, and GDPP drive the transport demand, where energy service demand grows slower than the underlying driver. The demand is influenced through a linear relationship with the drivers. Each transport demand in each region has its own relationship driver and demand coupling factor.	GDP, IVA (for freight) population, fuel price, non-energy price, load factor, mode preferences, energy efficiency, mode speed drive service demand per mode, on the basis of Travel money budget (TMB) and Travel time budget (TTB) formulation. A fleet module determines fleet composition within each mode, affecting mode cost, energy efficiency and fuel type for each mode.	The mobility demand and modal split result endogenously from household's utility maximization under constraints of revenues and time spent in transport. Each mode is characterized by a price and a speed. The price of cars mobility depends on fuel prices and the cost of car ownership, while other modes by the intermediate consumption shares and prices within the general equilibrium framework. When infrastructure use reaches congestion, the marginal speed of the mode decreases, which limits its use.	Fuel prices, vehicle costs, GDP, population, vehicle speeds, vehicle occupancy rates, passenger vehicles per capita, annual distance travelled per vehicle, etc. Travel money budget, travel time budget, income, travel prices and travel speed determine service demand for the different modes (mode choice). The optimization framework determines the fleet composition within each mode. Freight service demand is driven by population, GDP and price elasticity.	Passengers: - Cars: income increase the number of cars per capita, fuel price affects the yearly mileage - Rail and buses: income increase the mobility, fuel price increase modal shift from cars to public transport Goods: GDP growth affects the mobility per mode

Table A2.1: Drivers of energy demand in the transport sector of eleven IAMs. *(continued)*

	REMIND[6]	GCAM[7]	AIM-CGE[8]	DNE21+[9]	GEM-E3[10]	WITCH[11]
System boundaries	Input of final energy in different forms is required together with investments and operation and maintenance payments into the distribution infrastructure as well as into the vehicle stock. Material needs and embodied energy are not considered.	The full fuel cycle of each fuel is represented. This includes biomass from an agriculture and land use model. No other upstream inputs to the sector are considered (e.g. vehicle manufacturing, roads)	Indirect energy use is treated in energy transformation sector	Indirect energy use is not included. For example, emissions from car manufacturing process is classified into the industrial sector.	All GHG-emitting and energy producing/ consuming sectors are represented explicitly in the model	LDV and road freight are explicitly modelled, while other modes are embedded within a non-electric sector. Aspects such as infrastructure and the vehicle manufacturing are incorporated in the overall GDP and representation of final goods

Table A2.1: Drivers of energy demand in the transport sector of eleven IAMs.

	REMIND[6]	GCAM[7]	AIM-CGE[8]	DNE21+[9]	GEM-E3[10]	WITCH[11]
Relationship drivers and demand	GDP growth, the autonomous efficiency improvements, the elasticities of substitution between capital and energy and between stationary and transport energy forms. Mobility from the different modes is input to a CES function, the output of which is combined with stationary energy in a CES function to generate a generalized energy good, which is combined with labor and capital in the main production function for GDP.	GDP, population, and services prices, derived from vehicle speeds and vehicle levelized average operating costs. GDP sets the scale of the demand, and determines the wage rate, which determines the opportunity cost of each travel mode. In this way, increases in GDP will increase the per-capita demand for travel, and shift this demand towards the fastest modes.	Transport intermediate inputs and final demand. Passenger transport is determined by GDP with elasticity. Freight transport is determined by all industrial sectors inputs. They are formulated as multiplying input coefficient.	Scenarios on service demand of road transportations are developed for passenger cars and buses separately based on per-capita GDP and the historical trends. As for road freight transport scenarios of cargo trucks, overall cargo service per-capita is estimated by the GDP size, under assumption of modal shifts.	The mobility demand and its modal split result endogenously from household's utility maximization under constraints of income and firms under maximization revenues. Each mode is characterized by a price. The price of cars mobility depends on operational cost and the purchased cost. The price of other modes is determined in the general equilibrium framework by the intermediate consumption shares and prices.	A linear Leontief function combines energy, O&M, vehicle capital and carbon costs to select the optimal mix of vehicle types. Vehicle ownership is a main driver which is set via a calibration based upon GDP growth. Exogenous efficiency improvements are implemented within the model.

Table A2.2: Technologies and final energy carriers

	TIAM-UCL	IMAGE	Imaclim-R	MESSAGE	POLES
Modes and vehicle types	Passenger : 7 modes (two wheel, three wheel international aviation, domestic aviation, road auto, road bus, rail), Freight: 7 modes (light, commercial, medium, heavy truck, rail, domestic navigation, international navigation), and hundreds of technologies.	Passenger: 7 modes (walk, bicycle, bus, train, car, high speed train and airplane), 6 freight modes (national ship freight, international ship freight, medium truck, heavy truck, rail freight, air freight) . Tens of technologies per mode.	Passenger: 4 modes (non motorized, personal vehicles, airplane, other) and 3 freight (trucks & freight rail, airplane, shipping). Technologies: ICE, efficient ICE, hybrid, plug-in hybrid and electric.	5 passenger modes and 1 freight mode. Other modes are not explicitly modelled but their energy use is accounted for via an exogenous energy demand trajectory. Tens of technologies options per mode.	Passengers: 7 modes (cars, motorbikes, bus, rail, air). Goods: 5 modes (heavy vehicles, light vehicles, rail, other (inland water), maritime). Technologies: ICE, plugin hybrid-electric, battery electric, fuel cell
Final energy carriers	Diesel, Gasoline, Ethanol, Electricity, LPG, Methanol, Natural Gas, Hydrogen, Fischer Tropsch biofuels.	The transport model only considers the secondary energy carriers: Hydrogen, Gas, Electricity, Oil, Biofuel	Liquid fuels from oil, Synthetic liquid fuels from other fossils Liquid fuels from biomass, Electricity	All fuels from the MESSAGE energy systems model are considered in the transport module	Oil products, Biofuels (energy crops and cellulosic feedstocks), Gas, Coal (for rail), Electricity and Hydrogen
Energy consumption of vehicles.	Share estimates split fuel consumption between road modes and rail modes. The model invests in technologies in order to satisfy the energy service demands in order to maximize consumer and producer surplus. Final energy consumption is endogenous to the model solution.	Different vehicle types with different energy efficiency's compete against each other (based on the multinomial logit), which allows for a change of energy efficiency of the mode.	For personal vehicles : explicit technologies with a efficiency characteristic and leaning on the cost. For other modes: efficiency improvement triggered by fuel prices.	Different vehicle types with different energy efficiencies compete against each other, which allows for an average change of energy efficiency of the mode over time. The techno-economic parameters for each technology are exogenously assumed.	Unit consumption depends on: - price: long term elasticity to account for investment and short term to account for behaviour - income for behaviour, to control the spending on fuel for transportation (maximum "budgetary coefficient")
	TIAM-UCL	**IMAGE**	**Imaclim-R**	**MESSAGE**	**POLES**

Table A2.2: Technologies and final energy carriers *(continued)*

Determinants technology costs and shares	Investment costs, O&M costs, fixed costs – are based on exogenous assumptions and change over time in response to an exogenous learning curve. Vehicle market share is outcome of the model solution.	Net present costs based on literature, decreasing exogenously in time. We assumed that the technology costs is a global variable, as the technologies tend to be traded worldwide. Vehicle share is based on a multinomial logit.	All technology characteristics are fixed in time, except costs that endogenously decrease with a learning rate. Vehicle market share is based on logit function.	The techno-economic parameters are exogenously assumed and change over time. There is also regional differentiation for certain technologies and parameter assumptions. Market shares are based on least cost optimization.	Road vehicles: Efficiency, lifetime, investment cost, fixed and variable O&M. These parameters change overtime exogenously. Vehicle competition based total user cost and infrastructure possible development.	
Distribution between transport modes	Distribution is assumed exogenously, but the split between modes may slightly change due to responses to own price elasticities.	Time and costs are considered. Cost are weighted relative to time with a time-weight factor. The time-weight factor is determined by the travel money and travel time budget.	Households utility maximization under both constraints of revenues and time.	Time and costs are considered. Costs are weighted relative to time with a time-weight factor. The time-weight factor is determined by the travel money and travel time budget.	The different modes are mostly disconnected, limited by: differentiated elasticities to fuel prices and saturation effects (e.g. max. number of cars per capita, maximum air related mobility)	
	REMIND	**GCAM**	**DNE21+**	**GEME3**	**AIM-CGE**	**WITCH**
Modes and vehicle types	Passenger: 4 modes, Freight: 1 mode. For passenger transport: LDV, Aviation, Bus and Electric Trains. One generic freight transport.	Passenger: 10 modes. Freight: 4 modes. Off-road vehicles, mining, or agriculture are not part of the transportation sector, except for China and India. ICE, electric, hybrid, fuel cell and compressed natural gas for bus/ passenger. For other modes two or one technology options.	Road transportation: 5 modes. The other subsectors are generated in a top-down manner. Technologies: ICEs, ICE efficient, HEV, PHEV, electric, fuel-cell.	Passenger: 5 modes (Passenger Cars, LDV/Bus, Aviation, rail and inland navigation), Freight: 3 modes (LDV/ heavy trucks, rail, inland navigation). Technologies: pure conventional, hybrid, plugin hybrid-electric, battery electric, biofuels	5 passenger modes (bus, train, car (incl. 2- and 3-wheelers), train, airplane) Freight: 6 modes (national ship freight, international ship freight, medium truck, heavy truck, rail freight, air freight). Aggregated technology.	2 modes. Road passenger and freight, both featuring four vehicle types: ICE, hybrid, plug-in hybrid and battery electric.
	REMIND	**GCAM**	**DNE21+**	**GEME3**	**AIM-CGE**	**WITCH**

Table A2.2: Technologies and final energy carriers *(continued)*

	REMIND	GCAM	DNE21+	GEME3	AIM-CGE	WITCH
Final energy carriers	Liquids (Coal, Gas, Oil or Biomass (only second-generation with CCS for Coal and Biomass. Electricity (only LDV).Hydrogen (only LDV) (Coal, Gas or Biomass, all combined with CCS).	Liquid fuels (includes fuels derived from oil, coal, gas, and biomass), Electricity Natural gas (mostly natural gas; also includes biogas and coal gas),Hydrogen (from many fuels), Coal (for rail in China)	Gasoline, Diesel, Bioethanol and Biodiesel, CNG, Electricity, Hydrogen from coal, gas biomass and electricity Plus CTL (coal to liquid) and CTG (coal to gas).	Road: Oil, Electricity, Gas, Bio-gasoline and Biodiesel (traditional and second generation). Rail: Coal, Oil, Biodiesel and electricity. Airplane: Oil, Biodiesel. Ship: Oil, biodiesel.	Road: Oil, electricity, and biofuel (bus can use gas), Railway: electricity and coal, Ship: oil, biofuel and coal, Airplane; oil and biofuel.	Liquids can come from Oil or Biomass (traditional or second-generation). Electricity can come from coal (possibly with CCS), gas, oil, biomass (possibly with CCS), wind, PV, CSP, hydro or nuclear
Energy consumption of vehicles.	The general efficiency of one transport mode improves exogenously over time in the CES function.	The energy quantity is derived from the average vehicle intensity and the load factor. The energy intensity of each technology is assumed to change over time exogenously. Endogenous changes of energy intensity are due to (a) switching from ICE to hybrid vehicles, (b) switching from smaller to larger vehicles, (c) modal shifting, or (d) switching to fuels with lower end-use energy intensity.	Energy consumption is determined based on the exogenous scenarios on service demand of road transportations in combination with technology (fuel efficiency of vehicles, costs and implicit discount rate) choice.	Different passenger cars types with different energy efficiencies compete against each other based on Weibull. The efficiency of other transport modes improves exogenously over time in the CES function	Multiplying coefficient. Fuel efficiency improvement is considered.	The efficiency of LDV and road freight transport modes improves exogenously over time based on selected efficiency improvement targets or selected forecasts.

Table A2.2: Technologies and final energy carriers *(continued)*

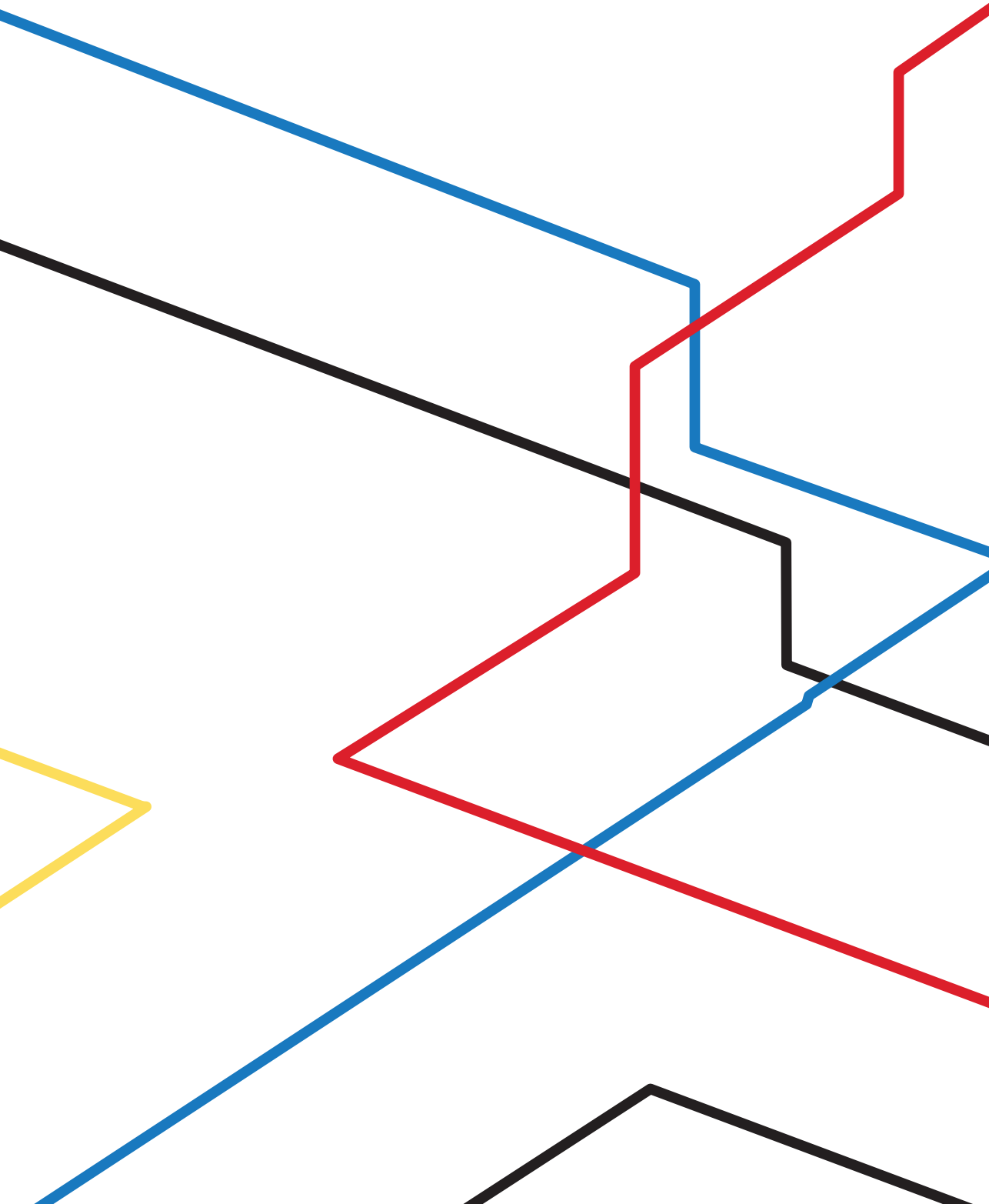
Determinants technology costs and shares	Efficiency, lifetime, investment cost, fixed O&M. Investment cost for battery electric and fuel cell vehicles decrease endogenously following a global learning rate towards a given floor cost. The distribution of LDV vehicles follow cost optimization with different non-linear constraints	Capital costs are amortized over an exogenous lifetime, assuming a 10% discount rate. Non-fuel operating costs include insurance, registration, taxes and fees, and standard O&M expenses. These can decrease exogenously for immature technologies such as electric cars or hybrid vehicles. Vehicle market share is based on logit function.	Fuel efficiency of vehicles and costs are assumed to be improved exogenously. Lifetime does not change over time. Market shares are based on least cost optimization	Capital costs are amortized over an exogenous lifetime, assuming a 12.5% discount rate. Non-fuel operating costs include insurance, registration, taxes and fees, and standard O&M expenses. Capital cost decrease endogenously for immature technologies such as electric cars or plugin hybrid vehicles assuming a global learning rate towards a given floor cost. Vehicle market share is based on Weibull function.	Not explicitly determined.	Efficiency, lifetime, investment cost, fixed O&M. Investment cost for battery electric vehicles decreases following a global learning rate as a consequence of endogenously modelled investments in R&D. The distribution of LDV and road freight vehicles follows cost optimization with different non-linear constraints.
	REMIND	**GCAM**	**DNE21+**	**GEME3**	**AIM-CGE**	**WITCH**

Table A2.2: Technologies and final energy carriers *(continued)*

Distribution between transport modes	The distribution between LDV and other modes is determined via the CES production function, driven by the elasticity of substitution (1.5) and the evolution of the efficiency parameters.	The modes compete using a logit share formulation, where the costs include both the vehicle cost and the time value cost. The time value cost is derived as the wage rate divided by the average transit speed, and modified by an exogenous time-value multiplier that is generally close to 1.	Travel demand is exogenously given for each mode. Modal shift is not endogenously evaluated.	The different type of passenger cars compete using a Weibull share formulation, where the costs includes both operational cost and purchase cost. The distribution between LDV and other modes is determined via the CES production function, driven by relative prices and the evolution of the efficiency parameters.	The distribution between modes is fixed and determined via separate demand calculations.

1) Anandarajah et al. (2011), 2) Girod et al. (2012), 3) Waisman et al. (2013),4) Riahi et al. (2012) , 5) Girod et al. (2013), 6) Luderer et al. (2012), 7)Kyle and Kim (2011), 8 Sano et al. (2015), 9) Fujimori et al. (2014c), 10) Karkatsoulis et al. (2014), 11) Bosetti and Longden (2013), Longden (2014), 1:11) ADVANCE (2015)

*The MESSAGE transport module used in this study is a simpler version than used in other papers (e.g.. McCollum et al., 2017). Specifically, this version is MESSAGE-Transport V.5; yet, for the purposes of this paper, the model did not make any explicit assumptions about heterogeneous behavioural features among consumers



Chapter 4

Transport fuel demand responses to fuel price and income projections: Comparison of Integrated Assessment Models

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Abstract

Income and fuel price pathways are key determinants in projections of the energy system in integrated assessment models. In recent years, more details have been added to the transport sector representation in integrated assessment models. To better understand the dynamics within these more complex models, this manuscript analyses transport fuel demand elasticities to projected income and fuel price levels. In order to isolate price effects on energy demand and create a transparent environment to compare fuel demand response, fuel price shocks were simulated under various scenarios. Interestingly, the models show very comparable oil price elasticity values for the first 10 to 20 years that are also close to the range described in the empirical literature. When looking at the very long term (30–40 years), demand elasticity values widely vary between models, between 0.4 and -1.9, showing either continuous demand or increased demand responses over time. The latter can be the result of long response time to fuel price shocks, availability of new technologies, and feedback effects on fuel prices. The elasticity calculation method proved to be a suitable method to evaluate model behaviour and its application is also recommended for other models as well as other sectors represented in integrated assessment models.

Keywords

Transportation, energy modelling, model evaluation, price elasticity, income elasticity

4.1 Introduction

Integrated Assessment Models (IAMs) have been developed to model the evolution of the global energy and land-use systems for the coming century. They have extensively been used to project greenhouse gas emissions and to identify cost-effective mitigation strategies (Clarke et al. 2009; Luderer et al. 2012). In the past, IAMs tended to represent energy demand sectors in a rather stylised manner, while presenting energy supply in more detail. Energy demand sectors are complex, both in terms of the many sub-sectors with numerous technologies and in the heterogeneity of consumers that use the services requiring energy. These sectors are therefore more difficult to represent in quantitative models.

Energy demand reduction can, however, have important contribution to emission reduction (Luderer et al. 2012; Riahi et al. 2012; Sugiyama et al. 2014). In recent years, more details of the energy demand side have been incorporated in IAMs, in order to better understand demand dynamics and the role of efficiency in mitigation strategies. This is especially the case for the transport sector, where infrastructure, behaviour and technology considerations have been addressed, as described in several articles in the Transport Research Part D special issue on transport modelling in IAMs (Carrara and Longden 2017; Dai 2016; Karkatsoulis et al. 2017; McCollum et al. 2017; Ó Broin and Guivarch 2017).

The models have various representations of the transport system, some with more technology detail, and others providing a more aggregated demand formulation. Several studies compare IAM transport sector outcomes (Edelenbosch et al. 2017a; Girod et al. 2013; Pietzcker et al. 2014), and show a variation in projected growth of transport service demand, fuel switching and efficiency change (Edelenbosch et al. 2017a). Intermodal comparison studies are informative, as they provide a range of plausible pathways. However, as the models have become more complex, it becomes less easy to understand why model results differ (Sugiyama et al. 2014). Kriegler et al. (2015a) indicate that, besides intermodal comparisons, diagnostic analysis which characterise model dynamics, are very relevant to explain model differences. This type of analysis is not aimed to explore realistic policy scenarios, but to identify typical model responses to a single policy signal. So far, a detailed diagnostic analysis of transport model responses to key drivers in IAMs has not been performed.

Income and fuel price levels are key model drivers. Income relates to the money available to spend on transport activities and fuel price affects the benefits of energy efficiency of technologies used and of switching to alternative fuels. Moreover, the implementation of a carbon tax, which is the commonly used mitigation policy instrument in IAMs, will impact fuel prices. Elasticities of transport fuel demand are used as measure for how sensitive

demand is to changes in –in this case- either income or prices. In this study, the transport models' implicit fuel demand elasticities are explored, by comparing demand responses to various fuel price and income trajectories. The aim is twofold; first to better understand model dynamics through a diagnostic experiment, and second comparing the model dynamics to empirical data as a validation test. A large number of empirical studies have analysed the sensitivity of transport demand to changes in fuel price and income (Litman 2013; McCollom and Pratt 2004), expressed in elasticities, to inform transport planners and policymakers (Small and Van Dender 2007). Moreover, quantifying the model response to elasticity values provides the opportunity to translate model dynamics of models that consider details of transport modes and technologies into relatively aggregate models. A comparable exercise has been performed for demand models by Hogan and Sweeney (1981). They conclude that the implicit elasticity calculation method is appropriate for comparing demand model dynamics, and they recommend modellers to make this a standard component of their documentation to better understand the model dynamics.

An overview of the various models and methods used to calculate elasticities and scenarios that were run by the models are discussed in Section 4.2. The models' transport consumption response to varying fuel prices and income scenarios compared to the empirical data is presented and discussed in Section 4.3. Underlying changes, such as efficiency effects and changes in the kilometres travelled, are addressed separately. Section 4.4 provides tentative conclusions about the variations between models and discusses the implications of the projections of energy transitions and the role of climate policy.

4.2 Methods

With everything else remaining constant, fuel demand elasticities measure the percentage change in demand due to a 1% increase in price or income. A set of scenarios was designed to estimate price and income elasticities for transport demand in six global integrated assessment models. Elasticities of fuel consumption, but also, for those models in this study containing sufficient detail, service demand and efficiency responses for specific transport modes. This section provides an overview of the models, fuel and income scenarios, and the elasticity calculation method.

4.2.1 Models and baseline scenario

The IAMs included in this study are IMAGE, MESSAGE, POLES, REMIND, TIAM-UCL and WITCH[23]. These form a set of well-known IAM models that contributed to key assessments

23 The MESSAGE transport module used in this study is a simpler version than the one used in other papers (e.g. McCollum et al., 2017) of the special issue "Transport in IAMs", that this paper is part of. Other models employed might also not exactly match those versions employed in other papers of the special issue.

and also cover a wide range of different methods (see Table 4-1 and Appendix).

Table 4-1: Overview of key characteristics of the transport models

Name	Model type	Solution methods	Service Demand driver per transport mode	End use technology representation
IMAGE	PE	Recursive dynamic simulation	GDP, population, fuel price, travel time, mode characteristics	All modes
POLES	PE	Recursive dynamic simulation	GDP/income, population, fuel prices	All modes
MESSAGE	GE	Intertemporal optimisation	GDP, population, fuel price	All modes (aggregated together)
REMIND	GE	Intertemporal optimisation with perfect forecast	GDP growth, fuel prices, elasticity of substitution in CES function	LDV
TIAM-UCL	PE	Intertemporal optimisation	Linear relation to GDP and population	All modes
WITCH	GE	Intertemporal optimisation with perfect forecast	GDP, population, elasticity of substitution in CES function	LDV and road freight

Of the six IAMs, POLES, IMAGE and TIAM-UCL have a more technology-rich representation of transport demand. The projected kilometres travelled, which are related to population and GDP, are distributed over the transport modes either based on exogenous assumptions (TIAM-UCL and POLES) or endogenously on their price and speed (IMAGE). Per transport mode, different technologies are considered that compete on the basis of exogenous technology cost and endogenous fuel cost. POLES and IMAGE are both recursive dynamic simulation models and TIAM-UCL is a linear optimisation model.

In REMIND, the mobility demand for all modes of transport are input to a nested CES production function that ultimately produces GDP. REMIND differentiates between four other transport modes besides light duty vehicles (LDVs). The representation of transport in the version of MESSAGE used in this study captures only fuel switching and price-induced demand responses (McCollum et al. 2014). Importantly, the entire sector is modelled as one; all motorised transport modes are aggregated together into a single demand category.

Finally, in WITCH, road transport kilometre demand (LDVs and freight) is derived based on GDP and population growth. This demand can be met by different vehicles (traditional, hybrid, plug-in hybrid, battery electric vehicles) and fuel types, which compete based on cost. The investment costs of batteries endogenously decrease, following a global learning rate via dedicated R&D investments. The remaining part of the transport sector is modelled

in a top-down fashion and included in the aggregated non-electric vehicle sector in the CES structure.

All models are run on the basis of a medium baseline, using the assumptions from the SSP2 scenario for population, income and other parameters (unless otherwise indicated).

4.2.2 Fuel price elasticity scenarios

In line with previous studies that tested demand elasticities inherent in models, scenarios with fuel prices shocks are compared to the original price pathway in the models' baseline scenario (Hogan and Sweeney 1981; Jaccard and Beylin-Stern 2014). The shocks are applied to 1) oil & natural gas, 2) biofuels and 3) electricity from 2020 to 2070, changing the price with respect to a reference price trajectory, by -50%, +50% and +100% (see Table 4-2). Based on experience with model demand responses to carbon prices the expectation was that fuel price shocks of 50% to 100% would be needed before there would be a significant demand response. The fuel price is increased at the final energy level for all demand sectors; however, the focus of our analysis is only on the transport demand response.

Table 4-2: Scenario design to calculate price demand and income demand elasticities. Descriptions of Scenarios 2 to 10 indicate the price jumps relative to the baseline scenario, for the three fuel types considered. Ref indicates the unaltered reference fuel price trajectory in the baseline of each model. Scenario descriptions of Scenarios 11 and 12 indicate the varying income pathways.

Scenario	**Price change per fuel type**			
		Oil & Natural gas	**Electricity**	**Biofuel**
1		Ref	Ref	Ref
2		-50%	Ref	Ref
3		Ref	-50%	Ref
4		Ref	Ref	-50%
5		+50%	Ref	Ref
6		Ref	+50%	Ref
7		Ref	Ref	+50%
8		+100%	Ref	Ref
9		Ref	+100%	Ref
10		Ref	Ref	+100%
Scenario	**Income change**			
11	SSP1 GDP assumptions			
12	SSP3 GDP assumptions			

Figure 4-1 shows the baseline transport oil price used in each model (at the end-use level; global average) (panel a), as well as the fuel price change, relative to the baseline, in the -50% scenario and +100% scenario (panel b). The WITCH and TIAM-UCL scenarios do not include end-use taxes in their prices, implying that these models use a lower price pathway. All models project oil prices to increase as a result of resource depletion in baseline, but the extent of this effect varies. The variations in oil price development between models ultimately resulted in different fuel shocks, in absolute terms. Price jumps are implemented as exogenous shocks. In two models (IMAGE, POLES), this is implemented by replacing the endogenous prices by an exogenous input. In the other models (TIAM-UCL, MESSAGE, REMIND and WITCH), where this would interfere with the model solution, price increases/ decreases were added to the endogenously calculated final energy prices – thus mimicking additional taxes or subsidies. Here, dynamic model responses and feedback effects could clearly be observed.

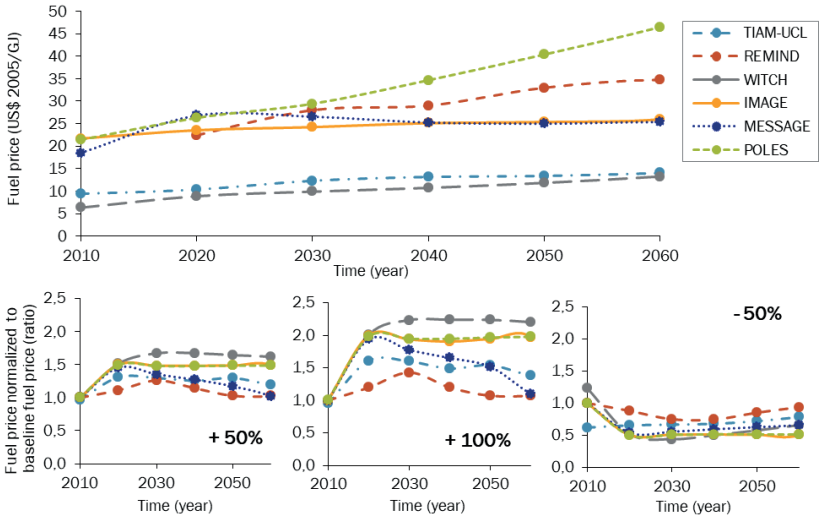

Figure 4-1: Global average price of transport oil in the baseline scenario (Scenario 1) (top) and the relative increase in oil price compared to this baseline (bottom), for the price shock scenarios of +50% (Scenario 5), +100% (Scenario 8) and -50% (Scenario 2).[24]

The most important model response is that, due to higher fuel prices, the demand for this particular fuel (and its primary resource, crude oil) is reduced (allowing to calculate the

24 Note that in the figure the average global prices are shown. The moving away effect at the global level can be larger than at the regional level as the average fuel prices also can be affected by regions, with lower or higher than average fuel prices, accumulating a larger share of the global transport final energy use.

elasticities – see further). As a result, however, final energy prices tend to move away from the price shock pathway towards the original price pathway, in the long run. This effect is the largest in MESSAGE, but can also be seen in the TIAM-UCL and REMIND projections. In REMIND, the perfect foresight feature leads to a reduction in the price change effect already by 2020 (when the shock is introduced). The reduction in demand due to the exogenous price increase, in this case, has led to a relaxation of the scarcity and thus to a reduction in the endogenous price component. Yet, despite the variance in fuel price pathways, since price demand elasticities are calculated relative to price changes (and not to price levels), even with smaller price changes it is still possible to compare elasticities between models.

4.2.3 Income elasticity scenarios

Two extra scenarios with different income pathways are run to analyse income elasticities (see Table 4-2, Scenarios 11 and 12 and Figure 4-2). In the baseline scenario, the models have implemented the Shared Socio-Economic Pathway (SSP) 2 assumptions on GDP and population growth. The SSPs are a scenario framework that defines pathways of the evolution of society and ecosystems in the next century. Within this framework SSP2 is the middle of the road scenario. The alternative GDP pathways are based on SSP1 and SSP3 which assume respectively low and high challenges for mitigation and adaptation. Within that narrative SSP1 follows higher and SSP3 follows lower economic development than SSP2 (O'Neill et al. 2014)[25].

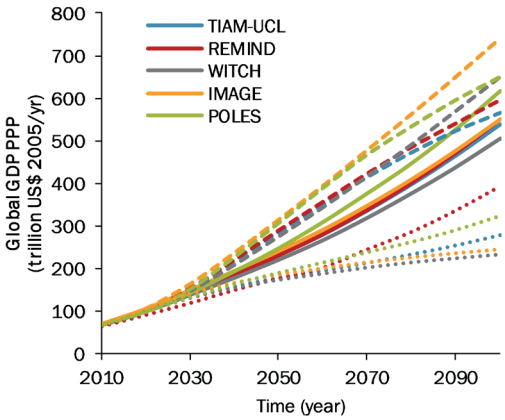

Figure 4-2: GDP pathways implemented in the models. The solid line is the SSP2 baseline (Scenario 1), the dashed line is the higher GDP pathway (Scenario 11) and the dotted line represents the lower GDP pathway (Scenario 12).

25 The SSP1, SSP2 and SSP3 GDP pathway assumptions are published on **https://secure.iiasa.ac.at/web-apps/ene/SspDb**

4.2.4 Price and Income elasticity calculation method

The scenarios described above allow to calculate elasticities. In the case of calculating elasticities on the basis of model runs, the various fuel quantities and prices can be compared at the same point in time and for the same region. This allows to compute the elasticities without having to correct for other covariates or confounding factors (which can obviously not be done for empirically derived elasticities). Based on two different scenarios (1 and 2), Q_{i1} and Q_{i2} denote the quantity consumed, which can be - service demand (kilometres travelled) , final energy use, or energy efficiency (energy use per kilometre travelled) of category or fuel *i*. Similarly, P_{i1} and P_{i2} and denote the price of fuel *i* in both scenarios. Given these four values, the arc price elasticity can be calculated through a logarithmic function:

$$\eta_{Q,i} = \frac{log\boldsymbol{Q}_{i2} - log\boldsymbol{Q}_{i1}}{log\boldsymbol{P}_{i2} - log\boldsymbol{P}_{i1}} \qquad \text{Eq. (1)}$$

where measures the price elasticity of quantity Q with respect to the price of fuel
In this case, various price projections for a given future year are compared, and there is no beginning or end point between those points. The arc elasticity can therefore be approximated by a mid-point formulation on the basis of the average value of the independent variables (Litman 2013):

$$\boldsymbol{\eta_{Q,i}} = \left(\frac{\Delta \boldsymbol{Q_i}}{\mathbf{0.5}\ (\boldsymbol{Q_{i1}}+\boldsymbol{Q_{i2}})}\right) / \left(\frac{\Delta \boldsymbol{P_i}}{\mathbf{0.5}\ (\boldsymbol{P_{i1}}+\boldsymbol{P_{i2}})}\right) \qquad \text{Eq. (2)}$$

where the percentage change between Scenarios 1 and 2 is calculated relative to the average value between the two.

The elasticities are calculated for the years 2030 and 2060. Some models work with 10-year time steps, which would make 2030 the first year for which price change effects can be analysed and 2060 the last. In the literature, there is a differentiation between short-term and long-term elasticities, as the full impact of a price change can take several years to wear out. Short term is often considered less than two years, while long term refers to more than 10 years. It has been found that long-term elasticities are higher (and can be up to three times as high (Dargay and Gately 1997)) than short-term elasticities. Compared to the literature, all those calculated in this study are long-term elasticities, in line with the models' long-term perspective, mostly with an end-of-the-century time horizon. Both the long term (10 years) and the very long term (40 years) are compared to the long-term transport elasticity values described in the empirical literature.

4.2.5. Cross-price market share semi-elasticities

To examine fuel consumption responses to price changes in other fuels, typically standard cross-price elasticities are used (e.g., (Ziemba 1980)). However, this approach does not always yield meaningful results: if market shares of alternative fuels are small, such as currently is the case for biofuel and electricity this result in difficult-to-compare high elasticity responses to a slight change in demand. Therefore, market share elasticities are computed (as introduced in (Bucklin et al. 1998)). The market shares of different fuels i are defined as:

$$\boldsymbol{MS_i = \frac{Q_i}{\sum_{j=1}^{I} Q_j}} \qquad \text{Eq. (3)}$$

Based on these market shares, the changes in absolute values of the market shares are computed for the different fuel types i due to changes in the price of fuel , resulting in cross-price market share semi-elasticities[26], which we define as:

$$\boldsymbol{\eta_{MSi,j} \equiv \frac{\frac{MS_{i,1} - MS_{i,2}}{\Delta P_j}}{0.5\,(P_{j,1} + P_{j,2})}} \qquad \text{Eq. (4)}$$

These market share elasticities can be interpreted as changes in the market share of each fuel due to a 1% increase in the price of fuel (or by multiplying them by 100, they represent the (approximate) market share change in percentage points due to a doubling of the price of fuel). These elasticities sum to zero, , since market shares always add to one. Therefore, these cross-price elasticities[27] isolate the fuel switching effect due to price changes as a result of efficiency improvements and demand changes discussed above.[28]

4.3 Models' inherent demand elasticity results

4.3.1 Oil and alternative fuel responses

The absolute change in energy demand, compared to the baseline in 2030 and 2060, of transport oil and alternative fuel (AF)[29] in response to the oil and natural gas price shocks (Scenarios 2, 5 and 8) are shown in Figure 4-3. In 2030 (i.e., 10 years after the applied shock) all models show a decrease in oil demand and an increase in alternative fuel under higher oil and natural gas prices, and vice versa. Most models show a stronger response to the price shocks in 2060 than those in 2030, with higher demand-price slopes (right side vs left side of graph 3). The POLES model is the only one to project the absolute change in oil demand

26 Note that the same arc elasticity approach is used as before. Moreover, the definition of the semi elasticity here uses the absolute change in a value due to a percentage change in the price.

27 In the following, cross-price market share semi-elasticities are referred to simply as cross-price elasticities for brevity.

28 If the total quantity $\sum_{j=1}^{I} Q_j$ does not change, the standard cross price elasticity $\eta_{i,j}$ can be obtained from this elasticity as $\eta_{i,j} = \eta_{MSi,j}/\overline{MS_i}$ where $\overline{MS_i}$ represents the average market share of fuel *I in both scenarios*.

29 Alternative fuel is defined as all fuels other than oil.

to be less while the fuel price jump becomes larger over time. WITCH shows a relatively mild response to the changing fuel price as well, while IMAGE, REMIND, MESSAGE and TIAM UCL show significant responses. In MESSAGE, oil demand ranges from 35 to 290 EJ/year in 2060. between the higher and lower price scenario, implying that the transport system has completely changed in response to 40 years of widely diverging price trajectories. As MESSAGE, TIAM-UCL and REMIND show strong feedback effects on the price trajectory, moving back to the original fuel price pathway, here very high price elasticities can be expected.

In all models, the decrease in oil is greater than the increase in alternative fuel demand, indicating that increased fuel prices also lead to efficiency improvements associated with the shift from internal combustion engines to alternative drive train technologies. However, there is clear variation in the size of energy reduction, on the one hand, and fuel substitution effects, on the other, across the models. MESSAGE, REMIND and WITCH show higher substitution rates (48%–83% of the oil change), while this is less the case in the more technology-rich models POLES, IMAGE and TIAM-UCL (2%–34%).

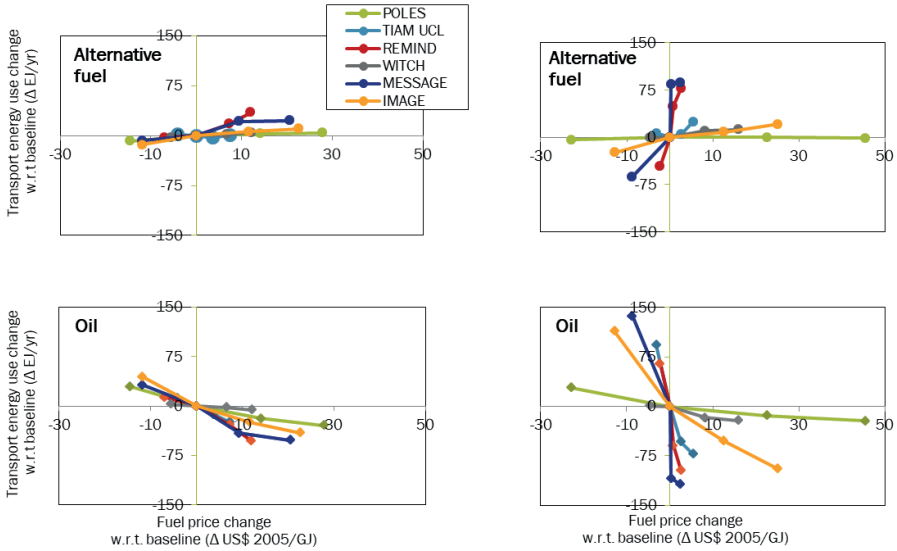

Figure 4-3: The oil (bottom) and alternative fuel (AF) (top) energy demand response to oil and gas price shocks – Scenarios 2, 5 and 8 - in 2030 (left) and 2060 (right). Alternative fuel is defined as any fuel other than oil.

4.3.2 Service demand and fuel consumption elasticities

For the models that include details on passenger transport modes (IMAGE, POLES and TIAM-UCL), Table 4-3 shows the mean and standard deviation in modal service demand (expressed in passenger kilometres (pkm) or tonne kilometres (tkm)) and energy efficiency elasticities of the three oil & natural gas price shock scenarios. This method gives insight into the underlying sectoral changes, for example changes in the kilometres travelled or in the fuel efficiency of each transport mode, which contribute to sectors' change in energy demand. At the same time, it provides the opportunity to compare model elasticities to empirical data, which are often reported at modal level. For the REMIND, WITCH and MESSAGE projections, the contribution of service demand and efficiency to energy demand elasticities have been specified for total transport, freight and passenger elasticities, as shown in Table 4-3.

The passenger service demand elasticity — the elasticity of the travelled passenger kilometres — in 2030, varies between -0.2 and -0.3 across all models and, in 2060, between -0.1 and -0.5. Freight service demand ranges from -0.1 to -0.5 in 2030 and from -0.1 to -1.3 in 2060. In the REMIND model, where there is no alternative for liquid fuel in freight transport, fuel-price shocks have a larger impact on transport prices than in passenger transport, resulting in higher elasticity values. In all models, but REMIND the transport service demand is not elastic to fuel prices (i.e. <1). WITCH service demand and POLES freight service demand projections are not related to energy prices, but are driven only by GDP and population, and changes in energy prices are reflected only in the choice of technology. Not capturing service demand price elasticity could lead to relatively downward bias for the overall energy demand elasticity. Indeed, of the six models, POLES and WITCH energy demand elasticity are on the low side of the spectrum. MESSAGE does not differentiate between passenger and freight transport demand, but relates total transport (useful) energy demand directly to economic and demographic drivers.

Fouquet (2012) has analysed the income and price elasticities of passenger transport demand between 1850 and 2010 in the United Kingdom, and shows that both elasticities have declined over time, from 3.1 and -1.5 to 0.8 and -0.6, respectively. Price elasticities depend on income effects as well as substitution effects. When incomes rise, the share of fuel expenditure in total expenditure declines, leading to lower price sensitivity. Moreover, with higher incomes, travel time is valued more, and fuel costs take up a relatively smaller share of the generalised cost of travel (in which money and time are accounted for) (Small and Van Dender 2007). Fouquet (2012) compares service demand to the price of service demand, instead of to the price of fuel. Therefore, the results in Table 4-3 cannot be compared directly to Fouquet's results. The described trends of service demand's reduced sensitivity to prices, over time, can be seen for some modes of transport, but others show the opposite trend.

Table 4-3: Mean service demand (pkm or tkm), fuel efficiency (MJ/pkm or MJ/tkm) and fuel consumption (MJ) elasticities to oil price per mode of transport and aggregated for freight, passenger and total transport. Calculated by comparing the oil & natural gas fuel-price shock Scenarios 2, 5 and 8 to the baseline. The standard deviation in the elasticity values of these three scenarios are indicated between brackets. In bold are the elasticities that are elastic (>1).

		IMAGE		**POLES**		**TIAM-UCL**	
		2030	2060	2030	2060	2030	2060
LDV	Pkm	-0.2 (0.1)	-0.1 (0.0)	-0.2 (0.0)	-0.1 (0.0)	0.0 (0.0)	-0.1 (0.0)
	Efficiency	-0.3 (0.2)	-0.7 (0.6)	-0.3 (0.1)	-0.3 (0.0)	-0.2 (0.0)	**-2.0 (0.7)**
	Energy	-0.5 (0.2)	-0.8 (0.6)	-0.4 (0.2)	-0.4 (0.0)	-0.2 (0.0)	**-2.1 (0.7)**
Public transport	Pkm	-0.2 (0.0)	-0.2 (0.1)	-0.2 (0.0)	-0.1 (0.0)	-0.1 (0.0)	-0.1 (0.0)
	Efficiency	-0.1 (0.2)	-0.4 (0.5)	-0.3 (0.0)	-0.2 (0.0)	0.0 (0.0)	-0.4 (0.2)
	Energy	-0.4 (0.2)	-0.6 (0.4)	-0.5 (0.0)	-0.4 (0.1)	0.0 (0.0)	-0.4 (0.2)
Aviation	Pkm	-0.7 (0.1)	-0.6 (0.1)	0.1 (0.0)	0.0 (0.0)	-0.3 (0.0)	-0.4 (0.1)
	Efficiency	-0.1 (0.1)	-0.6 (0.2)	-0.2 (0.1)	-0.2 (0.1)	0.0 (0.0)	0.0 (0.0)
	Energy	-0.8 (0.1)	-1.2 (0.1)	-0.1 (0.1)	-0.1 (0.1)	-0.3 (0.0)	-0.5 (0.1)
Walking & Cycling	Pkm	0.1 (0.0)	0.2 (0.0)				
Total Passenger	Pkm	-0.2 (0.0)	-0.2 (0.0)	-0.2 (0.0)	-0.1 (0.0)	-0.2 (0.0)	-0.3 (0.0)
	Efficiency	-0.3 (0.1)	-0.7 (0.4)	-0.2 (0.1)	-0.2 (0.0)	0.0 (0.0)	**-1.0** (0.6)
	Energy	-0.5 (0.2)	-0.9 (0.4)	-0.4 (0.1)	-0.3 (0.0)	-0.2 (0.0)	**-1.3** (0.5)
Total Freight	Tkm	-0.2 (0.1)	-0.1 (0.1)			-0.1 (0.0)	-0.1 (0.0)
	Efficiency	-0.1 (0.2)	-0.3 (0.3)	-0.2 (0.0)	-0.1 (0.0)	-0.3 (0.3)	**-2.0** (1.9)
	Energy	-0.3 (0.1)	-0.4 (0.2)	-0.2 (0.0)	-0.1 (0.0)	-0.4 (0.3)	**-2.1** (1.9)
Total Transport	Energy	-0.4 (0.1)	-0.7 (0.1)	-0.3 (0.1)	-0.2 (0.0)	-0.3 (0.1)	**-1.5** (0.7)
		REMIND		**WITCH**		**MESSAGE**	
		2030	2060	2030	2060	2030	2060
Total Passenger	Pkm	-0.3 (0.1)	-0.5 (0.2)				
	Efficiency	0.0 (0.0)	**-1.7 (0.7)**	0.0 (0.0)	-0.1 (0.2)		
	Energy	-0.3 (0.1)	**-2.3 (0.9)**	0.0 (0.0)	-0.1 (0.2)		
Total Freight	Tkm	-0.5 (0.1)	**-1.3 (0.5)**				
	Efficiency	0.0 (0.0)	0.1 (0.1)	0.0 (0.0)	0.0 (0.0)		
	Energy	-0.5 (0.1)	**-1.2 (0.5)**	0.0 (0.0)	0.0 (0.0)		
Total Transport	Energy	-0.3 (0.1)	**-1.9 (0.7)**	0.0 (0.0)	-0.1 (0.1)	-0.4 (0.1)	0.4 (3.8)

Most models show a response in efficiency change that is stronger for 2060 — ranging from -0.1 to -1.7 for passenger transport and -0.0 to -2.0 for freight transport — than for 2030. As a result, in all models except POLES, the long-term (2060) energy demand elasticity is higher than that in the medium term (2030), as is also noted in Section 4.3.1. This is

especially pronounced in TIAM-UCL's projections. This is because 1) models have a much longer time period to respond to higher/lower prices, and 2) new vehicle technology developments have led to cheaper alternatives, which, for example in the case of electric vehicle deployment, would lead to higher efficiency. Also, long-term feedback effects on fuel prices, as seen in REMIND, MESSAGE and TIAM-UCL projections, could further enhance this effect.

A large share of the empirical research on transport price elasticity has focused on road transport elasticities to the petrol price under different circumstances, and a few review studies have summarised these results in 'generic values'. Johansson and Schipper (1997) study 12 OECD countries, for the period from 1973 to 1992, and find long term elasticities to fuel prices of car service demand to range between -0.05 and -0.55, and of car fuel economy to range between -0.45 and -0.35. These figures are comparable to those in reviews by Graham and Glaister (2002), Goodwin et al. (2004) and Espey (1998). Interestingly, the models' LDV service demand elasticities range from -0.1 to -0.2, which is within that range[30]. The models respond very similarly; not covering the full uncertainty found empirically. For 2030, the efficiency response of the models (-0.3 in all models) is very comparable to the empirically found data; leading to an overall comparable LDV energy consumption elasticity in 2030. For 2060 however, both IMAGE and TIAM-UCL project a stronger efficiency response, resulting in an elastic (< -1) response that is beyond the range summarised in the reviews of empirically found elasticities. The availability of more fuel-efficient alternative types of vehicles increases the substitution effect on the price elasticity projected for the second half of the century.

The differences between price elasticities per transport mode, in the model projections, not necessarily imply modal shifts, because the elasticity is defined as a relative decrease in pkm to the transport mode's total pkm, and the transport modes differ in overall volume. Moreover, the various transport modes do not contribute equally to the overall transport volume (some, such as bicycles, have a smaller share). A change in fuel price can be expected to have a larger effect on the transport modes that are relatively high in energy consumption, such as LDVs and aviation. Fouquet (2012) argues that air transport is a 'luxury' form of transport and service demand would be more sensitive to fuel prices than would other modes of transport. IMAGE and TIAM-UCL indeed show higher service demand responses in aviation than in other modes of transport, and all three models show the largest efficiency response in the light duty vehicles (LDV).

30 Note that the IAM values are expressed in passenger kilometres (pkm) and thus car sharing effects and load factor change are accounted for in energy intensity change, which could explain the somewhat low values.

4.3.3 Market share elasticities of fuel

The transport sector is currently being dominated by oil products, but Integrated Assessment models show that fuel switching is an effective way to mitigate the greenhouse gas emissions from the transport sector, in order to achieve a stringent climate target (Edelenbosch et al. 2017a). The scenarios with oil, biofuel and electricity shocks of +100% (Scenarios 6, 7 and 8) and -50% (Scenarios 2, 3 and 4) are used to analyse how responsive fuel market shares are to fuel price changes for various carriers. Following the equations in section 4.2.5, Figure 4-4 shows the cross-price elasticities per fuel type. The interpretation, for instance for IMAGE, shows that a doubling[31] of oil prices will lead to a 50 percentage points decrease in the market share of oil in transportation by 2050, whereas the share of biofuels and electricity will increase by respectively 18 and 21 percentage points.

Fuel market shares are considerably more responsive to oil and biofuel price changes than to electricity price changes. For many modes of transport, switching to electricity means switching to an alternative type of propulsion. The lower sensitivity could be explained by the fact that technology cost, availability and consumer behaviour are larger hurdles than the costs of electricity in relation to this transition. The fuel market is the most sensitive to changing oil prices and decreasing biofuel prices, which both lead to oil substitution. Elasticities of all fuel types, in all models, increase over time, with the exception of the IMAGE biofuel response in the +100% scenario. POLES and WITCH show la low response, compared to the other models, projecting the sector to remain dependent on oil irrespective of fuel price changes, in line with the low responses to oil price changes as shown in Sections 4.3.1 and 4.3.2. MESSAGE and REMIND show a high response, which again partially can be explained by the feedback effects on prices, but also higher fuel switching flexibility due to less technology constraints.

Oil price increases are projected to lead to a switch from oil to biofuel in 2030 and, in some models, to fossil synfuel, while, in 2050, electricity also becomes an attractive alternative. Increasing electricity and biofuel prices lead to a reduction in the use of both fuel types, from which can be concluded that, under the baseline scenario, electricity and biofuel have a certain share in transport fuel use. In REMIND, intertemporal foresight and interactions with other fuel-consuming sectors may lead to the opposite effect; for example, with increasing oil shares under higher oil prices in 2030. Lowering fuel prices leads to strong early consumption, both in the transport sector and in others, which implies that long-term scarcities become more pronounced, in turn leading to increased long-term reliance on alternative fuels.

31 Scenarios (8–10) were precisely designed to implement a doubling of fuel prices, compared to those in the baseline. In the cross elasticity calculation, the price increase is calculated relative to the average price shock and the baseline scenario(ΔP_j)/(0.5 ($P_{(j,1)}$+$P_{(j,2)}$). Therefore, the relative price increase is + 2/3.

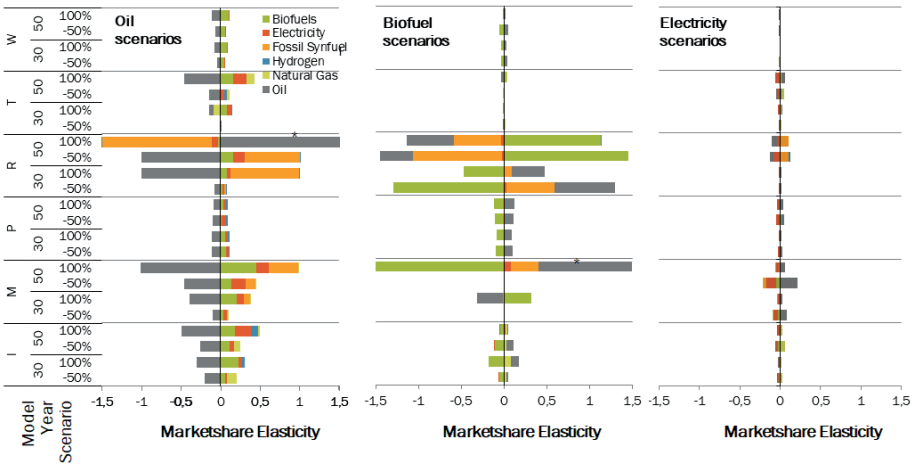

Figure 4-4: Market share elasticities in response to changes in oil, biofuel and electricity prices from +100% to -50%. Elasticities indicate the shift in market shares, for all the different fuel types for which the sum of the elasticities is 0. Negative elasticities in the -50% scenario imply an increase in use, as the elasticity is relative to the price signal. The models are indicated by their first letter (R=REMIND, I=IMAGE, T=TIAM-UCL, M=MESSAGE, P=POLES and W=WITCH). * In two scenarios (marked with *) the market elasticity was larger than 1.5 - due to very high price feedbacks- the results were normalised to 1.5.

4.3.4 Income elasticities

To assess the sensitivity of demand to income level, an approach similar to that described in Section 4.3.1 was used, distinguishing the effects of changes in efficiency and service demand. The results are presented in Table 4-4. There have been suggestions that at higher income the per capita kilometres travelled would saturate and that we are reaching peak travel (Dargay et al. 2007; Millard-Ball and Schipper 2011). The theory is that transport was originally perceived as a 'luxury' product which is sensitive to income changes. As incomes continue to rise, saturation effects will reduce income elasticity. This theory is supported by the already mentioned reduced travel demand to income elasticity between 1850–2010, in Fouquet (2012). This trend is not clearly reflected in all the model results, neither over time nor with increased income. The elasticity values for high and low incomes are rather comparable, although IMAGE, REMIND and WITCH do show lower service demand elasticities to higher income scenarios.

Table 4-4: Service demand (pkm or tkm), fuel efficiency (MJ/pkm or MJ/tkm) and fuel consumption (MJ) elasticities with respect to income changes (Scenarios 11 and 12) for freight, passenger and total transport.

	IMAGE		POLES		REMIND		WITCH		TIAM-UCL	
	low	high	low	high	low	high	low	high	low	high
								Passenger transport in 2030		
Pkm	0.50	0.38	0.49	0.65	0.45	0.32	1.19	0.91		
Efficiency										
Energy										
	0.11	0.20	-0.13	-0.17	-0.01	-0.02	-0.03	-0.10		
	0.61	0.58	0.36	0.47	0.44	0.31	1.15	0.81		
								Freight transport in 2030		
Tkm	0.87	0.35	0.43	0.83	0.42	0.30	1.17	0.93		
Efficiency										
Energy										
	-0.26	0.18	-0.01	-0.42	-0.06	0.00	-0.03	0.04		
	0.61	0.54	0.42	0.41	0.36	0.31	1.14	0.97		
Total	0.61	0.56	0.39	0.44	0.41	0.31	1.15	0.87	0.65	0.99
								Passenger transport in 2060		
Pkm	0.51	0.53	0.62	0.40	0.37	0.31	0.96	0.75		
Efficiency										
Energy										
	0.16	0.38	-0.09	-0.18	0.08	0.04	-0.06	-0.30		
	0.67	0.90	0.52	0.22	0.45	0.34	0.91	0.46		
								Freight transport in 2060		
Tkm	0.78	0.50	0.53	0.59	0.41	0.25	0.99	0.79		
Efficiency										
Energy										
	-0.08	0.03	-0.14	-0.15	-0.02	0.00	0.02	0.04		
	0.70	0.52	0.40	0.44	0.39	0.25	1.01	0.83		
Total	0.68	0.77	0.47	0.32	0.43	0.31	0.95	0.62	0.53	1.44

The energy efficiency response in IMAGE increases, due to a shift to higher intensity transport modes with higher income. In the other models, efficiency decreases, which could reflect the concept of a larger budget leading to an increase in technology use, which, in turn, leads to efficiency learning. Johansson and Schipper (1997) find that the long-term elasticity of vehicle fuel consumption (related to what here is called efficiency) with respect to income is between 0.05 to 1.6, and Graham and Glaister (2002) report this to be between 1.1 and 1.3. These two studies were conducted at LDV level, and, therefore, are not easy to compare to the model projections used in this study, as the effects of structural changes (shifting

transport modes) are not included, but it can be concluded that this positive relationship is not necessarily reflected in the models. Both studies also analyse long-term elasticity of service demand with respect to income; Johansson and Schipper (1997) find a range of 0.65 to 1.25, while Graham and Glaister (2002) report this to be between 1.1 to 1.8. For the United Kingdom, Fouquet reports a reduction in transport service demand to income elasticity of 3.1 to 1.0 (including air travel) between 1850 and 2010. Compared to these figures, the IAM service demand elasticity values are on the low side, with the exception of the WITCH model. Income elasticities of transport energy demand are reported to be greater than price elasticities provided in the literature (Goodwin et al. 2004). The models show service demand to income elasticities are indeed larger (especially in WITCH) but negative energy efficiency may lead to income energy demand elasticities (ranging from 0.31 to 1.44) that are comparable to price elasticities.

4.4 Discussion and conclusions

In this paper, we introduced fuel price shocks in models in order to determine the implicit demand elasticities. This can help to describe and understand model behaviour and projected results. In the experiments in the paper, ideally, the fuel price shocks would follow the exact same fuel price pathways in all models. However, the fuel price trajectories in the baseline already varies across models. Moreover, due to interference with some of the models solution methods, fuel prices could not follow a predefined pathway in all models. In those models price increases/decreases were added to endogenously calculated fuel prices to mimic the fuel price shocks. In some models, this method resulted in fuel prices moving away from the set pathway over time, as a result of lower fuel use. In REMIND, fuel prices also moved away but already in the early decades, due to intertemporal foresight. Because of the relative nature of elasticities, different fuel price pathways not necessarily have an impact on results, but we did find the demand response to be both pathway- and time-dependent. This is most clearly demonstrated by the results from the MESSAGE and REMIND models, projecting large demand differences, while fuel price differences became very small (in some cases, even negative) by 2060. Remaining as close as possible to the intended fuel price pathway would therefore improve the comparability of results between models. However, the scenarios do show how the different solution methods affect the model dynamics. It can be expected that the implementation of a carbon tax could result in similar model responses.

On the basis of the results, the following conclusions can be derived:

The proposed method in this paper to derive price and income elasticities as diagnostic indicators provides a transparent environment to test model dynamics.

The approach provides insights into model responsiveness, both for the medium and long term. It enables us to evaluate model behaviour and to distinguish a model's fingerprint. At the same time, it could be used to understand the effect of model development on model behaviour, through a before-and-after comparison. Modelling individual transport modes explicitly does not lead to major differences in energy demand responses (compared to models that only represent transport modes in a more aggregated way), and the detailed and less detailed models show similar elasticity values.

Efficiency and service demand elasticities to fuel price are within the range of values found empirically, and very close to each other in the medium term. Comparing model elasticities at modal level, and specifying between service demand and efficiency changes, shows that in 2030 energy demand elasticities are very comparable between models and close to the range reported in the literature. This shows that in terms of historical validation in the medium term the models perform well. LDV energy demand elasticities to oil and gas prices are projected to range from -0.2 to -0.5 in 2030. Total transport energy elasticity values, projected to range between 0.0 and -0.4 in 2030, are also comparable (although on the low side) to the values reported by Hogan and Sweeney (1981) that ranged between (-0.1 to -0.6) in the short term. For 2060, the models show more diverging behaviour, and elasticities cover a broader range as a result of fuel substitution, increased efficiency, service demand reduction and feedback effects on prices. Assuming service demand pathways exogenously, as is done in WITCH and POLES, on the other hand leads to a weaker demand response.

A division can be made between the models that become more responsive in the long term (2060) than in the medium term (2030). Some models clearly show higher fuel switching and energy demand reduction responses in the long term, while service demand response remains comparable. The projected elasticity of total energy demand in transport to oil and natural gas prices in 2060 range from 0.4 to -1.9, and for LDV energy consumption from -0.4 to -2.1. There are however different effects that can have caused this increased response. In IMAGE, REMIND, MESSAGE and TIAM-UCL, alternative technologies become more attractive (cheaper) in the long term, and therefore oil price changes can lead to a stronger response. In REMIND's freight sector, the opposite is visible, since no alternatives are available, therefore freight transport becomes more expensive and, thus, leads to higher price effects on service demand. MESSAGE, REMIND and TIAM-UCL also show large feedback effects on fuel price pathways in the long term, while demand does not immediately follow. This also shows that near term price policies could have long term effects.

Market share distribution responds more strongly to oil and biofuel price changes than to electricity prices. Oil will be substituted as the dominant fuel when oil prices increase. Biofuel price change sees in some models a strong effect but electricity price changes hardly have an impact on the projected shares. The models show that, in 2030, mainly biofuel is used as a substitute, and some models use fossil synfuel, while electricity shares increase as a result of higher oil prices in the long term. Furthermore, the models show a stronger response to biofuel price reductions than to reductions in the oil price. The models are not responsive to electricity price changes, indicating that other factors such as technology costs and behaviour might be more important in this transition. The models' response to price jump of 50% compared to a price jump of 100% is not clearly different. Elasticity values for most models are comparable per model under both these scenarios, implying a linear demand response. Again, here a clear difference can be seen between models that show a high response (REMIND, MESSAGE), medium response (IMAGE, TIAM-UCL) and a low response (WITCH and POLES).

Service demand projections are more responsive to income level than to fuel prices, which corresponds to findings in the literature. Saturation effects over time or with increasing income are not clearly visible. The model results are responsive to income projections and elasticity values range between 0.31 and 1.44. This is within the range reported in the literature. Even so, this range has a large impact on the projected transport demand, and could explain the varying transport sector service demand growth projections which have been seen in previous model comparison studies (Edelenbosch et al. 2017a). Reduced income elasticities over time, or in response to higher income shocks indicating saturation, cannot clearly be retraced in the model results. A better understanding of the uncertainty of income effects on service demand by exploring different income pathways as well as different service demand to income elasticities, is very relevant — as is having a better understanding of the role of saturation. The efficiency response to income change differs across models. In some models efficiency increases as a result of technology learning, while in others it decreases due to a shift to more energy-intensive transport modes.

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Appendix: Transport model descriptions of participating Integrated Assessment Models

REMIND transport

REMIND models the transport sector by using a hybrid approach combining top-down and bottom-up elements. Mobility demands for the four modelled transport sub-sectors (passenger-light duty vehicles (LDV), freight, electric rail, passenger-aviation and buses) are derived in a top-down fashion, since they are input to a nested CES production function that ultimately produces GDP. For the LDV mode, three different technology options (internal combustion engine, battery electric vehicle, and fuel cell vehicle) compete against each other in a linear bottom-up technology model.

The transport sector requires input of final energy in different forms (liquids, electricity and hydrogen) and requires investments and operation and maintenance payments into the distribution infrastructure (infrastructure capacity grows linearly with distributed final energy) as well as into the vehicle stock.

The main drivers/determinants of transport demand are GDP growth, the autonomous efficiency improvements (efficiency parameters of CES production function), and the elasticities of substitution between capital and energy and between stationary and transport energy forms. Furthermore, inside a model run, different final energy prices (due to climate policy, different resource assumptions, etc.) can lead to substitution of different transport modes inside the CES function, or a total reduction in travel demand.

The distribution of vehicles inside the LDV mode follows cost optimisation (perfect linear substitutability), although with different non-linear constraints (learning curve, upper limits of 70% on share of battery-electric vehicles and 90% on Fuel Cell vehicles) that in most realisations lead to a technology mix. Further information on the transport sector modelling in REMIND can be found in Luderer et al. (2015) and Pietzcker et al. (2014)

IMAGE travel model

The Integrated Model to Assess the Greenhouse Effect (IMAGE)is developed by PBL Netherlands Environment Assessment Agency, to assess environmental consequences of human activities in industry, transport, buildings, agriculture and forestry affecting energy use and land use at a global level (Stehfest et al. 2014). The transportation module IMAGE/ Travel model is described in detail by (Girod et al. 2012). In this study the GDP and population drivers are updated to SSP2 scenarios that can be accessed at https://secure.iiasa.ac.at/web-apps/ene/SspDb .

In IMAGE/Travel travelling costs form the basis of the modelling both in determining modal shares, as well as vehicle shares per transport mode, based on a multi nominal logit (MNL) model. The model represents 7 passenger transport modes and 6 freight transport modes. Modal costs depend on real cost per pkm, non-monetary preferences, and a time weight that captures the importance of time compared to monetary costs. Non-monetary preferences are used to calibrate the model to historical observations and account for factors that go beyond cost (e.g. driving a car is more expensive than other modes, but a popular travel choice). The concepts of the travel money budget (TMB) and travel time budget (TTB) are used to relate travel demand to income. Increasing income leads to increasing travel demand per capita which results in more time spent travelling. Through the concept of travel time budget (TTB), time gets more weight and faster modes are values more, as a result. This dynamic relation results in the empirically observed shift to higher speed modes when income increases (Girod et al. 2012).

All transport-specific model mechanics and data are documented in the main text and Appendix of (Girod et al. 2012), with the exception of the following updates. The costs per vehicle type, which determines vehicle choice, depend on energy cost, technology cost, non-energy cost (related to maintenance and vehicle purchase), and the load factor, which is regionally dependent. Energy efficiency in the model is captured in three ways: 1) Price induced efficiency improvement: in response to higher fuel price more efficient vehicles become cost competitive, 2) Autonomous efficiency improvement: technology costs of efficient technologies decline over time as a result of technological learning, 3) Modal shift: increasing fuel prices can also result in a shift toward more efficient modes (Girod et al. 2012) (Plotkin and Singh 2009). Reduction in transport GHG emissions are achieved through a carbon tax resulting, on the one the hand, in reduced competitiveness of technologies and modes with high dependency on fossil fuels, and, on the other hand, the increased price of travelling leads to less travel demand implemented through the concept of travel monetary budget (TMB).

Since Girod (2012) the LDV projected vehicle costs and efficiency have been revised to incorporate the most recent projections of LDV vehicle technology development, following the in depth study performed by the Argonne National Laboratory (Plotkin and Singh 2009).

MESSAGE Stylised Transport Sector Representation

The version of MESSAGE employed in this study ('MESSAGE V.5a') includes a quite stylised representation of the transport sector, which essentially captures only fuel switching and price-elastic demands as mechanisms to respond to climate and energy policies.

Importantly, the entire sector is modelled as one: all motorised transport modes, including light-duty vehicles, buses, trains, heavy-duty trucks, ships, and airplanes, are aggregated together into a single demand category. (Other MESSAGE model versions, in contrast, have a highly-detailed technological and socio-behavioural representation of the various modes, including a mechanism for switching transport modes; ((McCollum et al. 2017) for more information on the model version 'MESSAGE-Transport V.5'.) The following brief description elaborates the main characteristics of the transport module employed here.

The model chooses between different final energy forms to provide useful energy for transportation. This decision is based primarily on the energy service costs by fuel, taking into account fuel prices at the final energy level and the respective final-to-useful energy conversion efficiencies. In addition, cost mark-ups are applied to non-liquid fuels, in order to capture increased vehicle investment costs and market adoption hurdles, or 'behavioural barriers', which this stylised transport formulation is otherwise not well equipped to handle. The portion of the mark-ups capturing behavioural barriers are referred to as 'inconvenience' or 'disutility' costs. They represent, for instance, range anxiety, extent of refuelling/recharging infrastructure, and risk aversion. The conversion efficiencies vary by energy carrier. Useful energy demands (for the aggregate transportation sector of each region) are first specified in terms of internal combustion engine (ICE)-equivalent, which therefore by definition have a conversion efficiency of final to useful energy of 1. Relative to that, the conversion efficiency of alternative fuels is higher, for example electricity in 2010 has a factor of ~3x higher final-to-useful efficiency than the regular oil-product-based ICE. The assumed efficiency improvements of the ICE vehicles in the transportation sector, as well as switching transport modes and other lifestyle changes, are implicitly embedded in the baseline demand specifications (i.e., the scenario storyline). These come from the MESSAGE scenario generator[32] (see Riahi et al. (2007) for more information). Finally, the demand for international shipping is modelled in a very simple way with a number of different energy

32 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. These 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 seven 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 seven energy service demand categories. Finally, final energy is

carrier options (light and heavy fuel oil, biofuels, natural gas, and hydrogen). Demand is coupled to global GDP development with an income elasticity.

Additional demand reduction in response to price increases (e.g., in policy scenarios) then occurs via two mechanisms: (i) the fuel switching option (due to the fuel-specific relative efficiencies), and (ii) the linkage with the macro-economic model MACRO.

To reflect limitations of switching to alternative fuels, for example as a result of limited infrastructure availability (e.g., rail network) or some energy carriers being largely unsuitable for certain transport modes (e.g., electrification of aviation), cost mark-ups and share constraints are imposed on certain energy carriers (e.g., electricity) and energy carrier groups (e.g., liquid fuels) of the transport sector. In addition, the diffusion speed of alternative fuels is limited to mimic known bottlenecks in the supply chain, particularly those not explicitly represented in MESSAGE (e.g., non-energy related infrastructure). Both the share and diffusion constraints are typically parameterised based on transport sector studies that analyse such developments and their feasibility in much greater detail.

In the overall MESSAGE framework, price-induced demand responses for energy carriers at the final energy level result from a combination of three different factors: (i) adopting more efficient technologies, (ii) fuel switching and the resulting relative efficiency changes (e.g., differences between solids, gases and electricity), and (iii) demand response at the useful energy level. The latter changes in useful energy demand are modeled in MESSAGE via an iterative link to MACRO, an aggregated 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 (for each of the six end-use demand categories in the model: electric and thermal heat demands in the industrial and residential/commercial sectors (1-4), non-energy feedstock demands for industrial applications (5), and mobility demands in the transportation sector (6)) that the two models have reached equilibrium. This process is parameterised 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 behavioural measures (at a high level of aggregation), while considering the substitutability of capital, labour, and energy as inputs to the production function at the macro level.

converted to useful energy in each region by using the average final-to-useful energy efficiencies reported by the IEA for each country.

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

TIAM-UCL transport model

TIAM-UCL is a whole energy system model covering from energy resources to conversion to infrastructure to end-use sectors. This is a linear programming model that minimises total discounted energy system cost in the standard version and maximises societal welfare (total surplus) in the elastic demand version to compute a partial equilibrium.

The transportation sector is characterised by 14 energy-services plus one non-energy use demand segment (Table A4-1). Six of the energy-services are considered as generic demands: international and domestic aviation (TAI, TAD), freight and passenger rail transportation (TTF, TTP), domestic and international navigation (TWD, TWI). All other energy-services are for road transport.

Table A4-1: Energy-service demands in transport sector

Code TAD	Energy-service demand Domestic Aviation	Unit PJ
TAI	International Aviation	PJ
TRB	Road Bus Demand	Bv-km
TRC	Road Commercial Trucks Demand	Bv-km
TRE	Road Three Wheels Demand	Bv-km
TRH	Road Heavy Trucks Demand	Bv-km
TRL	Road Light Vehicle Demand	Bv-km
TRM	Road Medium Trucks Demand	Bv-km
TRT	Road Auto Demand	Bv-km
TRW	Road Two Wheels Demand	Bv-km
TTF	Rail-Freight	PJ
TTP	Rail-Passengers	PJ
TWD	Domestic Internal Navigation	PJ
TWI	International Navigation	PJ

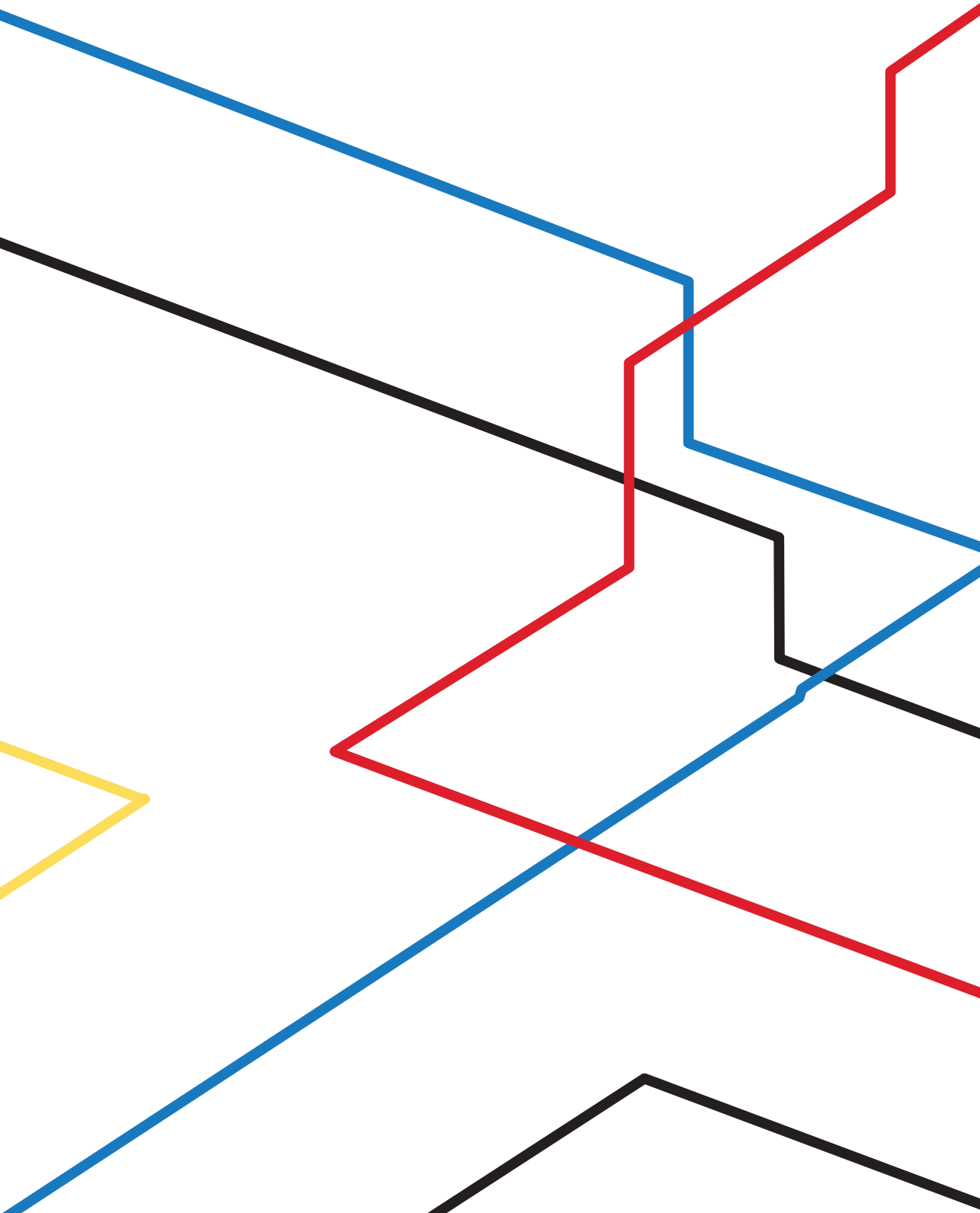
Demand for road transport energy-services is expressed in b-vkm and others are in PJ. Base-year energy-service demands are exogenous and are projected for the future using drivers such as GDP, population, household, sector output etc. Base-year transport sector final energy consumption is calibrated to IEA extended energy balance data for each region.

WITCH transport model

The WITCH transport model is documented in detail by Carrara and Longden (2017) as far as road freight is concerned, while the passenger transport modelling is described by Bosetti and Longden (2013) and (Longden 2014)

POLES transport model

A more detailed description of the POLES transport model can be found in Girod et al. (2013)



Chapter 5

Transport electrification: the effect of recent battery costs reduction on a future transition

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"Transport electrification: the effect of recent battery costs reduction on a future transition" (*in review for Climatic Change*)

Abstract

Although the rapid fall in the costs of batteries has made electric vehicles (EVs) more affordable and boosted their sales, EVs still account for only a fraction of total car sales. The future development of battery costs is uncertain and will affect the success of a transition to low-carbon transport. Integrated assessment models show that reducing greenhouse gas emissions is more challenging in the transport sector than in other sectors. Switching to EVs could significantly reduce passenger road transport emissions. In this study, we test the sensitivity of the projected sales of EVs to different battery costs and climate policy futures. We show that in addition to the pace of the battery costs decline, which has been so striking in the last years, for a long term global transition it is important to understand the lower boundary of battery costs. Only when battery costs reach 100$/kWh do battery electric vehicles take up a significant share (15%) of global car sales. If battery costs do not fall this far, policy incentives will be needed to achieve such a sizeable market share.

Keywords

electric vehicles, battery costs, transport, global energy demand

5.1 Introduction

If current trends continue, transport-sector greenhouse gas emissions are expected to rise faster than those from other energy end-use sectors (IPCC 2014f). Integrated assessment models (IAMs), used to analyse cross-sectoral strategies for achieving climate targets, show that in the transport sector, fuel switching forms a crucial strategy to reduce the sector's GHG emissions (Edelenbosch et al. 2017a; McCollum et al. 2014). For light duty vehicles (LDVs), which consume around half of the total transport energy consumption (IPCC 2014f), many models show that switching to electricity is an attractive solution (Thiel et al. 2016; Williams et al. 2012). However the degree and rate at which LDV transport can be electrified differs across models, depending on factors such as the assumptions about electric vehicle (EV) costs (Edelenbosch et al. 2017a; Grahn et al. 2016; Thiel et al. 2016). Here, battery costs are important.

The costs of EV batteries have fallen rapidly: from some 1000 US$ per kWh in 2008 to 485 US$ per kWh in 2012 (IEA 2013a). Nykvist and Nilsson (2015) argue that the literature is lagging behind actual technological advances, and actual battery costs are even lower. Using information from leading manufacturers of electric cars, they estimated the average costs per kWh in 2014 was 300 US$, whereas the average reported in the literature was 410 US$ per kWh. One of the leading battery models, the Argonne BatPac, even shows costs between 190 and 330 US$/kWh in 2015 (Sakti et al. 2015). It is indisputable that battery costs are falling rapidly. However, reported values are not always easy to compare, due to market mechanisms and variations in battery structure, chemistry, and technological design (IEA 2015c) and the debate on current battery costs, and their projected development is ongoing. The recent developments of battery costs as well as future assumptions could have significant implications for the projected transition to LDV electrification by energy and transport system models (IEA 2015c).

Another key assumption affecting EV purchase prices is the assumed battery energy capacity. Larger-capacity batteries cost more to buy, but have a longer driving range, so are more appreciated by consumers (Hidrue et al. 2011). IAMs typically use average vehicle use data, representing the needs of the average consumer. Although technically speaking, the energy requirements of the large majority of vehicle-days can be fulfilled by a vehicle with a battery size of only 19.2 kWh (Needell et al. 2016), the available EVs vary greatly in battery capacity and attract different types of users. Ellingsen et al. (2016) describe four typical types of EVs, ranging from a mini car with a battery of 17.7 kWh and a range of 133 km to a luxury car with a battery of 60 kWh and a range of 317 km (Linda Ager-Wick et al. 2016). Most of the vehicles sold in 2016 by the leading manufacturer Tesla Motors had an even larger battery of 75 or 90 kWh, and battery packs of 100 kWh have now been introduced. Thus the

variation might be even larger than suggested by Ellingsen et al. (2016).

To understand how recent technological developments might affect the anticipated technology transition in the transport sector, IAMs need to take account of a more diverse set of EV purchase price scenarios than the current "single trajectory assumptions". We assessed how the speed and magnitude of a transition to battery electric vehicles (BEVs) is influenced by four factors: i) the battery costs per kWh, ii) the impact of carbon pricing, iii) the impact of targeted EV policy incentive schemes, and iv) battery capacity. We used a state-of-the art IAM, i.e. the Integrated Model to Assess the Greenhouse Effect (IMAGE), which contains a relatively detailed transport submodule compared to other IAMs.

In the analysis, we first focus on the short term, incorporating the current EV policy incentive schemes. Next, we focus on the longer term (up to 2050) under varying policy and battery capacity assumptions. The calculations in this paper confirm that EV deployment is indeed highly sensitive to the projected battery costs. However, the ultimate cost (the floor cost) is found to be even more important than the rate of cost decline. Given the standard IMAGE model assumptions, a floor cost of 100 US$/kWh could, even in the absence of climate policy, make BEVs competitive with alternatives and thus allow BEVs to make up 15% of the market in 2045. A higher battery cost of 150 US$/kWh, however, would not achieve cost parity and thus leads to only a negligible share if no policies to stimulate EVs are in place. The key question is not only how rapidly costs fall, but also how low they can go.

5.2 Scenario analysis

We defined several scenarios that differ with regard to i) the battery costs per kWh, ii) carbon pricing, iii) EV subsidy schemes, and iv) battery capacity (see Table 5-1). The battery costs scenarios are designed based on the range of current costs estimates and possible implications for future costs. The carbon pricing and EV subsidy schemes include different assumptions on future climate policy and continuation of current policies. Finally, the battery capacity scenarios examine the sensitivity of the results for a broad range of alternative battery capacity assumptions.

Table 5-1: Scenario framework

Battery costs	Climate policy	EV subsidies	Battery capacity (sensitivity)
• Reference (REF) • Market leaders (ML) • Optimistic market leaders (OML)	• No climate policy (default) • Carbon tax rising to 249 US$/t$CO_2$ in 2050	• Current subsidies removed after 2020 (default) • Current incentives scaled globally to 2050	• 45 kWh (default) • Sensitivity tested from 30-90 kWh

Battery costs

As mentioned earlier, assumptions about current BEV battery costs vary widely. In 2015, Nykvist and Nilsson calculated an average cost of 410 US$/kWh, which fell to 300 US$/kWh when they averaged only the estimates of market-leading BEV manufacturers. The associated 95% confidence intervals for their log models were respectively 250–670 US$/kWh and 140–620 US$/kWh (Nykvist and Nilsson 2015). In our reference scenario, the battery costs follow Argonne National Laboratory's battery costs projections, which for 2015 are in line with the average projections Nykvist and Nilsson (2015) describe (Nykvist and Nilsson 2015). In the other two scenarios, lower battery costs of 300 US$/kWh are assumed in 2015 (see Figure 5-1).

Nykvist and Nilsson published their research in 2015; in late 2016, General Motors released the Chevrolet Bolt EV, priced at 37500 US$, and disclosed that battery cells cost 145 US$/kWh, which would fall further to 100 US$/kWh by 2022 (EVObsession 2015). The pack integration costs are conservatively estimated to be about 50%, which implies that the pack cost is currently 218 US$/kWh and could be 150 US$/kWh by 2022 (Voelcker 2016). Tesla Motors has revealed pack costs of less than 190 US$/kWh (Voelcker 2016). Given these figures, in the second scenario, the "market leaders" scenario (ML), battery cost falls to 150 US$/kWh by 2025. In the third scenario, the "optimistic market leaders" scenario (OML), it is assumed that battery costs would have fallen to 125 US$/kWh by 2025 (the US Department of Energy battery pack costs target for 2022 (Faguy 2015)), and to 100 US$/kWh by 2045. Lowering costs to 100 US$/kWh by the second half of the century is consistent with the more optimistic assumptions in Sakti et al. (2015). In the ML and OML scenarios the battery costs follow different pathways but the other elements that impact the vehicle cost are assumed to remain at their original cost price projection. For all three scenarios, the additional costs, compared to a conventional ICE, are shown in Table 5-2. For more details on the LDV costs assumptions, see the Appendix.

Table 5-2: Vehicle cost details of the three battery cost scenarios in 2015 US$, based on the Argonne National Laboratory "Literature review" scenario. The battery capacity of the BEV with a range of 240 km is 45 kWh in 2015, which by mid-century has decreased to 38 kWh.

		2015	2025	2030	2045
1. Reference (Ref)	Battery cost (US$/kWh)	394	321	284	219
	Cost of battery	17704	13369	11202	8301
	Additional cost vis-à-vis ICE	25462	19140	15980	11487
2. Market leaders (ML)	Battery cost (US$/kWh)	300	150	150	150
	Cost of battery	13484	6185	5907	5690
	Additional cost vis-à-vis ICE	19132	8364	8037	7571
3. Optimistic Market leaders (OML)	Battery cost (US$/kWh)	300	125	125	100
	Cost of battery	13484	5154	4922	3794
	Additional cost vis-à-vis ICE	19132	6818	6560	4725

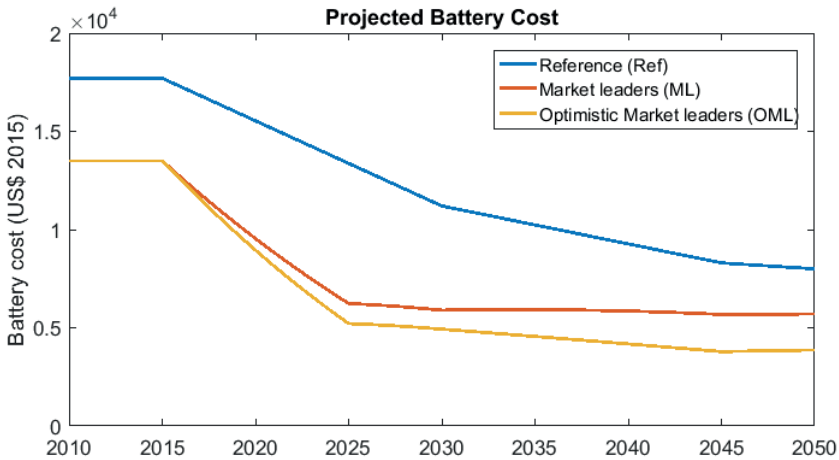


Figure 5-1: Projected battery costs in the Reference (Ref), Market leaders (ML) and Optimistic Market leaders (OML) scenarios.

Climate policy

In IMAGE, climate policy is usually modelled by introducing a carbon price (i.e., a price assigned to CO_2 emissions) into the model, which represents a generic measure to simulate policy measures that reduce emissions cost-efficiently throughout all the different sectors. In the

transport sector, the carbon price reduces the competitiveness of transport technologies and transport modes that rely on fossil fuels, and also the demand for transportation.
To reflect the possible influence of climate policy, we ran the default case without climate policy and included a climate policy scenario in which a globally uniform carbon price was applied, following the standard IMAGE SSP2-2.6 price trajectory (van Vuuren et al. 2017c). In the IMAGE model baseline, this leads to a radiative forcing of 2.6 W/m^2 in 2100 (i.e. starting at 47 US$/$tCO_2$ in 2020 and increasing to 249 US$/$tCO_2$ in 2050).

EV subsidies

The impact of a carbon price could be even greater if vehicle choice would be pure rational, as consumers can save money in the long term by buying efficient EVs instead of conventional internal combustion engines (ICEs). However consumers expect very short payback periods (two to three years (Tran et al. 2012)) which makes it unlikely that efficiency will be an important factor in an LDV technology transition. In accordance with the finding reported in Train's literature review of 1985 (Train 1985), this is represented in IMAGE through discount rates for buying cars which decrease with income, falling from 20% for an average per capita income of 10,000 US$ to 5% for a per capita income of 55,000 US$ (Girod et al. 2012). Alternative policy measures, such as subsidies, that directly reduce the cost difference of the EVs compared to ICEs can be more effective, in terms of financial support per vehicle, in stimulating EV deployment (Jin et al. 2014). Our default scenario assumes that current EV subsidies are removed in 2020. To examine possible effects of long-term EV subsidies we also formulated a scenario, where the average current EV subsidy levels (which vary, depending on whether vehicles are battery-operated or plug-in) are implemented globally from 2020 onwards, after which they are kept constant relative to vehicle costs.

Sensitivity to battery capacity

Novel vehicle technologies are typically introduced first in expensive vehicles (for which consumers are prepared to pay more because of the extra functionality) and later in mid- and low-price vehicles, but hybrid electric technology was first introduced in compact cars, as this segment is more sensitive to fuel savings (Weiss et al. 2012), and the lighter the vehicle, the less energy capacity the battery requires (Linda Ager-Wick et al. 2016). Later, hybrid electric technology was applied to larger vehicles too. The EV sales data shows a diverse portfolio of battery capacity introduced in different vehicle price categories, with marked regional differences in preference for battery capacity (EV-volumes 2017). Larger-capacity battery packs in high-price vehicles, enabling longer ranges at high costs, are currently gaining market share in the US, for example, while short-range "city cars" account for an important share of the market in Japan and China. In the US in 2016, the average

battery capacity of the top 3 BEVs sold (which is at least 62% of the BEV market) was 67 kWh. In China, the average battery capacity of the top seven of the BEVs sold (at least 48% of the BEV market) in that year was 36 kWh (EV-volumes 2017).

Clearly, the diversity of battery capacities available is a key element in the transition to EVs attracting different types of users and determines both costs and the car's range. In aggregated global models, however, often one BEV battery capacity is assumed, as consumers are represented as a homogeneous group. The optimal battery capacity could differ over time related to the development of consumer preferences, storage and load schemes. A detailed representation of consumer heterogeneity was beyond the scope of this research and possibly beyond the scope of a global IAM, but we did test the sensitivity of the results to assumptions about average battery capacity by investigating battery capacities ranging between 30 kWh and 90 kWh, in steps of 10 kWh, for all three scenarios. Note that although we considered different battery capacities, the other vehicle costs we used in our modelling are based on average cars assumptions; more detailed modelling is needed to understand trends in different car market segments.

5.3 EV sales in the short term

Figure 5-2 shows the short-term effect of battery costs projections on vehicle sales for three countries with subsidies (Japan, USA, and China) and one without (Brazil) in 2020 (IEA 2015d). The figure shows that the range of future battery cost estimates already has an effect in the short term on the projected EV penetration. In China for example, there is no BEV deployment under the reference assumptions in 2020, but deployment would be 5% under the ML assumptions and 18% under the OML assumptions. The combination of the high subsidy for BEVs and transition to less costly batteries eventually results in BEVs that are cost competitors with ICEs. China's policy ambition is to have 5 million EVs on the road by 2020, which is roughly comparable to the ML costs scenario projections. In the US, the BEV subsidy is slightly lower but smaller plugin in electric vehicles (PHEVs) receive a substantial subsidy, hence the difference in market shares.

The incentive schemes seem to strongly affect EV sales in the ML and OML scenarios: in those scenarios, transition is quick (5 years). In our example of Brazil, where no subsidies are in place, none of the costs scenarios show a transition to EVs. This also holds for other regions without subsidies. In the reference costs scenario, with the subsidies in place, PHEVs attain small market shares in Japan and the USA, but BEVs do not enter the market, as their costs remain too high. The effect of financial incentives on BEV deployment has been empirically observed (Mock and Yang 2014). The small market share of EVs in 2015 falls within the models' uncertainty range: it was 0.7% in the US, 1.0% in China, 0.6% in Japan (IEA

2016b), and are too small to be used to validate our model results against.

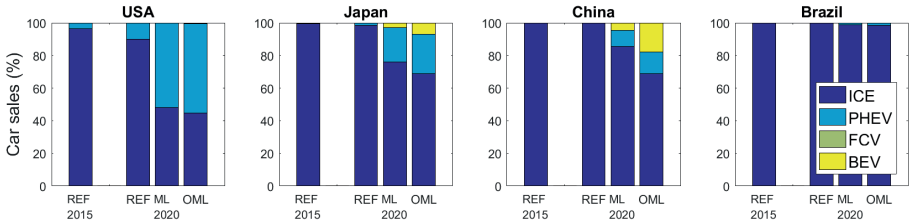


Figure 5-2: Reference car sales in 2015 alongside projected car sales in the US, Japan, China, and Brazil in 2020 under reference (REF), market leaders (ML) and optimistic market leaders (OML) battery costs assumptions.

5.4 EV sales in the long term

Deployment in the absence of climate policy and EV subsidies

The trend in battery costs also has important implications for EV take-up in the longer term (Figure 5-3 first row; note that current subsidies have been removed after 2020). While in the reference and ML scenarios BEVs remain too expensive to attain a significant share in the global market, the decrease of battery costs in the OML scenario to 100 US$/kWh leads to BEV achieving a 15% share in 2045 without any additional policy. The additional vehicle price in the latter case is approximately 4700 US$ according to our assumptions, while in the ML scenario it is approximately 7500 US$, (see Appendix). According to Tran et al. (2012), only 6% of consumers would be willing to pay more than 3000 US$ extra for a BEV, which is more pessimistic than the results from our modelling. However, both studies show that only when the additional price of BEVs has fallen to a few thousand dollars do BEVs become an attractive option. So, besides the pace of the battery costs decline that has been observed in the last years, it is also important to understand the critical lower boundary (the floor price) of battery costs.

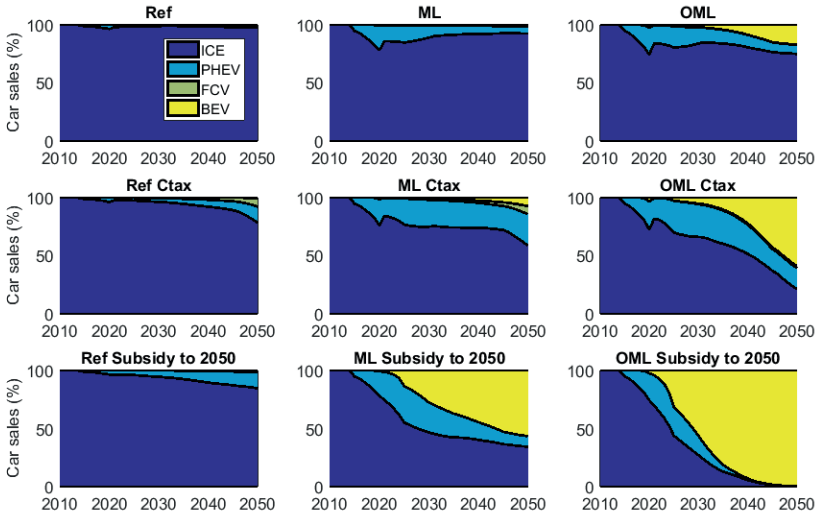


Figure 5-3: Global vehicle sales for the three battery costs scenarios (Reference (REF), Market leaders (ML), Optimistic Market leaders (OML)). In the top row, no additional policy measures are assumed after 2020; in the second row the reference carbon price to meet a 2-degree scenario is in place; in the bottom row, average current national direct subsidies are introduced globally into all IMAGE regions between 2020–2050.

Impact of climate policy

As the payback period of consumers is very short and the effect of a carbon price is small if the price penalty (extra investment cost) of EVs is too large. The second row of Figure 5-2 shows that this is the case in the REF scenario. In the original baseline the "normal" representation of climate policy is therefore not effective. However, if the costs difference between BEVs and conventional technologies is in the range of the OML scenario, a carbon price can have a large impact. The projected costs of transport technologies thus strongly influence the effectiveness of a carbon price to induce a transition to EVs. In the ML scenario, which follows progressive EV market leader statements but in which battery costs do not decrease below 150 US$/kWh, BEV deployment remains below 10%, even under the assumption of stringent climate policy, showing that again the key obstacle to transition is the floor price.

Impact of EV subsidies

The model results confirm that EV sales responds to direct EV capital cost subsidies: see the effect of the subsidy removal in 2020 (top two rows of Figure 5-3) and the high EV sales

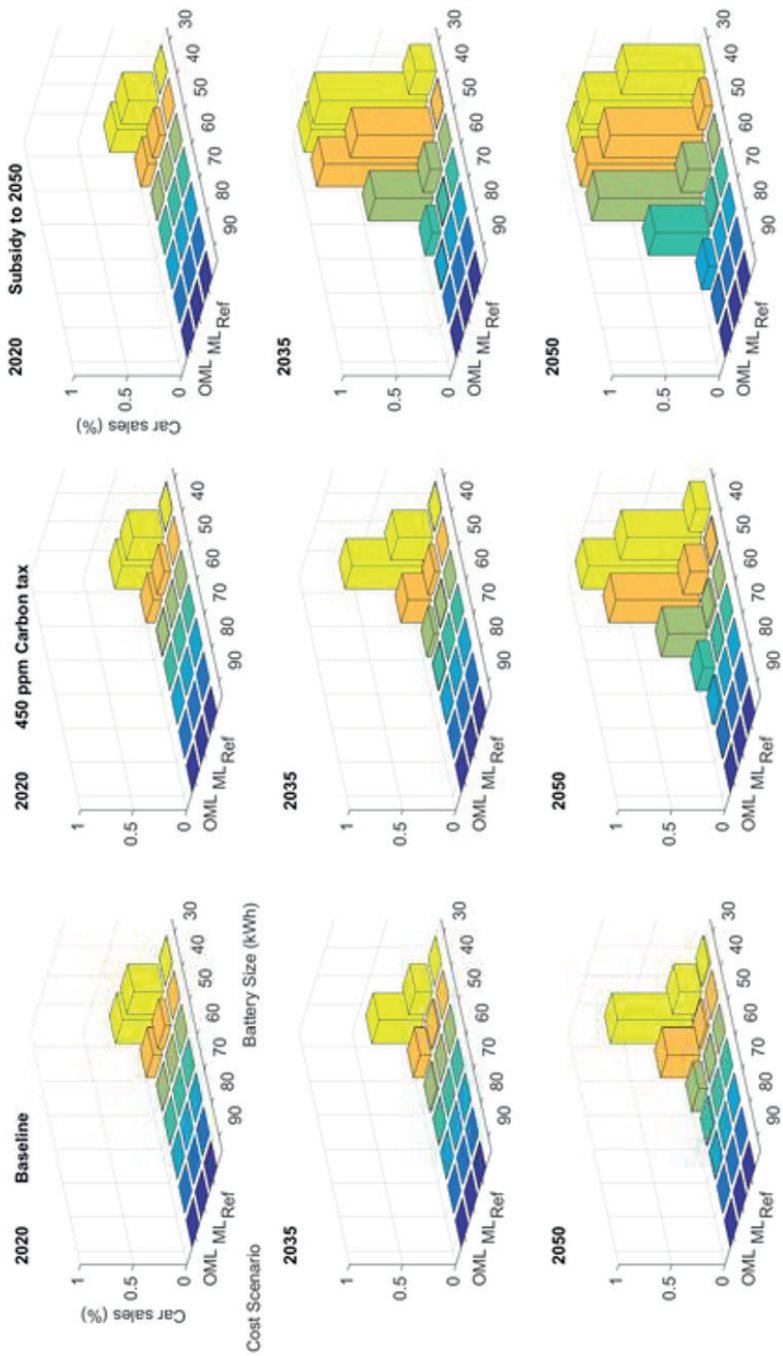


Figure 5-4: Global BEV share in the vehicle fleet for three scenarios under varying assumptions of average battery capacity.

under the assumption of continuation of current subsidies (but implemented globally) up to 2050 (third row). Subsidies are often present to stimulate initial sales and many countries have stated that EV subsidies will be removed after a certain number of vehicles have been sold (Mock and Yang 2014). This scenario, in which subsidies are not only maintained but are also applied globally, does not aim to be realistic, but shows that the models' representation of climate policy (through a carbon price or alternative measures) can have a large effect on the sector's projected mitigation potential. A lower discounting of the future will have a similar impact.

BEV range and battery capacity

The direct sensitivity of the BEVs' assumed average battery capacity on BEV car sales can be seen in Figure 5-4, depicting the results for the battery capacity sensitivity scenario's. This demonstrates the importance of understanding what BEV battery capacity required is valued equally to an average conventional car. In the most optimistic costs scenario (OML) a BEV with a battery capacity of 60 kWh, which corresponds to a range of approximately 350 km, would attain 2% of global market sales in 2050 in the baseline scenario and 11% under the carbon tax scenario. However, a smaller capacity battery of 30 kWh, corresponding to a range of approximately 180 km, could account for the majority of the sales in the OML (but not in the ML) scenario in 2050, even without additional climate policy or EV subsidies. At the other end of the battery capacity spectrum, the model shows that vehicles with battery capacities of 90 or 80 kWh will not become competitive against ICE even with the attractive subsidies in place and optimistic (OML) technology cost assumptions. However, the added benefits of increased vehicle range are currently resulting in the deployment of larger-capacity battery EVs (see the next section). The market share for which the smaller-range vehicle is competitive, at least given current charging speeds, will be smaller than that for vehicles with a longer range.

5.5 Discussion and conclusions

Transitioning from conventional ICEs to EVs could be a way to mitigate transport GHG emissions (assuming electricity is generated with low GHG emissions). EVs are currently more expensive than conventional vehicles, mainly because of the costs of the battery. Yet although our calculations show that the rapid fall in battery costs in recent years could accelerate a transition to EVs in the future, they also show that for long-term EV use, the battery floor cost is even more important.

There are important scenario assumptions that influence these findings. The assumed average battery capacity needed to compete with a conventional ICE is an important

uncertainty. 2016 sales show a large variation in average battery capacity, and the outlook is highly uncertain. It could be assumed that all regions will follow the US trend and Tesla's product line and transition to BEVs with larger-capacity batteries. Alternatively, and consistent with ongoing urbanization, the demand could increase for the smaller BEVs that have gained a foothold in China and Japan. Advances in battery technology that significantly speed up charging could reduce the need for large-capacity batteries. From our battery capacity sensitivity analysis, it can be concluded that the projected BEV share is very sensitive to the battery capacity required, but more research is needed.

The consumer's attraction to a car, quantified by discrete choice studies as willingness to pay for longer-range vehicles is not taken into account in our model, nor is the effect of the battery capacity assumption on car weight, technology learning or vehicle use (e.g., urban or rural environment). Hidrue et al. (2011) show that the median willingness to pay for a BEV with a range of 300 miles, 1 hour charging time and 20% faster acceleration is 9625 US$, while for a 100-mile BEV with less attractive characteristics it would be -5606 US$. Compared to a conventional car, certain BEV configurations can thus be seen as advantageous and others as disadvantageous. Clearly, taking the above preferences into account would change our scenario results significantly. Still, our scenarios show that in a simplified model that assumes one homogenous consumer market, and in which decisions are based on costs, average battery capacity is a key assumption.

Willingness to pay varies per person (Hidrue et al. 2011). In global models, such as IMAGE, it can be too constraining to consider different consumer preferences, as these differ over time and place, limited data is available and this would make the model considerably more complex. Therefore, generally simple robust relationships obtained by assuming average technologies and consumers. In IMAGE, for example market heterogeneity is represented by the more stylized multinomial logit equation. However, in a technology transition, heterogeneous consumer preferences can also play an important role. The relationships between market deployment and willingness to pay can be dynamic, (for example, through social influence), and so can those between market deployment and technology cost (through learning effects). Early adopters and thus also heterogeneity in preferences can trigger a transition; ideally, these dynamics should be accounted for, even in models with global scope.

The discount rate is important in the decision to buy a car. A large advantage of the EV is that the energy costs per km are much lower, but future savings are less valued by consumers. The literature suggests that consumers expect a short payback time on vehicle purchase, which affects the effectiveness of the current representation of climate policy (a global

carbon price) in the model. Under these discount rate assumptions, as long as the extra cost of EVs is higher than that of conventional cars, the carbon price will have a limited effect. Continuing current EV subsidies and applying them globally would be more effective to mitigate transport emissions. Other sector-specific policy measures, such as emissions standards (the current EU target is to achieve a fleet average for all new cars of 95 grams of CO_2 per vehicle km), could also be more effective and could push car manufacturers to invest in and subsequently subsidize low-emission vehicles.

In conclusion, the fall of battery costs for EV applications has sparked the initial sales of PHEV and EVs, with two million electric cars on the road worldwide in 2016, bringing a transition to EVs closer to reality. If battery costs continue to drop, as several electric car manufacturers have suggested can occur already in the near term, this trend can be expected to continue. However, in the long-term when assessing the feasibility of a full transition to meet stringent climate targets the lower limit of battery costs and battery capacity development are the important determining factors.

Appendix: Model description and vehicle assumptions

Integrated Model to Assess the Global Environment (IMAGE)

IMAGE is an integrated assessment models (IAMs), developed to model the interaction between human systems and natural systems. It is traditionally used to project energy system developments and their relation to climate change but is currently applied to address a broader set of environmental issues such as air and water quality, water scarcity, depletion of non-renewable resources (fossil fuels, phosphorus), and overexploitation of renewable resources (fish stocks, forests), covering the time period out to 2100. IMAGE projections have been used in many global studies, such as the IPCC Special Report on Emissions Scenarios (SRES), the UNEP Third Global Environment Outlook (GEO-3) and the Millennium Ecosystem Assessment (MA) (Stehfest et al. 2014). An elaborate description of the IMAGE model can be found on www.image.pbl.nl.

To model the energy supply and demand, The IMage Energy Regional Model (TIMER), which simulates the global energy-system has been integrated into the IMAGE model. TIMER assesses future energy demand and energy efficiency trends and the possible transition pathways towards renewable energy sources by assessing dynamic relation such as inertia, learning by doing in capital stock, trade between regions and depletion of energy resources. It models 12 primary energy carriers in 26 regions. TIMER is an energy simulation model. The system state in every future year up to 2100, depends entirely on the previous year system state, based on a single set of deterministic algorithms.

IMAGE transport

The IMAGE transport model is described in detail by (Girod et al. 2012). The transport model is a state of the art IAM transport model, characterized by high detail, in terms of its technological, socio-demographic, and regional resolution. Travelling costs form the basis of the modelling both in determining modal shares, as well as vehicle shares per mode, based on a multi nominal logit (MNL) model. The model represents 7 passenger transport modes and 6 freight transport modes. Modal cost depend on real cost per pkm, non-monetary preferences, and a time weight that represents the importance of time compared to monetary costs. Non-monetary preferences are used to calibrate the model to historical observations and account for factors that go beyond cost (e.g. driving a car is more expensive than other modes, but a popular travel choice). The travel money budget (TMB) concept is used to relate travel demand to income. Increasing income leads to increasing travel demand per capita which results in more time spent travelling. Through the concept of travel time budget (TTB), time gets more weight and faster modes are values more, as a result. This dynamic relation results in the empirically observed shift to higher speed modes when income increases. Input to the modelled scenarios are "middle of the road" Shared Social-Economic Pathway (SSP2) population (IIASA set) and GDP projections (OECD set), which can be assessed through the guest login button on https://secure.iiasa.ac.at/web-apps/ene/SspDb . The model is calibrated to passenger km and energy data from 2005 based on (IEA 2012c; Schäfer 2009)

The costs per vehicle type, which determines vehicle choice, depend on energy cost, technology cost, non-energy cost (related to maintenance and vehicle purchase), and the load factor, which is regionally dependent. Energy efficiency in the model is captured in three ways: 1) Price induced efficiency improvement: in response to higher fuel price more efficient vehicles become cost competitive, 2) Autonomous efficiency improvement: technology costs of efficient technologies decline over time as a result of technological learning, 3) Mode shift: increasing fuel prices can also result in a shift toward more efficient modes. Reduction of transport GHG emissions are achieved through a carbon tax resulting on the one the hand in reduced competitiveness of technologies and modes with high dependency on fossil fuels, and on the other hand through the concept of TMB the increased price of travelling leads to less travel demand.

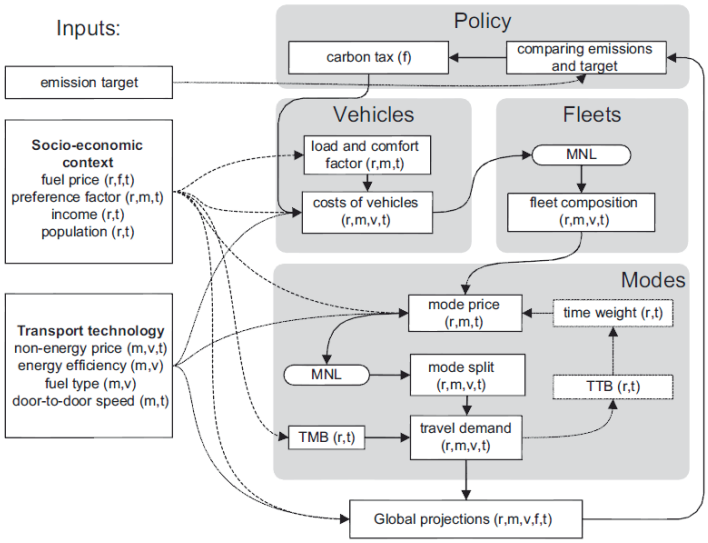


Figure A5-1: Schematic overview of the IMAGE transport model. The indices r, m, v, f, t, respectively, denote region, travel mode, vehicle type, fuel type and time (Girod et al. 2012).

LDV cost assumptions

We updated and revised the projected Light Duty Vehicle (LDV) costs and efficiency in IMAGE described in Girod et al. (2012). Current assumptions on vehicle costs are based on the "Literature Review" scenario of the in-depth study by the Argonne National Laboratory (ANL) (See Table A5-1). That bottom-up study estimated future drivetrain cost by using component cost equations with input variables (energy storage capacity, power, etc.) (Plotkin and Singh 2009). The extra cost of the EV compared to the conventional ICE is therefore not merely the costs of the battery. Excluding battery cost, the drivetrain cost of a BEV is slightly less (600–800 US$). The estimated range of a midsize car is 240 km, which in 2015 corresponded to a battery capacity of 45 kWh. Furthermore, it is assumed that vehicle retail price is 1.5 times the vehicle cost (Plotkin and Singh 2009), which increases the cost difference between the technologies.

Table A5-1: LDV vehicle cost and efficiency assumptions in IMAGE transport model, based on (Plotkin and Singh 2009)

	ICE[1]	ICE	ICE	ICE	HEV	HEV	HEV	FC	PHEV 10k	PHEV 30k	PHEV 10k	PHEV 30k	BEV 240k
Fuel 1	Oil	Hyd	Oil	Bio	Oil	Oil	Bio	Hyd	Oil	Oil	Bio	Bio	Elec
Fuel 2									Elec	Elec	Elec	Elec	
Energy Efficiency Fuel 1 (MJ/pkm)[2]													
2010	1.64	1.13	1.16	1.16	0.94	0.89	0.89	0.73	0.76	0.48	0.76	0.48	0.40
2030	1.28	1.13	1.06	1.06	0.71	0.66	0.66	0.57	0.58	0.37	0.58	0.37	0.33
2045	1.20	1.13	1.00	1.00	0.67	0.62	0.62	0.50	0.54	0.34	0.54	0.34	0.30
Energy Efficiency Fuel 2 (MJ/pkm)													
2010	0	0	0	0	0	0	0	0	0.08	0.17	0.08	0.17	0
2030	0	0	0	0	0	0	0	0	0.06	0.13	0.06	0.13	0
2045	0	0	0	0	0	0	0	0	0.06	0.12	0.06	0.12	0
Additional vehicle cost (2007 US$)[3]													
2015	0	7160	4274	4274	3654	6552	6905	10658	6164	10118	6164	10118	29090
2030	0	8060	4736	4736	4041	6476	6828	8148	5929	8605	5929	8605	18257
2045	0	5547	4587	4587	3741	6252	6605	7158	5411	7458	5411	7458	13124

[1] In this table the following abbreviations are used ICE: Internal Combustion Engine, HEV: Hybrid Electric Vehicle, PHEV: Plug-in Hybrid Electric Vehicle, EV: Electric Vehicle, Hyd: Hydrogen, Elec: Electricity, Bio: Biofuel.

[2] The general assumed load factor is 1.6. In the model this has been corrected per region in order to calibrate the model to historical observations.

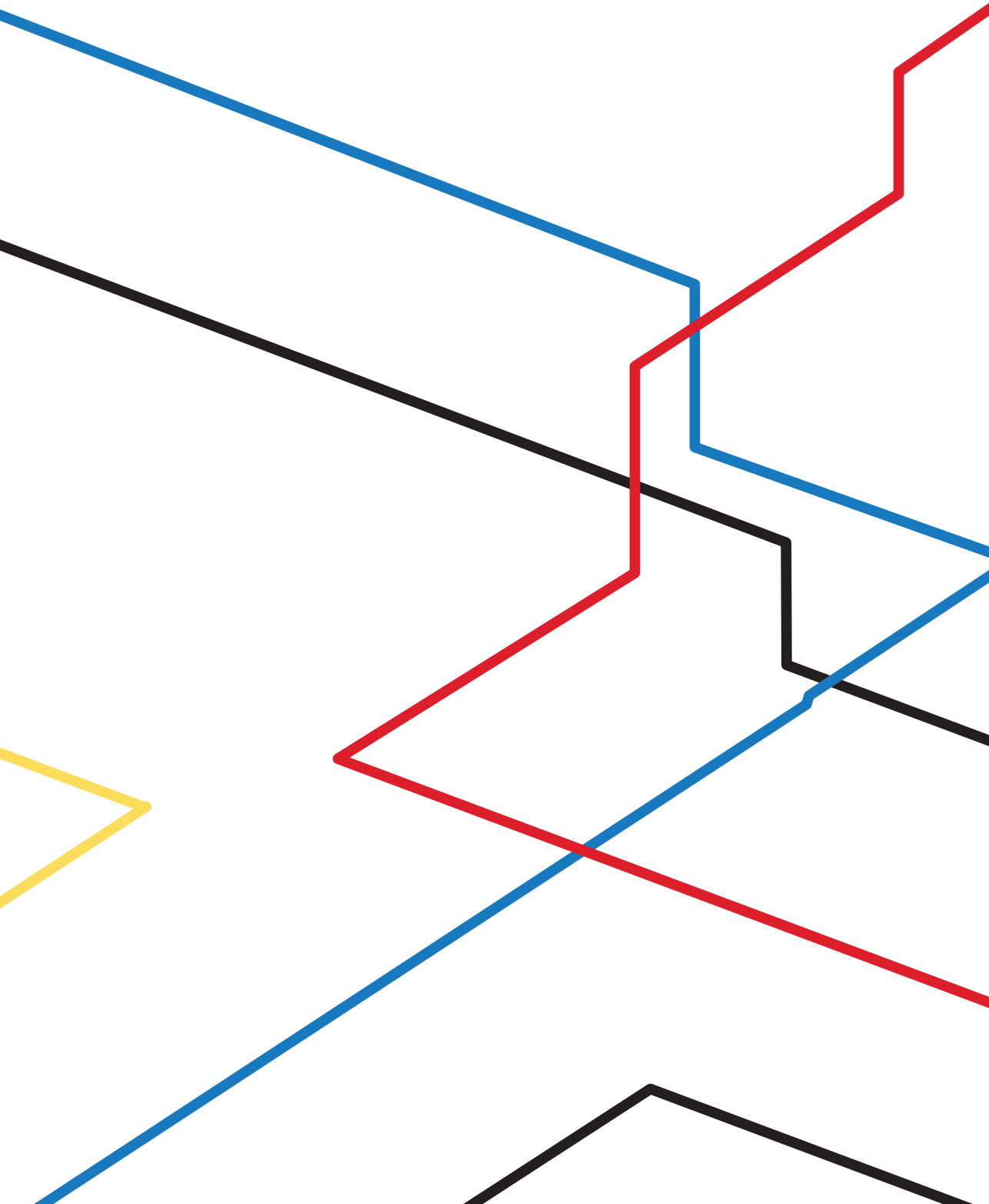
[3] The additional vehicle costs have been calculated with respect to the standard ICE oil vehicle (first column).

Current subsidy

To better represent short-term EV sales, all scenarios in this study take into account present direct BEV and PHEV subsidies programmes. The subsidy levels were based on an overview of direct subsidies in place in 2013 at the national level (Mock and Yang 2014). Only direct subsidies are included, not fiscal incentives in the form of tax breaks. In 2013 direct subsidies were paid in China, Japan, the US, France, Sweden and the UK. In IMAGE western Europe is modelled as one region. Therefore, the national level subsidies of the western European countries were averaged over all countries' first vehicle registrations (ITF 2016). We assumed that in all three scenarios the current EV subsidies were introduced in 2010 and continued to be paid until 2020.

Table A5-2: Direct EV subsidies at purchase in US$, accounted for a standardized BEV and PHEV, based on Mock and Yang (2014). For Western Europe, the subsidies have been averaged over the vehicle sales per country (ITF 2016). In all scenarios in this study subsidies are introduced in 2010 and removed in 2020. In the policy subsidy scenario, the average of the subsidies in Japan, China, US and Western Europe was calculated and then applied globally between 2020 and 2050, decreasing over time in proportion to the decline in vehicle costs.

	BEV (Renault Zoe), range 240 km	PHEV (Volvo V60) , range 50 km
Japan	8723	4708
China	9969	5815
USA	7477	5400
Western Europe	3128	2733



Chapter 6

Transitioning to electric cars: Interactions between social learning and technological learning

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"Transitioning to electric cars: Interactions between social learning and technological learning" *(submitted to Environmental Research Letters)*.

Abstract

Making a transition to electric vehicles could be a promising approach for mitigating rapidly-rising greenhouse gas emissions in passenger car transport. Integrated Assessment models (IAMs), which have been used extensively to evaluate climate mitigation policy efforts, have strongly focused on how emissions can be reduced through technological change processes. To date IAMs have hardly dealt with the behavioural aspects of technology transitions. Here, we extend the transport representation in IMAGE, one global IAM, to explore how technological learning and social learning may interact affecting electric vehicle transition dynamics. We find that technological learning and social learning processes can mutually reinforce each other. Increased electric vehicle market shares can induce technological learning which reduces technology cost while social learning affects diffusion to other adopter groups. Both learning processes affect market shares and can stimulate each other in a positive feedback loop. This shows the importance of market heterogeneity, niche groups and targeted policy in driving low-carbon technology transitions – and that information on social dynamics as well as technology parameters is needed to understand climate mitigation potentials.

Keywords

transport modelling, vehicle choice, social influence, technological learning

6.1 Introduction

Passenger car transport represents one of the fastest growing sources of greenhouse (GHG) emissions. IAM projections show that transitioning to advanced propulsion technologies can significantly mitigate these emissions. This includes fuel cell vehicles, electric vehicles, or biofuels depending on the feedstocks used and conversion processes (Edelenbosch et al. 2017a; IPCC 2014a). Improved technology performance and reduced production costs are essential to make new technologies competitive as alternatives to the internal combustion engine. In energy system models and IAMs this required progress of 'technological learning' is often incorporated either through learning rates describing cost reductions per doubling of cumulative production or exogenous technology improvement assumptions. Empirical studies also show that, in addition to costs, many other behavioural factors strongly affect vehicle choice. These factors include aesthetics, performance, attitude, lifestyle and social norms; none of these are represented in IAMs (McCollum et al. 2017; Mundaca et al. 2010; Stephens 2013; Tran et al. 2012).

Modelling behavioural influences on consumer choice is extremely complex. There are a large number of factors that would need to be represented to be complete (Stern et al. 2016). Finding the right level of detail and distinguishing robust patterns necessary for modelling purposes is a challenge. Behavioural factors also tend to be heterogeneous (John et al. 2000). Faced with the same set of observable conditions, clearly not all consumers make the same decision. In a technology transition, this is especially important because market heterogeneity can affect consumer adoption propensities through social influence effects. Social influence describes how interactions with others affect one's own preferences (Rogers 2003; Young 2009). When early adopters move to a new technology, this impacts others' decision making processes, for example, by changing their perspectives on status, reliability and safety of a new vehicle (Axsen and Kurani 2012b; McShane et al. 2012). Adopters' preferences are therefore dynamic and respond reflexively to changes in adoption environment.

The IAMs used for analysing long-term global response strategies have relatively aggregated descriptions of subsystems like transport to ensure key relationships are transparent and analytically tractable. Including more detail (e.g. behavioural features and consumer groups) increases the number of (uncertain) assumptions that have to be made. Moreover, for long-term projections detailed representations of sectors could become meaningless as uncertainties increase (Krey 2014). The appropriate level of detail depends on the research question that is addressed. While an aggregated representation is appropriate to understand what technology changes are required in the transport sector to meet stringent climate targets, without the consideration of behaviour, IAMs are less suited to evaluating how this

technology transition can take place. This limits the models' applicability to evaluate sector-specific policies promoting alternative vehicle uptake.

The lack of formal treatment in IAMs of the behavioural aspects of consumer decision making has been recently criticized (Mercure et al. 2016; Rosen 2015). Some efforts have recently been undertaken in response, focusing on consumer choices for light duty vehicles (LDVs) (McCollum et al. 2017). LDVs are of particular interest in the transport sector as they account for approximately half of current transport energy consumption (IPCC 2014f). McCollum et al. (2017) performed a multi-IAM study which included heterogeneous consumer preferences for certain non-financial attributes of vehicles. They found that sectoral policies explicitly targeting consumer preferences are required to enable widespread adoption of alternative fuel vehicles, particularly among later-adopting consumers. In a separate study, Pettifor et al. (2017) used a different approach by drawing on empirical data on risk aversion to new vehicle technologies among different consumer groups. They reasoned that a single aggregated 'risk premium' is affected by social influence effects between the heterogeneous adopter groups with differing adoption propensities identified in diffusion of innovations theory (Rogers 2003). By including these effects in two global IAMs, they could identify the potential accelerating effect of social influence on low-carbon vehicle transitions.

In this study we explore how a dynamic representation of consumer behaviour through both social learning and technological learning influences the long-term technology transition to battery electric vehicles (BEVs). This study is the first attempt to represent the dynamics of social and technological change in a single IAM, and to systematically compare and contrast the two interdependent processes. The result is a step-change improvement in the representation of critical drivers of technological transition.

6.2 Modelling vehicle choice

6.2.1 Technological learning

Technology costs are often found to decrease with increasing experience of production and use, a phenomenon referred to as learning by doing and represented by a learning or progress curve (McDonald and Schrattenholzer 2001). The relationship is generally formulated as the percentage, the learning rate (LR), by which the unit cost decreases for each doubling of experience represented by cumulative installed capacity or production. IAMs tend to include technological learning either by prescribing exogenous assumptions on costs decline as a function of time (drawn from different sources representing a number of processes that lead to cost reduction) or by including the learning curves directly in the model. There are different views on the best representation. Endogenous learning curves

seem to emphasize better the importance of experience, but exogenous assumptions can also represent the role of other factors driving cost reductions such as R&D (Anandarajah and McDowall 2015)(McDonald and Schrattenholzer 2001). The two representations also lead to different model outcomes as they could lead to a preference either for delaying action or for promoting early learning to reduce future costs (see Van Vuuren et al., 2002).

6.2.2 Social learning

Social learning about the benefits and risks of new technologies is central to technology diffusion. In his seminal work on 'diffusion of innovations', Everett Rogers defines diffusion as the process by which an innovation is communicated over time among the members of a social system (Rogers 2003). These members are heterogeneous in their preferences, particularly towards risk and uncertainty. Earlier adopters are risk-tolerant or risk-seeking, preferring new relatively untested technologies which offer novel attributes. Later adopters are risk-averse, preferring to wait until perceived technology risks are lowered by observing the experiences of early adopters. Heterogeneous adopters are therefore interdependent, connected through social communication processes. Although the specific mechanisms of social learning are diverse - ranging from word of mouth to visible 'neighbourhood effects' and social norm compliance - the basic insight that heterogeneous consumers exchange information through social networks (Rogers (2003:342) has been repeatedly confirmed both in general terms (e.g.(McShane et al. 2012; Peres et al. 2010)) and in studies specific to vehicle choice (e.g.,(Axsen and Kurani 2012a; Grinblatt et al. 2008)).

In this paper, we use the term 'social learning' to emphasize the analogy with technological learning as a process by which costs/barriers are reduced. Both processes jointly explain diffusion; and both processes take time. However, it is important to emphasize that it is not time *per se* that decreases perceived risks or costs but rather the experience of others (social learning) and the experience of manufacturing and using technologies (technological learning).

6.3 Methods

6.3.1 Experimental design

In the original transport module of the IAM IMAGE, vehicle choice is made on the basis of technology cost and discounted energy cost through a multinomial logit (MNL) equation (Girod et al. 2012). The MNL distributes market shares over the different types of vehicles, in year by year time steps (t), where the cheapest vehicle attains the largest share. The lambda (λ) in the MNL equation, determines how sensitive the model is for cost differences

between the vehicles (i). A lower lambda leads to less price sensitivity, which results in a more heterogeneous vehicle fleet.

$$VehicleShare_{i,t} = \frac{\exp(\lambda \cdot Cost_{i,t})}{\sum_i \exp(\lambda \cdot Cost_{i,t})} \quad \text{Eq. (1)}$$

In this study, the vehicle choice formulation is adjusted to distinguish between the vehicle adoption propensities of the different consumer groups identified by (Pettifor et al. 2017). The lambda is set to a high value, so that in each group the optimal choice (i.e. the vehicle with the lowest perceived cost) is chosen. The new formulation allows both LDV technology costs and the risk premiums to be affected by market deployment endogenously, through the two processes of social learning and technological learning.

6.3.2 Technology costs

The battery costs are by far the most determining element for the cost difference between the BEVs and conventional internal combustion engines (ICEs). As a result, the electrification of the transport sector is strongly affected by the future development of battery costs (Edelenbosch et al. 2017b). We focus therefore on technological learning for battery costs. Since Girod (2012) the LDV projected vehicle costs and efficiency have been revised to incorporate the most recent projections of LDV vehicle technology development. The vehicle costs are based on the in depth study performed by the Argonne National Laboratory (Plotkin and Singh 2009). This bottom up analysis distinguishes between different elements of the car that contribute to the total cost, such as the engine, battery, motor and controllers, and make projections of the cost developments over the coming decades. The EV battery cost have recently rapidly decreased (Nykvist and Nilsson 2015). Therefore our starting point is the estimated battery cost according the sectors market leader of 300 US$ per kWh in 2014 (Nykvist and Nilsson 2015). In the exogenous battery cost scenario we assume that battery costs could reach 125 $/kWh by 2025 (Faguy 2015), and evolve to 100 US$/kWh over the course of the century. In line with LRs reported in the literature, in the endogenous cost scenario a battery cost LR of 7.5%[33] (uncertainty range from 6-9%) (Nykvist and Nilsson 2015) is assumed and a floor price of 100$/kWh, affecting plug-in electric vehicles (PHEVs), battery electric vehicles (BEVs) and fuel cell vehicles (FCVs) purchase cost. For other costs elements of the vehicle, the standard representation is used, i.e. technology will develop in time based on prescribed scenario assumptions. A more detailed description of the vehicle cost assumptions, the IMAGE transport model and the details of the new model formulations can be found in the Appendix.

33Learning rate equals the cost reduction for doubling in cumulative production

6.3.3 Risk Premiums and social influence

Rogers (2003) distinguishes consumer segments by the use of point estimations (mean and standard deviation) in a normal distribution based on empirical research. The innovators and early adopters have high initial adoption propensities and so high risk tolerance; early majority, late majority and laggards are increasingly risk averse and have low initial adoption propensities. Pettifor et al. (2017) developed a modelling approach which dynamically relates the adoption propensity (quantified as risk premiums) of each adopter group and social influence. To quantify risk premiums for new technologies, such as BEVs, for which limited market data is available, discrete choice experiments provide willingness to pay (WTP) estimates of consumer preferences for non-financial vehicle attributes. Based on a systematic review of relevant discrete choice studies, Pettifor et al. (2017) quantify the mean risk premium[34] () and standard deviation of the risk premium), which are then used to calculate risk premiums as a measure of adoption propensity for four different adopter groups. Negative initial RPs indicate attraction to new technologies (risk-seeking) and high positive initial RPs indicate aversion to new technologies. Following Rogers (2003), the early adopters[35] and innovators combined occupy 16% of the market share; the early majority and late majority both account for 34% of the market; and the laggards the final 16%. Risk premiums decline as market share grows, using market share as a proxy for social influence.

In the new model formulation heterogeneity is represented explicitly by the four consumer groups with differing adoption propensities (risk premiums) towards new technologies. Making use of point estimates (the mean and standard deviation) Rogers' S-shaped adopter curve divides the distribution of adoption propensities into 'ideal types' referred to as adopter groups (See Appendix). These groups are distinguished from each other by risk aversion and market share. For example, the innovators and early adopters represent 16% of the total market and occupy the area 3 standard deviations below the mean.

Initial risk premium values distinguish between the adopter groups in terms of their willingness to pay for an electric vehicle. The EA group, being less risk averse, have a negative risk premium whereas the EM, LM and LG groups have a positive risk premium. Risk premium values are taken from a synthesis of discrete choice studies measuring stated preferences for AFVs. Using all available willingness to pay ratios for AFVs in the literature, we assume they are normally distributed to calculate mean risk premium$(\bar{x}\,\mathrm{RP})$ and standard deviation risk premium $(\bar{\sigma}\,\mathrm{RP})$. These are then used to calculate initial risk premium values for EA, EM, LM, and LG using Rogers (2003) adoption propensity curve (See Appendix). Based on a

34 The risk premium does not distinguish specific types of non-financial preference which affect adoption propensity. Using a single aggregated measure allows robust empirical calibration to stated and revealed preferences.

35 Our Early Adopter (EA) group contains the both the early adopters and innovators described by (Rogers 2003)

meta-analysis of 21 empirical studies that measure the effect of social influence on vehicle purchase propensities this relationship is quantified. For every one standard deviation increase in market share, the propensity of vehicle adoption affecting the risk premiums, increases by 0.241 standard deviations, which is called the social influence effect size.

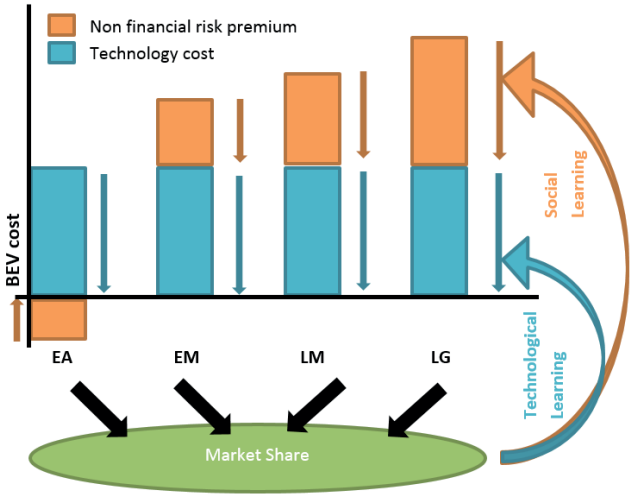

Figure 6-1: The schematic overview of the simplified dynamic relationship between technological learning, social learning and market deployment of new technologies. Four adopter groups are distinguished: early adopters, early majority, late majority and laggards. At a given time point, all four groups face the same technology cost but different monetized risk premiums. Net perceived costs therefore differ per group, with the lowest perceived cost vehicle selected by the cost-minimizing decision algorithm, resulting in changes to market share which in turn stimulates further technological and social learning.

6.3.4 Scenario framework

Heterogeneity of consumers, technological learning, social learning and policy measures can all influence vehicle choice. Figure 6-1 demonstrates how these processes are related in the model setup (see Appendix for further detail). Different scenarios are compared in which these four influences on vehicle transition dynamics vary in order to assess their relative and combined effects. In the Ref (reference) scenario, technology costs decline exogenously over time and risk premiums are frozen for the four adopter groups. In the TL (technological learning) scenario, risk premiums are also frozen, but technology cost reductions occur endogenously based on a learning curve. In the Ref + SL (social learning) scenario, social learning is included but with exogenous technology cost assumptions. Finally, in the TL +

SL scenario both technological learning and social learning occurs. All scenarios are tested with and without climate policy. The latter is implemented in the form of an economy-wide carbon price. This is a standard approach for representing climate policy in IAMs (and should be seen as a generic placeholder for other forms of policy for inducing emission reductions). Three carbon tax scenarios are compared: 1) a global carbon tax of 40 $/tCO_2$[36] in 2020, increasing gradually at 3% per year; 2) a constant global carbon tax of 130 $/tCO_2$, i.e. the value that tax path 1 reaches in 2060; 3) a global carbon tax peak from 2020 to 2040 of 273 $/tCO_2$ returning to a constant of 72 $/tCO_2$ in 2040, the same value that tax path 1 reaches in 2040. A visualisation of the carbon tax pathways is provided in the Appendix.

Table 6-1: The scenario framework with varying assumptions of four elements of a transition tested.

nr	Scenario	Technological learning	Social learning	Heterogeneity	Policy
1	Ref	Exogenous	RPs remain at 2010 level	Explicit	None
2	TL	Endogenous	RPs remain at 2010 level	Explicit	None
3	Ref + SL	Exogenous	Endogenous	Explicit	None
4	TL + SL	Endogenous	Endogenous	Explicit	None
5	TL Ctax exp	Endogenous	RPs remain at 2010 level	Explicit	Tax 1
6	Ref + SL Ctax exp	Exogenous	Endogenous	Explicit	Tax 1
7	TL + SL Ctax exp	Endogenous	Endogenous	Explicit	Tax 1
8	TL Ctax cons	Endogenous	RPs remain at 2010 level	Explicit	Tax 2
9	Ref + SL Ctax cons	Exogenous	Endogenous	Explicit	Tax 2
10	TL + SL Ctax cons	Endogenous	Endogenous	Explicit	Tax 2
11	TL Ctax peak	Endogenous	RPs remain at 2010 level	Explicit	Tax 3
12	Ref + SL Ctax peak	Exogenous	Endogenous	Explicit	Tax 3
13	TL + SL Ctax peak	Endogenous	Endogenous	Explicit	Tax 3

6.4 Vehicle choice projections

6.4.1 Technological learning

In the TL (technological learning) scenario, the early adopter group shifts to PHEVs in the first half of the century given their preference for new technologies (represented by a negative risk premium which remains constant as there is no social learning). However, they are not yet attracted to the more expensive BEV technology (Figure 6-2 right panel). The deployment of PHEVs leads to reduction of both PHEV and BEV costs through technological learning (Figure 6-2 left panel). In the Ref (reference) scenario, BEV costs are projected to reduce rapidly in this period as well, based on exogenous assumptions (see Appendix). Once a certain BEV cost threshold has been passed (Figure 6-2 left panel), depending

36 40$/tCO$_2$ is the value proposed recently by the Climate Leadership Council. (Baker et al. 2017)

heavily on the learning rate (indicated by the TL range), early adopters shift from PHEVs to BEVs. This shift leads to a faster BEV cost reduction until the battery floor price is reached (at approximately 30% deployment under average learning rate assumptions). By the end of the century early adopters move on to fuel cell vehicles (FCVs). In both Ref and TL (reference and endogenous technological learning) scenarios, alternatives to the internal combustion engine (ICEs) are only chosen by early adopters. The early adopter group and technological learning play an important role in this initial phase of a technology transition. With slower learning rates, BEVs remain relatively expensive and the transition might not take place at all. Even though the technology is competitive in terms of costs, if risk premiums remain at current levels purchasing a BEV is not an attractive option for the early majority, late majority and laggards.

It should be noted that while the cost development of the exogenous and TL experiments are quite similar, in the latter case the costs are responsive to other simulated processes in the model including both market deployment and policy incentives.

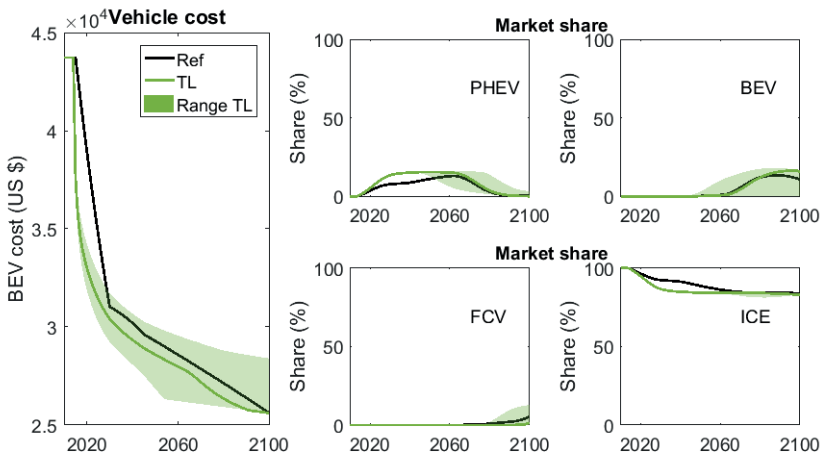

Figure 6-2: Battery electric vehicle (BEV) cost over time in the Ref and TL scenarios (left panel). The resulting BEV, Plug in electric vehicle (PHEV), Fuel cell vehicle (FCV) and internal combustion engine (ICE) market shares at the global level (middle and right panel). The shaded colour indicates the scenario range.

6.4.2 Social learning and technological learning

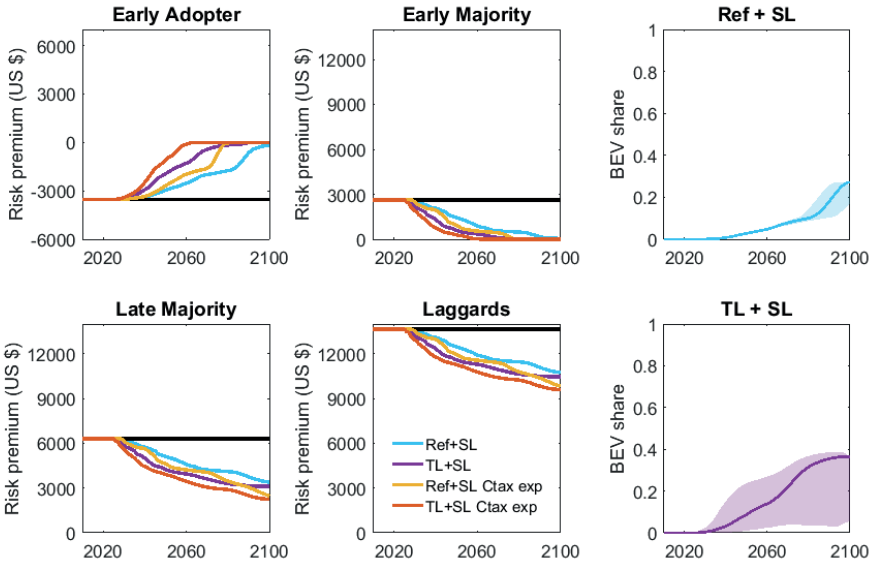

Figure 6-3: Risk premiums towards BEVs for the Early Adopter, Early Majority, Late Majority and Laggards in scenarios with social learning (SL) including those with exponential carbon tax (Ctax exp) (left and middle panels). Resulting global market shares for BEVs at the global level, with shaded colours indicating the scenario range (right panel).

In the SL (social learning) scenarios, the market deployment of BEVs drives down the risk premiums of the early majority, late majority and laggards while for early adopters it leads to less attraction meaning risk premiums that are less negative. Figure 6-3 shows how the BEV risk premiums change over time for all four adopter groups in the Ref + SL and TL + SL scenarios.

The effect of social learning can be seen in the diffusion of BEVs from early adopters to the early majority (Figure 6-3 middle and right panels). The risk decline leads to higher BEV deployment which again leads to more risk decline (social learning). When BEVs become mainstream, early adopters become more attracted to distinctive alternatives, such as fuel cell vehicles (seen previously in Figure 6-2). Similarly, PHEVs become less attractive to early adopters which has increased the BEV share in the first half of the century compared to those scenarios where social influence is not accounted for. The Ref + SL scenario range shows that social influence effect size has little impact on the initial phase of the transition,

but does significantly affect the speed of diffusion from early adopters to other groups.

The lower right panel of Figure 6-3 show how the combined effect of technology and social learning leads to a faster technology transition and larger market penetration under assumptions of average learning rates and social influence effects. There are different phases during the technology transition in this scenario. First PHEV use by early adopters leads to battery learning reducing BEV costs. The early adopters then shift to BEVs which results in increased technological learning and risk decline for the other adopter groups. The early majority starts to adopt the BEV enlarging both learning effects. At approximately 30% market deployment (with average learning rates) battery costs reach their floor price. Risk premiums continue to decrease for the late majority and laggards groups. But additional policy is still needed to overcome the risk premium barrier for these groups.

Only under the stimulus of a very high carbon tax (the exponentially-increasing 'Ctax exp' scenario) does the late majority group also transition to BEVs (see Figure 6-4). Risk premiums for the late majority and laggards remain considerable even after BEV deployment reaches 50% (see Figure 6-3). There are two possible explanations for this. First, the initial risk premiums (based on a synthesis of available WTP values) likely include other factors besides social influence. Second, the social influence effect (based on a meta-analysis of empirical studies from 1999 to 2013) is likely conservative, under-estimating the 'true' size of the effect.

The different carbon tax paths show that once the transition is put in motion the learning processes reinforce the transition path. Notably, in the TL + SL scenario a carbon tax is more effective (in terms of market share increase) than in the TL or Ref + SL scenario. In the TL + SL scenario market share jumps 20 % in a period of 10 years in response to the peak carbon tax while the other two scenarios without both technological and social learning show a much more limited response. All three mechanisms increase the relative attractiveness of BEVs: the carbon tax by increasing fuel price differentials between electric and liquid fossil fuels; technological learning by decreasing the upfront cost differential between BEVs and ICEs; and social learning by decreasing perceived risks of BEVs. These three effects are mutually reinforcing. Consequently, results are dependent of the estimation of learning rates, social influence effect sizes, and risk premiums by adopter group.

The importance of social learning and technological learning during the different phases of the technology transition (technological learning affecting the initial phase, social learning affecting further diffusion) can be traced back to their equational forms. The social influence effect equals the reduction in risk premium after an increase in market share, while the technological learning rate equals the cost reduction per doubling of cumulative

battery production for BEV application. Because of the exponential form of the learning rate equation and the limiting floor price, the fastest learning happens in the initial deployment phase, while social influence has a linear relation to deployment (with higher and lower coefficients in specific periods of adoption).

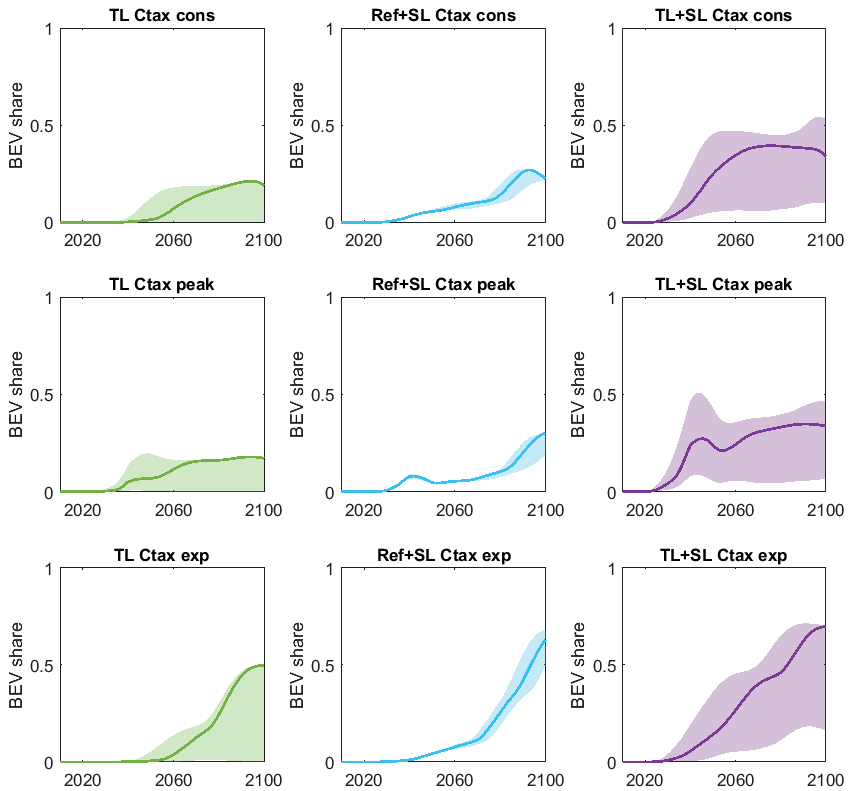

Figure 6-4: Global market shares for BEVs for the constant (top row), peak (middle row) and exponential carbon tax (bottom row). The shaded colour indicates the scenario range.

6.5 Modelling technology transitions

IAMs show that technology plays a crucial role in reducing greenhouse gas emissions across regions and sectors (Krey et al. 2014; Kriegler et al. 2014) and in determining policy cost and feasibility to meet specified climate targets (Bosetti et al. 2015). At the same time, key processes related to a technology transition such as technology development and social

learning are extremely simplified in IAMs. In this paper, we show how including these specific processes in a LDV choice model affects IAM technology transition dynamics. Other factors affecting behaviour which could be contextual or cultural might play an important role too but are currently not accounted for. Based on our results we come to the following conclusions.

Technological learning and social learning are successfully represented in a LDV choice model within an IAM framework. While both processes impact vehicle choice in expected ways, their interaction is interesting and revealing. The model demonstrates the different phases of a technology transition and its relevant dynamics. It shows how niche or early adopter groups can drive technology innovation by stimulating market demand. The adoption of alternative technologies that are still relatively expensive by these groups play an important role in the development of technology in the technological learning phase. The recent sales of luxury BEVs that are in higher vehicle price ranges and contemporaneous rapid reductions of battery costs is an example of this dynamic (EV-volumes 2017; Nykvist and Nilsson 2015). Moreover, the deployment of alternative technologies by early adopters could also reduce behavioural barriers perceived by other consumer groups.

BEVs can become dominant if technological learning and social learning processes work to mutually reinforce each other. Through social learning and technological learning new technologies can become more attractive to consumers. Generally speaking, technological learning affects the timing of adoption by early adopters while social learning affects diffusion to other adopter groups. The two learning processes also stimulate each other in a positive feedback loop. This results in a path dependency where policy incentives stimulating EV deployment, such as a carbon tax or dedicated transport sector policies, can spark positive learning feedbacks. In the scenario where both technological and social learning effects are accounted for, we see that the carbon tax leads to an increase in BEV market share. Often the optimal carbon tax pathways in IAMs increases over time. Learning processes show the path dependency of a technology transition acting and indicate that implementing policy rather sooner than later might be more effective.

Acknowledgements

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Appendix: Extra information on modelling methods

IMAGE model description

See Appendix Chapter 5.

Rogers' adopter propensity curve

Based on the adoption propensity curve the distribution of adoption propensities is divided into the adopter groups.

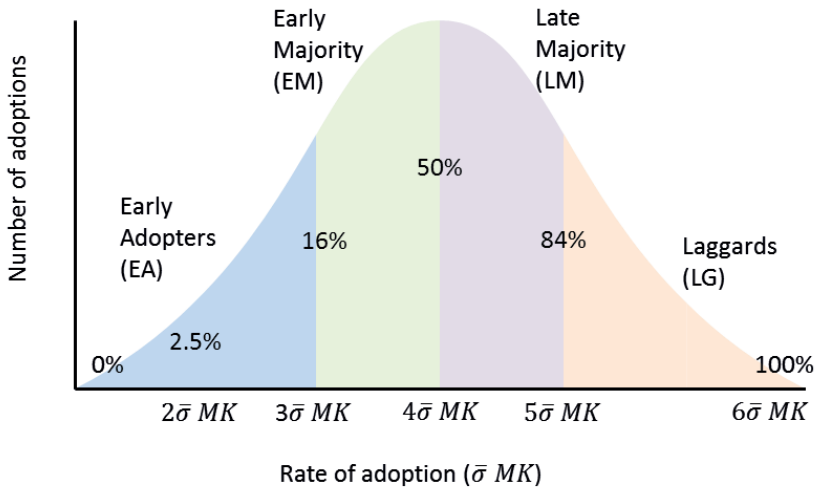


Figure A6-1: Calculation of $\bar{\sigma}$ MK using (Rogers, 2003) adoption propensity curve.

Implementing risk premiums in IMAGE

Risk premiums (in $/pkm) have been added to the travel cost, which entails vehicle technology costs, energy costs, subsidies and taxes. In IMAGE the multinomial logit operates over three dimensions: mode, technology and region. A fourth dimension has been added, namely the consumer groups. Each year, the multinomial logit equation, as shown in equation 1, assigns shares to the vehicle technology, i, based on costs. The lambda factor, λ, determines how sensitive the MNL is to cost differences. A higher lambda results in higher sensitivity, and thus a larger share for the cheapest technology (i.e., a single technology can come to dominate more of the vehicle mix).

In the LDV mode, for each consumer group, for each region, the vehicle shares are calculated in the fleet module based on the travel cost. The total average LDV travel cost, called mode price in Figure 1, is then calculated by aggregating the results for all consumer groups, weighted by the groups' market share, and for all technologies, and is sent to the modes

module. In Figure A6-2 more detailed overview of the vehicle and fleet module in shown, along with in red the adjustments made to risk premiums, disaggregated for consumer groups.

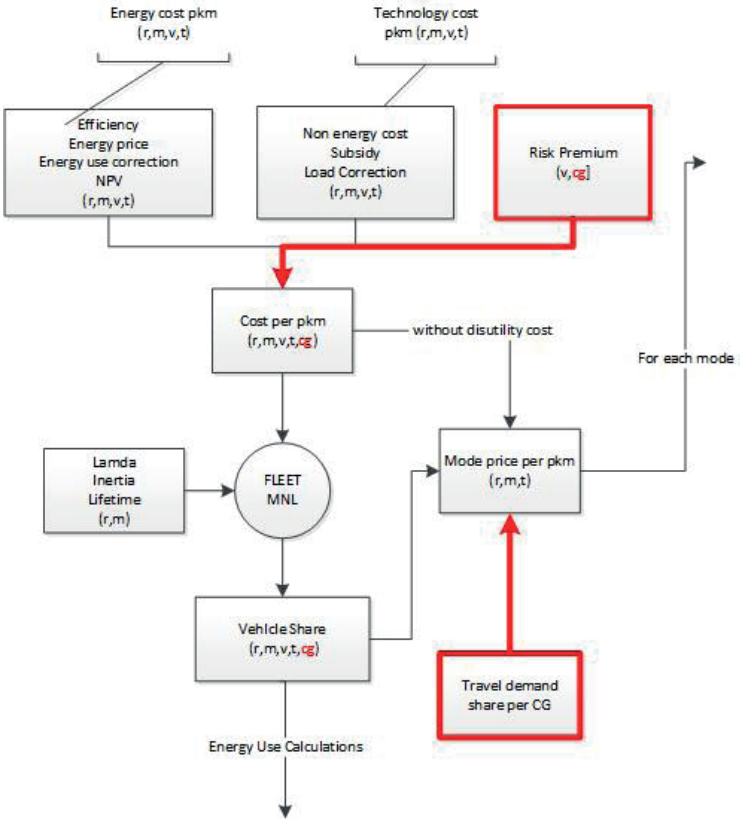


Figure A6-2: Schematic overview of the vehicle and fleet module in IMAGE. In red the adjustments made in this project to account for risk premiums and heterogeneity in risk premium, by disaggregating between different consumer groups. The indices r, m, v, t, cg respectively, denote region (r), travel mode (m), vehicle type (v), time (t) and consumer group (cg).

Carbon tax Scenarios

In this study we distinguish between 13 scenarios which include three carbon tax pathways as a representation of climate policy, which are visualized in Figure A6-3. The carbon tax pathways are inspired by the model diagnostics exercise in which different stylized carbon tax pathways were designed to better understand model response (Krey et al. 2015). Here we have used different values but the pathways have a similar form.

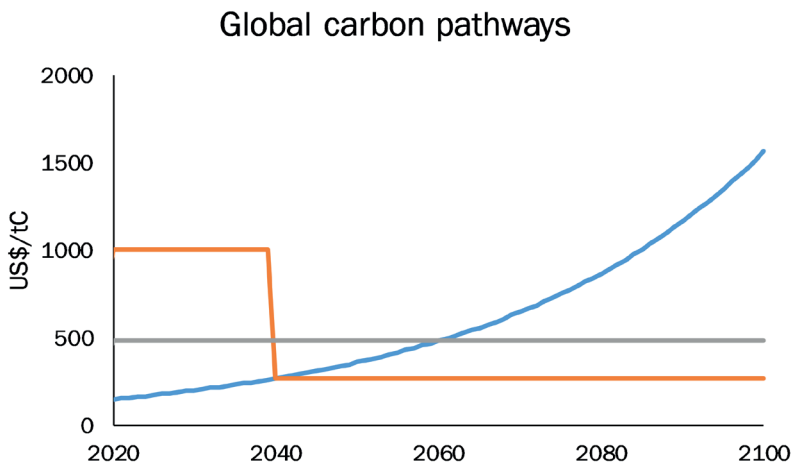
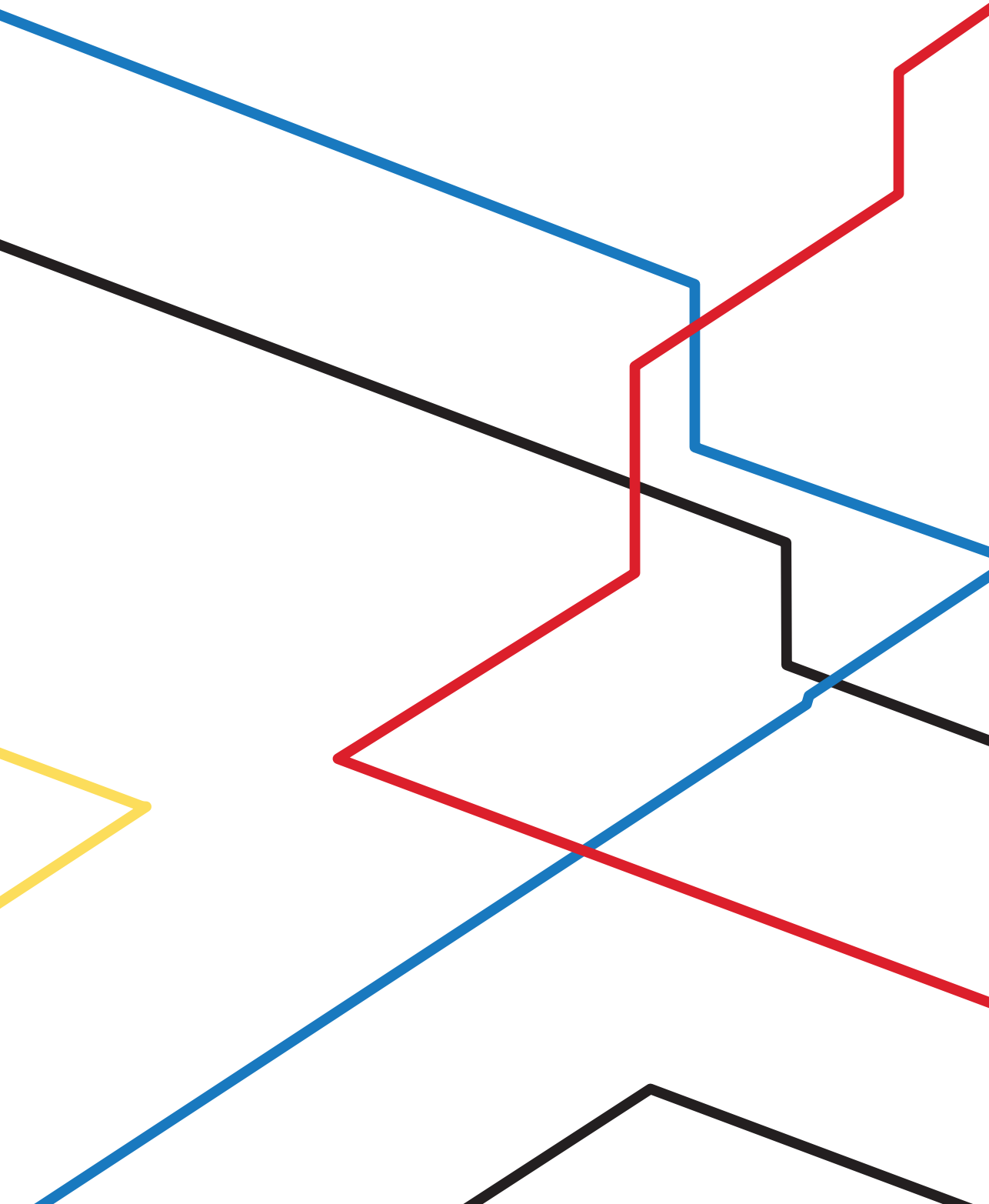


Figure A6-3: Global carbon tax pathways applied in scenarios number 5-13.



Chapter 7

Mitigating energy demand emissions: The integrated modelling perspective

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"Mitigating energy demand emissions: The integrated modelling perspective" *(submitted to Global Environmental Change)*.

Abstract

Mitigating carbon emissions in the current energy system will require fundamental changes of both the energy supply and the energy demand sectors. Previous model-based analyses, however, have focused mostly on energy supply transformations, while the energy demand sector changes are less well understood. In this study, this issue is addressed by analysing in detail the projected future energy demand projections, and the required demand-side changes to reach stringent mitigation targets using a suite of integrated assessment models. We examine industry, transport and buildings sector pathways across four models and three different reference scenarios from the Shared-Socioeconomic Pathway framework which is used as a set of common future perspectives by the climate research community. The demand side mitigation efforts are compared to more detailed, sector-specific, technology-oriented assessments of abatement potential based on a literature review for the year 2030. The results indicate that strong emission growth in the industry and transport sector can be attributed to increasing final energy per capita and population growth. In the stringent mitigation scenarios energy efficiency, electrification and switching to low carbon fuel are all required, however in the second half of the century fuel switching is dominant. In the green growth SSP1 scenario the required emission reduction is significantly less than other scenarios. The technology assessment shows that there is a higher potential to reduce demand-side emissions through energy efficiency improvements than currently envisioned in the integrated assessment models.

Keywords

energy demand modelling, energy efficiency, model comparison, Shared Socioeconomic Pathways;

Introduction

Model-based analysis is used frequently to analyse future trends in the energy system and to explore the implications of various mitigation strategies. The models used for this include energy system models, integrated assessment models (IAMs) and macro-economic models. Traditionally, these models focus mostly on energy supply sectors. Indeed, decarbonizing energy supply by switching to low carbon energy supply technologies (renewable energy sources, nuclear power or applying carbon, capture and storage), can be an effective strategy to mitigate greenhouse gas emissions (Krey et al. 2014; Kriegler et al. 2014). However, more than half of the energy related greenhouse gas (GHG) emissions directly currently occur in the energy demand sectors, i.e. buildings, transport and industry sectors (IPCC 2014d). To achieve stringent climate targets, such as remaining within 2 degree global warming, which is aimed for by the Paris agreement, requires reducing all energy system emissions towards zero before the end of the century (IPCC 2014a), therefore energy demand emissions will have to be cut drastically as well. Additionally, energy demand policies can have important co-benefits, such as improving energy security and reducing environmental pollution (GEA 2012; IEA 2014).

There are several reasons why models have focused more on energy supply than demand. First of all, there is a high level of diversity of the demand sectors. This means that modellers are faced with a choice to either include many functions and technologies, at the costs of transparency and including assumptions that could lose meaning within the long-term and global scope of these types of models, or include a more stylized representation of energy demand. The latter could potentially represent overall sector behaviour well, but is less easy to relate to tangible mitigation measures. The second reason is that energy demand decisions are often influenced by other less well defined criteria than the "rational" cost-optimization" which is more applicable to supply-side decisions (Krey 2014; McCollum et al. 2017)

The advantage of IAMs is that they offer a system level perspective on climate change mitigation pathways with interactions across sectors, which is not offered by other more detailed sector-specific tools. Sugiyama et al. (2014) show that across a set of 18 IAMs energy intensity declines in response to climate policy, but the significance of this effect differs widely across models. Yet the underlying reason behind such a wide divergence was not explained. Also, Marangoni et al. (2017) show that across the recently developed Shared Socio-economic Pathways (SSPs) energy intensity and economic growth are the most important determinants of future carbon emissions from the energy system, both with and without a climate policy. Given the importance of integrated energy-system models in advising policy-makers, it is very relevant to understand what these models currently say

with respect to future energy demand developments, and what drives the different energy demand pathways.

In this study, therefore, we analyse in more detail IAM future energy demand projections, focusing on the underlying trends, as well as the projected demand-side changes required to reach a stringent mitigation target from an integrated perspective. We compare not only different models but also different scenarios. The recently developed Shared Socio-economic Pathways (SSPS) provide a unique set of consistent socio-economic developments to discuss possible trends across demand sectors under different assumptions, in scenarios with and without climate policy (O'Neill et al. 2014; van Vuuren et al. 2014). While several IAM comparisons have been performed at the sector level (Edelenbosch et al. 2017a; Edelenbosch et al. 2017c; Pietzcker et al. 2017), there has not been a demand sector model comparison of this level of detail yet, nor a study assessing different demand scenarios.

More specifically, sector-specific dynamics are analysed through decomposition analysis. The projected carbon emissions developments of the SSPs across the three largest energy demand sectors (buildings, industry and transport) are allocated to changes in population, final energy per capita, electrification and fuel switching. In order to compare the model strategies to reduce demand sector emissions to other more detailed sector-specific tools, we will also compare the top down modelling decomposition results with a technology-oriented assessment of abatement potential based on literature review for the year 2030. Finally, in the last section, we will analyze the energy service[37] and energy efficiency change in the demand sectors using the underlying results of the technology-rich IMAGE model.

7.2 Methods

7.2.1 Scenarios used

The SSPs together form a scenario framework in which future radiative forcing levels, affecting climate change, are combined with alternative pathways of socioeconomic development. The scenario framework is recently developed by the climate change community and the scenario assumptions and key outputs have been described in detail in special issue in Global Environmental Change (Riahi et al. 2017; van Vuuren et al. 2017b). Varying trends in key factors affecting climate change, such as population dynamics, economic growth, technological change, social, cultural and institutional changes and policies, have been combined into five consistent and plausible narratives, or reference scenarios, (SSP1 to SSP5) (O'Neill et al. 2015; O'Neill et al. 2014). Comparing models that share common narrative assumptions on socio-economic trends has as advantage that they are more comparable

37 Energy service here refers to the human activity obtained through the use of energy and to satisfy a human need (Blok and Nieuwlaar 2016). For example, referring to mobility, lighting, heating, industrial products such as steel or cement.

than those that do not (van Vuuren et al. 2014). By using the SSP framework we can therefore distinguish between across model and across scenario agreements and uncertainties to improve our ability to draw conclusions from the demand sector comparison.

The scenarios differ in their climate change mitigation and adaptation challenge, due to varying reference emissions in the absence of climate policy as well as the projected "mitigative and/or adaptative capacity" of the projected future society. In this study the scenarios SSP1, SSP2 and SSP3 are compared, that span the range from low to high "mitigative and adaptative capacity". The three scenarios are "reference pathways" in which no climate change, climate impacts or new climate policies are assumed. SSP1 explores a story in which society is oriented towards a more sustainable development. This is translated into assumptions on rapid technological change directed toward environmental friendly purposes, lessened inequalities, educational and health investments, resulting in relatively low population growth and high land productivity. SSP3 is the opposite of SSP1 with moderate economic growth, rapidly growing population, regional conflicts pushing countries to focus on regional issues, slow technological change especially in the energy sector, low investment in human capital and inequality. SSP2 is the "middle of the road" scenario and forms the intermediate case between SSP1 and SSP3 (O'Neill et al. 2014).

Based on these narratives a common set of inputs were developed to guide the quantitative interpretation of the scenarios (Riahi et al. 2017), which have been adopted by multiple IAMs. To analyse the sectoral emission reduction potential, the sectoral developments of SSP1 and SSP2 reference scenario are compared to its mitigation scenario in which the nominal RCP forcing level 2.6 W/m2 in 2100 is met - in line with 66% chance of keeping the increase in the global average temperature below 2 °C above pre-industrial levels (Riahi et al. 2017). Since not all models were able to meet 2.6 W/m2 in a SSP3 world, additionally the three scenario are compared when meeting a forcing level of 3.4 W/m2 are compared, which corresponds roughly with 20-40 % chance to stay below 2 °C.

7.2.2 Models

In this study, we use the results of four IAM models (out of a total of six quantifying the SSP scenarios) i.e. those models that distinguish between all demand sectors separately. These IAMs are AIM/CGE, GCAM, IMAGE and MESSAGE-GLOBIOM. AIM/CGE is a general equilibrium model, GCAM partial equilibrium and IMAGE and MESSAGE-GLOBOIM are hybrid models. While the first three have a recursive dynamic solution algorithm, MESSAGE-GLOBIOM is an intertemporal optimization model (see Table 7-1) (Riahi et al. 2017). We have excluded two IAMs, REMIND and WITCH, because the versions used to generate the SSPs did not distinguish enough sectors in energy demand.

Table 7-1: Model characteristics (ADVANCE 2015; Riahi et al. 2017)

Model	AIM/CGE	GCAM	IMAGE 3.0	MESSAGE-GLOBOIM
Solution method	Recursive dynamic	Recursive dynamic	Recursive Dynamic	Intertemporal optimization
Model category	General Equilibrium (GE)	Partial Equilibrium (PE)	Hybrid (systems dynamic model and GE for agriculture)	Hybrid (systems engineering partial equilibrium linked to aggregated GE)
Hosting institute	NIES	PNNL	PBL	IIASA
SSP reference	(Fujimori et al. 2017)	(Calvin et al. 2017)	(van Vuuren et al. 2017c)	(Fricko et al. 2017)

7.2.3 Decomposition

We use a decomposition method to analyse trends in energy demand, in particular to identify the role of the different strategies for GHG reduction discussed in the introduction. There are several decomposition methods, broadly categorized in the Laspeyres based methods and the Divisia based method. The simple Laspeyres decomposition method calculates the change in emissions if one factor would change while all others would stay at their base year value. Although the interpretation is easy, the summation of all factor contributions do not equal the total emission change. Here we use the Shapley/Sun method, also based on the Laspeyres method, but instead no residual term remains. It also passes the factor and time reversal test, and it solves for negative emissions, unlike the Divisia method (Ang 2004). Leaving no residual term means that the factor contribution to the actual emission change is calculated. In a low emission scenario, the growth of population, for example, will thus have a smaller effect than the same population growth in a high emission scenario. Similarly, final energy growth has a larger effect when carbon intensive fuels are used. As a consequence, the same factor change will have a different impact in different scenarios. When comparing the decomposition analysis across scenarios, a larger or smaller factor contribution therefore cannot directly be interpreted as the factor itself being larger. It means that within the context of that scenario its contribution is more important.

Through index decomposition analysis the contribution of the projected change in the following elements to the direct sectoral carbon emissions are calculated:

1. Population growth (Pop)
2. Final energy use (FE) per capita
3. Electricity and hydrogen use (Elec) share
4. Direct emissions of non electric fuels.

Each of these elements contribute to the sectors' direct emissions following Equation 1.

$$Direct\ emissions = Pop * \frac{FE}{Pop} * \frac{1-Elec}{FE} * \frac{Direct\ emissions}{1-Elec} \quad \text{Eq. (1)}$$

with $$\frac{FE}{Pop} = \frac{Energy\ service\ demand}{pop} * \frac{FE}{Energy\ service\ demand} \quad \text{Eq. (2)}$$

The final energy per capita development of the IMAGE model is further decomposed in to change in energy service demand and energy efficiency improvements following Equation 2. Specifically, the passenger kilometres travelled, building floor space and steel production are used as proxies for the respectively transport, buildings and industry energy service (i.e., activity levels).

7.2.4 Technology-oriented assessment

Technology-oriented studies look at sectoral greenhouse gas emission reduction potentials as well, also referred to as bottom-up potentials. A recent study focusses on the global mitigation potential per sector for a cut-off cost-level of 100 US$/tCO2e (UNEP 2017) based on literature review. This is defined as the "technical potential that is economically attractive from a social perspective". Although all emitting sectors were part of the analysis, here the focus is on the energy demand sectors, industry, buildings and transport. The study presents a broad literature review which focuses for the energy demand sectors mainly on efficiency measures to reduce energy use, using average emission intensity in 2030 from the World Energy Outlook (WEO) to calculate sectoral emission reduction potentials. These are compared to a reference level, which is in the case of the energy related emissions based on the WEO current policy scenario (IEA 2016c). In the appendix a comparison between the UNEP GAP baseline emissions to the IAM baseline emissions and the method used is described in more detail.

7.3 Results

7.3.1 Baseline developments

Figure 7-1 shows the baseline sectoral CO2 emissions in the four IAMs, three sectors and three SSPs. The Figure shows that there is a considerable range across the models, but also that there are significant differences between the sectors and SSPs. In a SSP1 world, the assumed efficiency improvements and electrification trend imply that all sectors are projected to emit more-or-less the current direct annual emissions. In SSP3 and SSP2 in contrast, emissions are projected to increase in all demand sectors, especially in the industry sector in SSP3 and transport in SSP2. The IAMs project a relatively slow growth of direct carbon emissions in the buildings sector. Models project a much faster growth in the

industry and transport emissions in SSP2 and SSP3. Across models there is large uncertainty in the industry and transport sector future emissions, shown by the wide range that these sector emissions span, especially in the year 2100.

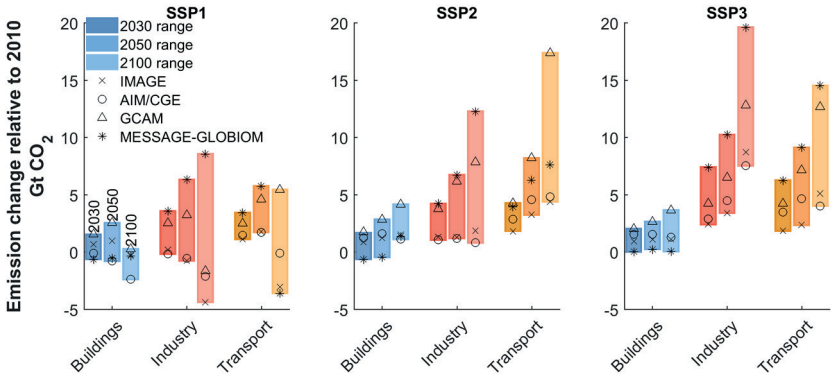


Figure 7-1: Baseline annual sectoral CO2 emission change in 2030, 2050 and 2100 compared to 2010 values. The bars indicate the range across models while the markers the model specific results.

Figure 7-2 shows the contribution of the factors population growth, final energy per capita, electrification and fuel switching to the change in emissions per sector and per scenario (results of decomposition). In all three sectors in general, population growth and increasing final energy consumption per capita lead to higher direct emissions, while electrification leads to lower direct emissions. Different trends in the baseline carbon content of non-electric energy are shown, depending also on the scenario assumptions. The projected ranges across the models shown earlier in Figure 7-1 can largely be attributed to uncertainty in the final energy per capita development in transport and industry as well as fuel content. Also in the buildings sector, a large discrepancy between models lies in the types of fuel used. Currently many households are dependent on traditional biomass (40% of global population), mostly used for cooking in developing countries (Nejat et al. 2015). Models differ with respect to the question whether this trend will continue or alternatively whether a shift to cleaner fuels will take place.

In the baseline, where no climate policy is assumed, the sectors in general experience an autonomous electrification trend. In the buildings sector this trend is the most apparent and robust across models and scenario's. This is in line with recent developments with electricity-based applications, like appliances and air-conditioning growing faster than fuel-

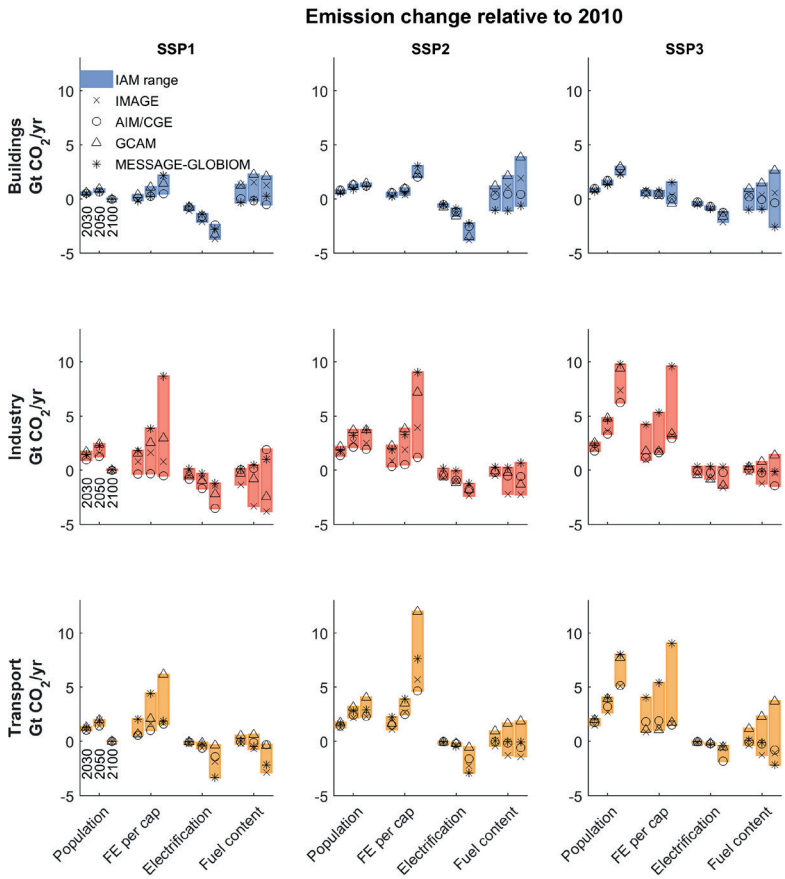


Figure 7-2: Decomposition of direct carbon emissions per end use sector in the baseline scenario compared to 2010 values. This figure shows for each sector how population, final energy per capita, electrification[38], or shifting to less or more carbon intensive fuels for the remaining non-electric final energy shares contribute to increasing emissions (positive values) or decreasing emissions (negative values) in 2030, 2050 and 2100 (compared to 2010). The different markers indicate the model specific values.

based applications, like space heating and cooking, associated with higher affluence. Moreover, over time electricity is expected to experience a slower cost increase than other carriers. In both the transport and industry sector, which are currently largely dependent on fossil fuels, electrification lead to lower direct emissions, while fuel shifting shows diverging emission effects on emissions. Carbon emissions can decrease due to higher biomass or

38 Electrification refers to share of electricity and hydrogen.

natural gas shares, or increase for example due to use of fossil synfuel for transportation. Compared to current practices, the combined contribution of electrification and fuel shifting reduces direct emissions on average between with 0.8 and 2.9 Gt CO2 in the industry sector and 0.9 and 3.2 Gt CO2 in the transport sector in 2100.

A clear difference across scenarios is the projected level of electrification leading in SSP1 to slightly lower emissions, and the population growth, leading in SSP2 and SSP3 to higher emissions. The highest final energy per capita increase can be seen in SSP2, in SSP3 final energy per capita is lower due to lower economic growth, while in SSP1 final energy per capita is reduced due to sustainability measures. This effect is particularly visible in the transport sector (although MESSAGE-GLOBIOM shows the highest transport emissions in SSP3). Increased population growth has a larger effect on transport and industry emissions than buildings emissions as these sectors are more emission intensive per capita, particularly in SSP3.

7.3.2 Mitigation scenarios

Figure 7-3 compares the sectoral emissions in a stringent climate scenario (2.6 W/m2 for SSP1 and SSP2, and 3.4 W/m2 for all three scenarios) to the SSP baseline emissions. The difference between the baseline and mitigation scenario indicate the sectoral avoided emissions. The industry and transport sector show the highest avoided direct emissions as these two sectors have also grown the most compared to 2010 values (seen previously in Figure 7-2). The buildings sector is projected to have a lower direct emission reduction potential. This can be explained by its large electricity share in the baseline, therefore emitting less direct emissions. Buildings electrification levels are projected to increase further to 73-93% (model range) in 2100 under 2.6 W/m2 assumptions in the SSP2 scenario compared to 57-65% under no climate policy assumptions.

In all sectors and for all models the required avoided emissions to meet the climate target is less in an SSP1 scenario than in the other scenarios. In the industry sector for example the emissions reduction compared to baseline to meet a 3.4 W/m2 target is 2 Gt CO2 in an SSP1 on average in 2050, while in an SSP2 scenario the amount of emissions reduced on average is 5 Gt CO2. For comparison, to meet a 2.6 W/m2 target emissions would need to be reduced on average with respectively 5 Gt CO2 and 8 Gt CO2 in SSP1 and SSP2. The amount of avoided emissions compared to baseline spans quite a range within a specific scenario between models depending on the baseline assumptions as well on the foreseen emission reduction potential compared to present emission values. The latter is particularly uncertain for the industry sector, where in 2100, in some models the emission change relative to 2010 surpasses 15 GtCO2. Figure 7-4 shows that the high avoided emission scenarios are for the

largest part the result of reduced fuel content of the non-electric energy, which especially takes place in the second half of the century. In certain industrial scenarios, this can even lead to negative emissions. In the lower avoided emission scenarios, the contribution of final energy reduction, electrification and fuel content to emission reduction are more comparable.

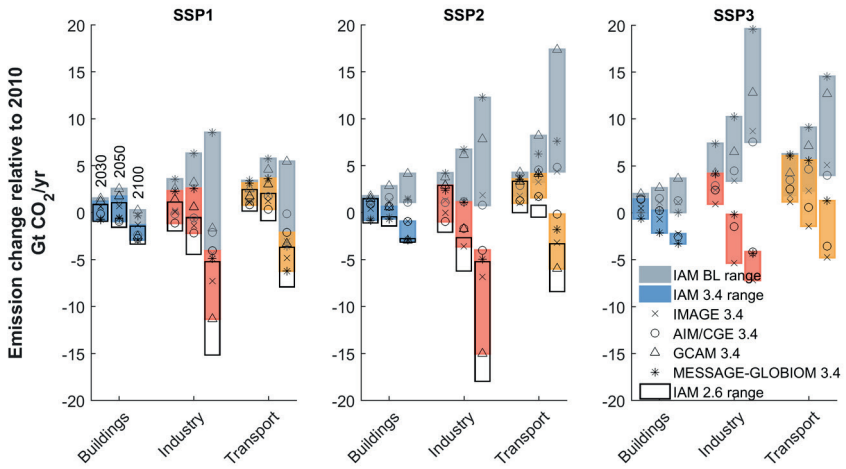


Figure 7-3: Annual sectoral CO2 emission change in 2030, 2050 and 2100 compared to 2010 values in a mitigation (Mit) pathway (2.6 W/m2 for SSP1 and SSP2, and 3.4 W/m2 for all three scenarios) compared to baseline (BL), indicating the avoided carbon emissions. The bars indicate the range across models while the markers the model specific results.

In the transport sector fuel switching can strongly reduce emissions too in the second part of the century. In SSP2 2.6 W/m2 at the end of the century the sectors' emissions have reduced compared to baseline on average with 13.6 GtCO2 of which 7.5 GtCO2 can be attributed to fuel switching. In SSP1 2.6 W/m2, in contrast, the emission reduction required is 5.4 Gt GtCO2, due to lower baseline emissions, of which 3.3 Gt GtCO2 comes from fuel switching. In 2100 the electrification, fuel content and final energy per capita levels are comparable between the two mitigation scenarios, but in SSP1 these developments have largely occurred in the baseline. In SSP3 reduction of final energy per capita has a larger contribution to emission reduction than in the other sectors.

On average between models and across scenarios, comparing the contribution of the three components we find final energy reduction and fuel switching are the most prominent in the first half of the century, and while electrification become more significant in the second half the contribution of fuel switching dominates in this period.

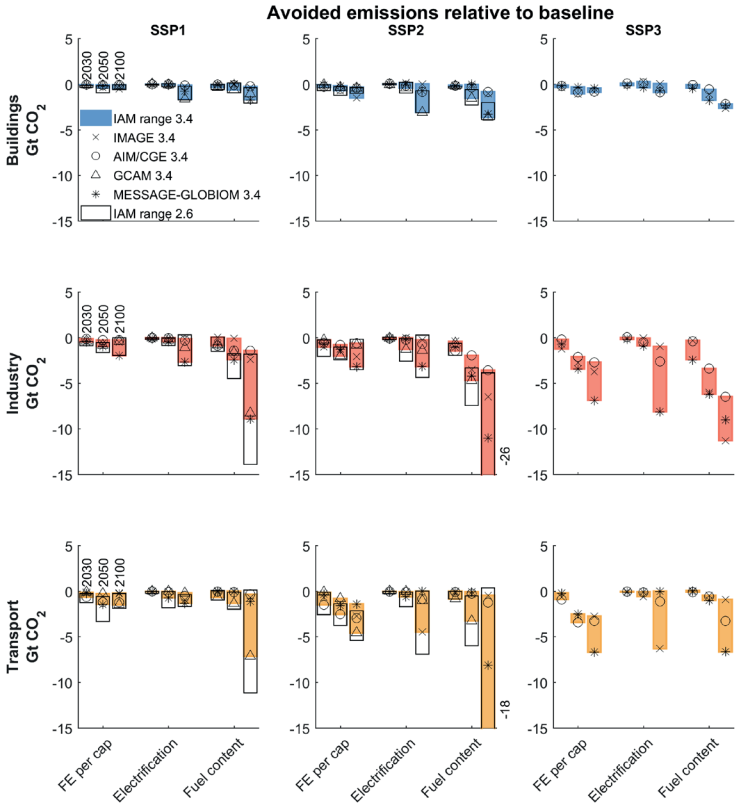


Figure 7-4[39]: Decomposition of direct carbon emissions per end use sector in the mitigation scenarios compared to baseline. The contribution of final energy per capita, electrification, or shift to less carbon intensive fuels for the remaining non-electric final energy shares to emission reduction in 2030, 2050 and 2100 is shown. In the SSP2 GCAM values are not plotted but presented in numbers beside the industry and transport figures.

7.3.3 Energy service growth compared to energy efficiency

This section takes a deeper dive to energy efficiency and service demand change affecting final energy requirements, specifically for the IMAGE model. Compared to the other models IMAGE is at the lower end of the final energy growth range in all sectors and scenarios.

39 GCAM is not included in the SSP3 mitigation comparison.

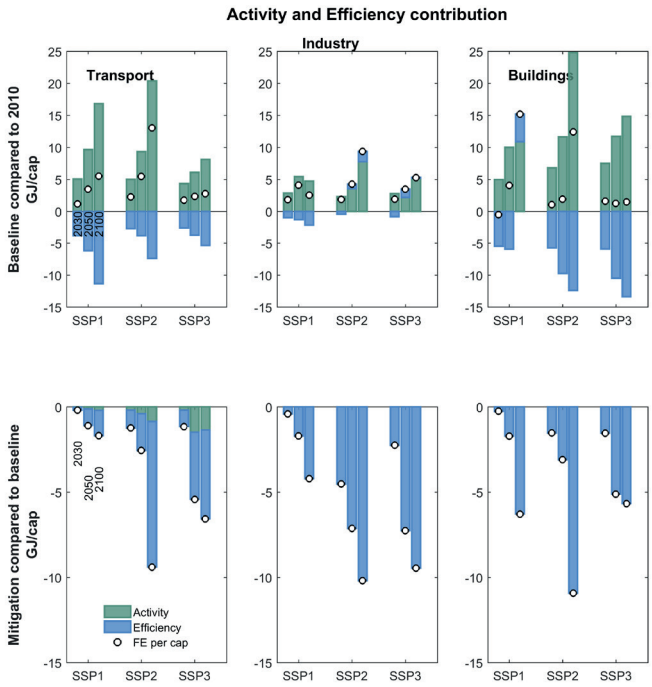


Figure 7-5: Decomposition of carbon emissions change in the IMAGE projections due to activity or energy efficiency change. The upper panel shows contribution to increasing emissions (positive values) or decreasing emissions (negative values) in 2030, 2050 and 2100 compared to 2010. The lower panel compares the 3.4 W/m2 scenario to baseline in 2030, 2050 and 2100. The passenger kilometres travelled, building floor space and steel production are used as proxies for the respectively transport, buildings and industry energy service.

Globally the demand for energy service per capita is projected to continue to grow in all sectors by IMAGE. Especially in the transport and buildings sector the effect of the potential growth on increased final energy per capita is striking. In SSP2 in both sectors final energy per capita would more than double compared to current values due to increase service demand. Energy efficiency developments generally compensate the resulting final energy demand to some extent, with some exceptions. Compared to SSP2 the lower SSP1 transport final energy per capita is mainly the result of energy efficiency improvements, while in SSP3 the service demand has grown slower. Mitigating emissions is largely the effect of energy efficiency. Only in the transport sector does reduced demand for energy services lead to emission reduction as well.

7.3.4 Emission reduction potentials 2030

Table 7-2: Comparison of average avoided CO2 emissions in the IAMs under a SSP2 2.6 W/m2 pathway in Gt with the CO2 emission reduction potentials found in the sector-by-sector analysis bottom up analysis. The negative sign in the ranges indicates increased emissions instead of avoided.

	Buildings	Industry	Transport
IAM total sector	*0.7 (0.3 to 1.0)*	*2.6 (0.9 to 3.2)*	*1.7 (0.9 to 2.7)*
IAM eff	*0.4 (0.0 to 0.7)*	*1.1 (0.2 to 2.0)*	*1.3 (0.0 to 2.5)*
IAM electrification	*0.0 (-0.1 to 0.0)*	*0.0 (0.0 to 0.2)*	*0.0 (0.0 to 0.3)*
IAM fuel switch	*0.3 (0.2 to 0.4)*	*1.4 (0.6 to 1.9)*	*0.3 (0.0 to 0.8)*
Technology-oriented assessment	*1.6-2.1*	*2.1-3.3 (incl. CCS 3.3 – 4.6)*	*4.1 – 5.3*
BU eff	*1.2 - 1.8*	*1.6 – 2.8*[40]	*3.0 – 4.5*
BU electrification			
BU fuel switch	*0.4 – 0.8*	*0.4 – 0.6 + 0.9 – 1.5 (CCS)*	*0.6 – 0.8*

Table 7-2 compares the SSP2 "middle of the road" scenario avoided emissions under a 2.6 W/m2pathway and emission reduction potentials based on the bottom up potential sector by sector analysis. There are various climate policy measures included in the technology oriented study affecting CO2 and non CO2 emissions directly and indirectly. For straightforward comparison here the focus is on the direct CO2 emissions. In the buildings sector it includes energy efficiency standards in new buildings, thermal retrofit of existing buildings, and switching to renewable heating. In the transport sector fuel efficiency measures, including modal shift and shifting to electric vehicles for the road transport, and using alternative fuels such as biomass are assessed. Industrial direct CO2 emissions could be reduced due to energy efficiency measures, use of renewable heat and carbon capture and storage. Even though the importance of reduction of material use due to for example circular economy measures, recovery and reuse of materials is emphasized, the effect of these type of measures have not been quantified for 2030 and not be accounted for in the technology oriented study. The results show that there is more technical potential to reduce demand side emissions, in particular through energy efficiency improvements, and most notably in the transport sector, than currently implemented in the models.

40 Part of the eff reduction is electricification (about 9% of cars).

7.4 Discussion

The analysis leads to a number of conclusions with respect to the IAM. A number of caveats, however, need to be kept in mind.

Focus on aggregated and global results

In this paper model results have been discussed at the global level while underlying regional developments will contribute to the observed trends. Increased energy service demand does not imply that in all regions service demand increases; in certain regions it may grow rapidly while in others a certain saturation level is reached. Therefore, it would be interesting to look at the regional trends – and also to analyse how these potentially influence the global trends. Similarly, in SSP2 and even more in SSP3 the emission reduction through final energy per capita change is larger than in SSP1 and increases over time. Whether this is due to energy service demand changes or energy efficiency improvements is not deciphered for all models. The IMAGE results show that there is quite some difference between the scenarios in these two component developments.

Technology assessment comparison

When discussing emission mitigation potentials, a clear definition of the baseline scenario is very important. The reference baseline emissions used for the sector by sector analysis projects slightly lower emissions in 2030 in the transport, industry and buildings sector (see Appendix). This can be explained by the different scenario assumptions: the WEO reference is a current-policies scenario while the SSP2 baseline is a scenario without climate policy.

The numbers for the sector-by-sector assessment originate from different sources which do not always have sufficient transparency and are not necessarily comparable. Nevertheless, in case they are available, different estimates come to comparable outcomes.

Also, the 2030 IAM avoided emission in a 2.6 W/m2 scenario are not directly comparable to the 2030 technical potential. Still, the higher technical emission reduction potential – in spite of the baseline emissions being lower – show that there is more room for emissions reductions in the short term. A previous study that compared top-down (incl. IAMs) sectoral emission mitigation potentials to bottom estimates concluded that there seem to be no systematic difference in the reported emission reduction values from the two approaches, when a 100$/tCO2-eq carbon tax is applied (van Vuuren et al. 2009). An explanation between the different results possibly is that the applied carbon tax in 2030 to meet 2.6 W/m2 is lower than 100$/tCO2-eq. This shows that the IAM demand reductions are within the sectoral technical potential, but also that demand sector emissions could be reduced

further – already in the short term- mainly through energy efficiency improvements.

7.5 Conclusions

Projecting global emissions from energy demand over the coming century comes with many uncertainties. Conforming to a stringent mitigation target leads less room for emission ranges than in a baseline, but sectoral efforts and the underlying strategies to achieve this target can widely differ across models and scenarios, depending also on baseline assumptions. This multi-model, multi-scenario, and multi-sector study of IAM projections attempts to distil robust trends across the demand sectors developments while disentangling the underlying uncertainties.

Robust findings across scenarios and models are:

Model-based projections show that baseline emissions can grow rapidly in industry and transport sectors. Direct emissions from the buildings sector, in contrast, are projected to grow slowly or even stabilize. The SSP3 scenario shows the highest increase for industrial emissions (on average 12 Gt CO2 increase in 2100) and SSP2 for the transport sector (on average 8 Gt increase in CO2). Annual emissions continue to grow in these scenarios and are the highest in 2100. One factor contributing to the slow emission growth in the buildings sector is the continuing increase in electrification rates.

The emission growth in the industry and transport sector can be attributed to increasing final energy per capita and population growth. Key uncertainty across scenarios and models is growth of final energy per capita over the coming decades, largely determining the sector's carbon emissions. This finding is in line with a recent published study testing the sensitivity of the SSPs CO2 emissions to key drivers characterizing the scenarios. They find that economic growth and energy intensity assumptions, together forming the final energy per capita, are the most important determinants (Marangoni et al. 2017).

A key uncertainty concerns the possible presence of final energy saturation levels. While it can be shown that in the past final energy consumption in transport, buildings and industry has increased as a function of income growth, some models assume that in the future a saturation of service demand or energy demand will occur. In both IMAGE and GCAM this saturation is related to the amount of time that person would spend travelling and the speed of transport modes (Edelenbosch et al. 2017a); however, the two models show varied per capita final energy levels especially in the

long term. While GCAM transport final energy continues to grow to 33 GJ/cap in IMAGE this levels off at 22 GJ/cap in 2100. The resulting emission increase compared to 2010 run from 5 to 12 Gt. Estimating saturation point lies is commonly done by a combination of regression analysis based on historic data, analysing regions that have possibly reached saturation combined with expert judgement but ultimately it is difficult to know. The range of final energy per capita across models reflect this uncertainty, demonstrated especially in the industry sector projections, while the different storylines of the SSPs disentangle this uncertainty to a certain extent.

To mitigate demand sector emissions, energy efficiency, electrification and fuel switching all play an important role. While in the first half of the century energy efficiency and fuel switching play a comparable role, in the second half of the century (across models and scenarios) fuel switching is the dominant response. The scenario and model results show that different strategies to reduce demand sector emissions are required to meet stringent climate policy. The extent of the required emission reduction depends strongly on baseline assumptions. The effects of electrification and fuel switching generally increase over time. In the near term incentives to switch fuels can be limited because electricity may still be carbon intensive, while in the longer term energy reductions will have less effect if fuel sources such as electricity and liquid fuels have been decarbonized (IPCC 2014a).

The technical assessment shows that in the short term there is more room for energy efficiency improvement than accounted for in the IAM middle of the road 2°C scenarios. The IAM energy efficiency improvements are within the technical potential estimated by the bottom-up analysis. From the technical perspective considerable additional demand-side emissions reduction could be achieved in all three sectors through energy efficiency. Whether the full potential is not reached because either alternative emissions reduction measures in other sectors or within the demand sectors are more attractive from a cost-effectiveness criteria or the technical potential is not fully recognized in the model set up is an interesting next question.

The SSP scenarios show that the growth of the demand sector and the technology development largely affects the sectors mitigation challenge. IAMs have in the past often included demand side mitigation at an aggregated scale, and the underlying measures contributing to energy demand sector changes are not always easy to translate to tangible policy measures. More recently IAMs have started to include more demand side details, such as physical activity and technology measures. The different developments assumed across SSP scenarios are not presented

as active climate change policy measures but do affect the climate change mitigation challenge. Certain developments assumed by SSP1, which required significantly less emission reduction to meet the set climate targets, such as like increased technology development affecting energy efficiency or car sharing and material recycling to reduce energy service demand and thus energy requirements can be affected by policy. However, these measures show little response to cost effective emission mitigation, generally implemented in IAMs through a carbon tax. A next interesting step would be to design scenarios in which policies affecting demand sector developments, which include also energy efficiency improvements, are explicitly included to better assess the effects of targeted demand sector policies.

Appendix: Scenario Bottom-up sector-by-sector assessments

For energy-related CO2 emissions, the World Energy Outlook's Current Policy Scenario (CPS) is taken as the reference (IEA, 2016). In this scenario, energy-related CO2 emissions increase from 32.2 Gt in 2014 to 38.6 Gt in 2030. In the latter year, power sector emission accounts for 16.3 Gt of emissions (42%). For detailed sectoral breakdown, see Figure A7-1. Emission projections for non-CO2 greenhouse gas emissions are taken from EPA (2012) as this is the most comprehensive source available. Total non-CO2 GHG emissions are projected to increase from 11.4 Mt CO2eq in 2010 to 15.4 Mt CO2eq in 2030.

The reduction potentials are corrected towards the baseline used in this chapter, specifically, when their estimations use a baseline that differs significantly from the one described in section 7.4.2. Some of the studies provide the energy-related emission reduction potential in energy units produced or saved. To convert the energy units to CO2 emission reduction, this chapter uses the average global emission intensities for 2030 from the World Energy Outlook 2016. The exception is the reduction potentials related to power generation. Avoided electricity production will reduce the amount of fossil-based energy and therefore the average emission intensity of fossil-fuel based power (Blok and Nieuwlaar 2016). We calculate from WEO (IEA 2016c) average emission intensity in 2030 as 758 kg CO2/MWh. However, with increasing reduction of electricity demand and increasing use of low-carbon electricity sources, the various options will start to overlap. We will come back to this when dealing with the electricity sector.

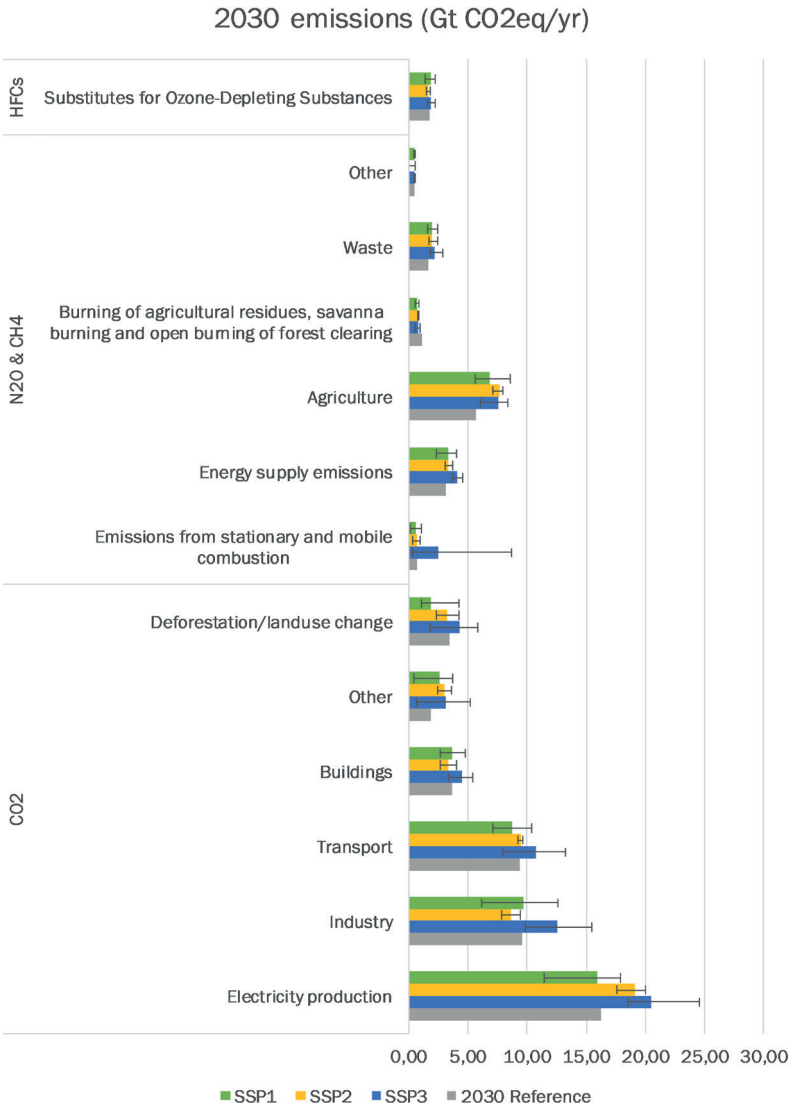
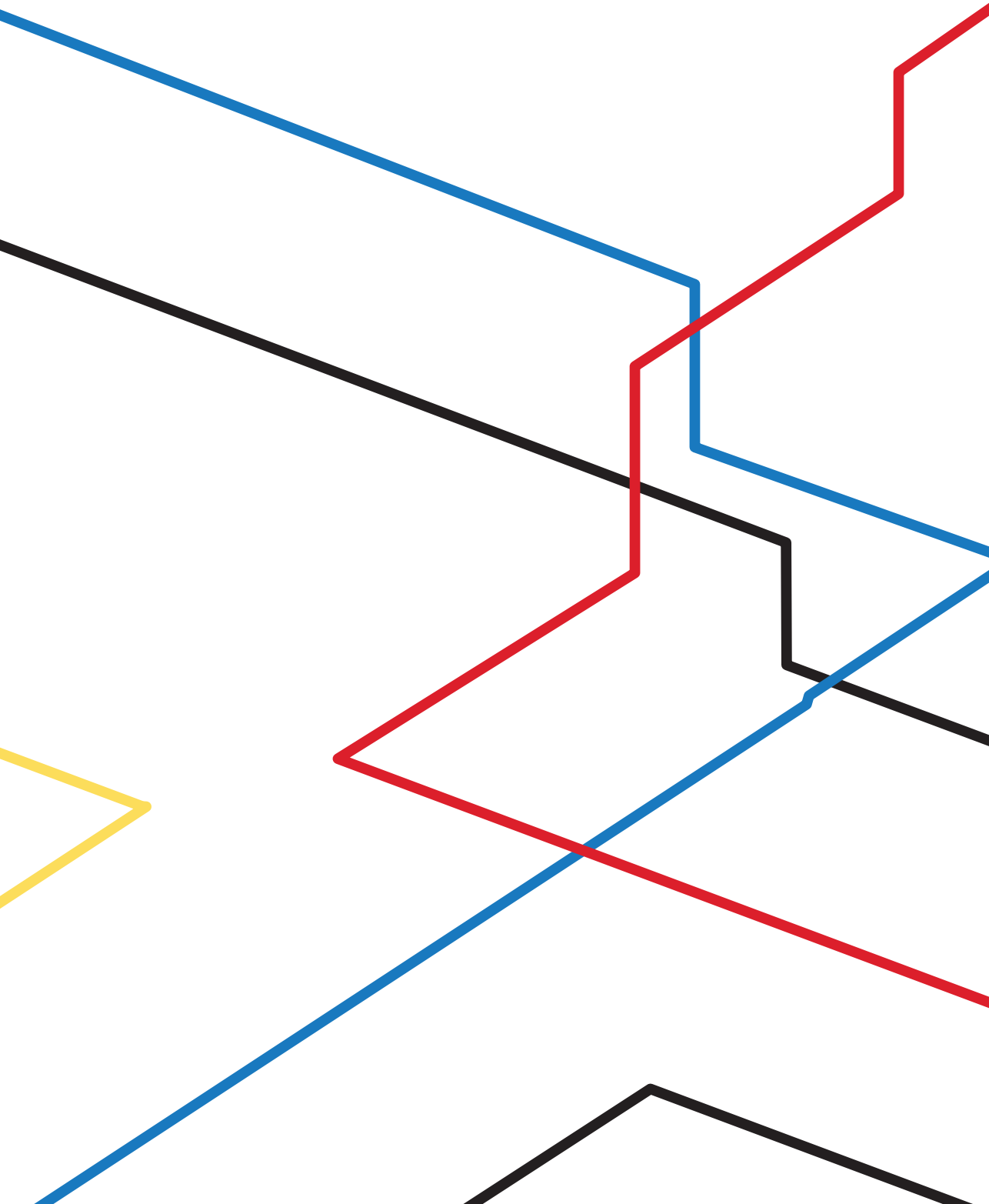


Figure A7-1: Comparison of the 2030 baseline emissions in the sector-by-sector analysis with the SSP1, SSP2 and SSP3 baselines assumed in the 6 SSP integrated assessment models[41]. The IAM results show the mean and the 15-85% percentile range.

41 The six integrated assessment models are AIM/CGE, GCAM 4, IMAGE 3.0, MESSAGE-GLOBIOM, REMIND-MAGPIE and WITCH-GLOBIOM.



Chapter 8

Summary and Conclusions

8.1 Focus of the thesis and key questions

The energy demand sectors industry, transport and buildings are together directly[42] responsible for around 51 % of the global energy-related CO_2 emissions. Indirectly, the demand for electricity and fuels in these sectors also forms the driver of the emissions in the energy supply sectors[43]. In other words, changes in energy demand play a major role in determining future CO_2 emissions.

The energy-demand sectors are complex systems: they are characterized by many subsectors, technologies, heterogeneous end-users with different preferences and needs, and rapid changes. This complexity is not easy to capture in global, long-term models analysing climate change mitigation pathways. Moreover, choices made in the demand sector by the relevant actors are affected by many criteria and therefore cannot be well captured by the algorithms typically used in models, i.e. "rational" cost-optimization (which is more applicable to supply side decisions). In an attempt to avoid all these complexities, modellers typically choose to represent energy demand in a very stylized way: i.e. describing energy demand as function of activity levels, an elasticity of demand and a price elasticity. An indirect consequence, however, is that much less attention has been paid to the use of energy and the role of energy reduction in a global setting to achieve climate targets. However, as interest in model outcomes now focuses more-and-more on concrete policies and measures, these aggregated descriptions become less useful and easy to interpret. More detailed information is, for instance, needed to support policies that look into questions on how to implement the Paris Agreement. Additional details also allow to relate models better to sector specific studies examining current mitigation potential.

However, adding more detail also comes at a costs. For long-term global projections more detail does not imply greater accuracy. In fact, details can lose meaning over time as uncertainties increase. Given the heterogeneity of many demand-side processes it is not clear whether adding a more detailed representation would improve capturing the sectors dynamic behaviour.

Within this context in this thesis the following question is addressed:

> ***How can the representation of energy demand side dynamics be improved in global models assessing long-term climate change?***

In order to do so, we need to first understand in more detail how currently energy demand

42 Directly refers to the emissions from sources occurring within the demand sector.
43 The energy supply sector is defined here as comprising all energy extraction, conversion, storage, transmission, and distribution processes excluding those that those where final energy is used to provide energy services in the energy demand sector (industry, transport, buildings, agriculture and forestry)

is represented in integrated assessment models (IAMs). We examine the projected global futures of the industry, transport and buildings sectors. Model outputs are related to model assumptions and structure at the sector level. Several analyses are made to compare model projections with historic data, sector specific studies and with the projections of other models. Such comparisons aim to distil robust trends across models, while better understanding the underlying uncertainties. Moreover, this enables us to reflect on how "well" the models perform. This first part of the thesis focusses on the first three of the following questions. Then, we dive in to the complexity of demand sector dynamics, focusing specifically on modelling a technology transition, to address the fourth question posed. Here we study the importance technology development, consumer heterogeneity and social influence affecting the projected sector transitions.

This leads to the following four sub questions:

- *How do IAMs represent energy demand and what do they project?*
- *How do energy demand sectors in IAMs respond to climate policy?*
- *How do IAMs perform in their energy demand representation?*
- *How can complicated demand processes such as technology transitions be represented in global models?*

8.2 Main findings of the thesis

8.2.1 How do IAM represent energy demand and what do they project?

Global energy demand is projected to continue to grow over the coming decades if current trends remain unchanged. At the same time, improved energy efficiency partly offsets the rapidly increasing demand. Chapter 2, 3 and 7 show how the growth of global population and the economy will, in line with historic developments, continue to increase future energy consumption. Some models directly relate these economic and demographic drivers to energy demand, others to energy service demand, such as the demand for materials, industrial products or kilometres travelled. Energy service demand are in some models specified per sub sector, such as demand for cars or bus transport, or in the industry sector for example cement and steel demand. If and which sub sector division is made differs per model. The sub sector shares, i.e. the structure of the sector, are either set exogenously over time or respond to price or saturation constraints or in some transport models travel time. Most models include a representation of current and future technologies to fulfil the required service demand but also in this case the level of detail differs. The technologies then compete on the basis of relative costs, leading to energy efficiency improvements or fuel switching when fuel prices increase. In some cases, technology development is driven by exogenous assumptions while in other cases by

learning by doing functions. An important difference across the models is also the solution type used. The different models analysed in the thesis include intertemporal optimization models as well as simulation models.

While in the short term the overall trends across models are comparable, in the long-term global energy demand is very uncertain. It does not come as a surprise that global energy demand over several decades is rather uncertain. The range of the model projections show a wide range of possible futures. These depend on the assumed development of technology, demographic changes, policy, lifestyle changes, structural changes and natural resource availability. In fact, this range most likely is even larger. IAMs contain a representation of how the different developments across sectors relate to each other and affect global energy demand. The uncertainty in the global energy demand future across models shows also the uncertainty in the underlying developments. Will more roads and houses be built increasing material demand? Will the desire to travel more and by faster modes continue? Will the cost of battery electric vehicles continue to decrease? Will cars continue to become more efficient? An important question is thus if current trends will continue. Based on historic data relationships can be distilled, which in models are extrapolated towards the future. One key issue in energy demand projections is whether there is a saturation point to the demand (collectively or individually) and where does that lie. One could imagine that there is maximum amount of roads or houses that can built for example, even if only limited by the space that is available; similarly, there could also be limits to the amount of kilometres a person travels. On the other hand, there are also technical limitations to energy efficiency improvements. For the next 10 or 20 years we might have an idea of what is technically feasible, but what happens after that? There is not an exact answer but the model projections and scenario analysis show us a range of possibilities.

In SSP2 (the middle of the road scenario), direct carbon emissions are projected to increase in 2050 by -0.4-2.9, 1.2-6.7 and 3.3-8.2 Gt CO_2, for buildings, industry and transport sector, respectively. In SSP1, emphasizing a more sustainable development, lower carbon emissions are projected. In SSP3 (fragmented world scenario) industrial emission are higher. The last chapter of this thesis compares models and different scenarios for all three demand sectors. Key uncertainties are population growth and growth of final energy per capita over the coming decades, largely determining the transport, industry and buildings sector's carbon emissions. Table 8-1 show the final energy demand ranges in the buildings, industry and transport sector in 2010 and by 2050 and 2100. Already in 2010 there is a large difference in industrial energy demand following different sector boundaries. Feedstock for example account for 17% of industrial energy

use (see Figure 8-2). The difference across models emphasizes the importance of clear boundary definitions when comparing model projections. The same chapter also shows how the alternative baseline scenarios SSP1 and SSP3 strongly influence the final energy consumptions and the required emission reduction to meet a specific climate target. Model differences however are often more pronounced than scenario differences (see Figure 8-1).

Table 8-1. Final energy demand in EJ in the buildings, industry and transport sector in 2010, 2050 and 2100. The values are rounded to nearest ten.

2010			
Buildings	120-130		
Industry	120-140		
Transport	90-100		
2050	**SSP1**	**SSP2**	**SSP3**
Buildings	170-190	180-220	190-240
Industry	150-270	190-240	210-300
Transport	120-190	160-190	150-230
2100	**SSP1**	**SSP2**	**SSP3**
Buildings	160-250	240-360	200-370
Industry	120-280	210-350	300-460
Transport	110-180	200-300	200-360

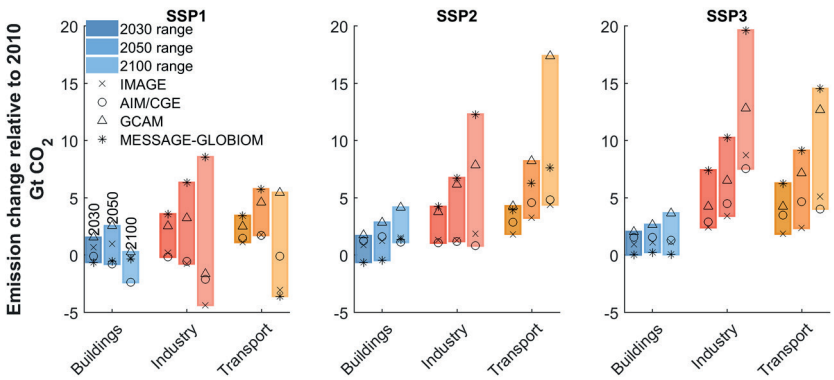


Figure 8-1: Baseline annual sectoral CO_2 emission change in 2030, 2050 and 2100 compared to 2010 values. The bars indicate the range across models while the markers the model specific results.

Growth of global industrial energy demand is mostly determined by developments in Non-OECD countries, while in OECD countries demand remains more-or-less constant. The industrial energy demand in 2100 in Non-OECD regions ranges across model projections from 150 to 400 EJ[44]. Chapter 2 compares industrial energy consumption projections of a set of eight models. This thesis concentrates on the global level. However, at the root of global developments are the regional developments. The industrial energy intensity[45] annual reduction rates Non-OECD countries range from 1.8 to 2.2%. This is significantly faster than historically seen and would require these regions converging more to patterns seen in OECD countries in the past. While the models agree on this, the range still leads to large differences in the long-run for final energy consumption (see Figure 8-2). The models differ strongly in the detail of activity and technology representation of the industry sector. However, the results did not show any systematic different between models with or without sector detail.

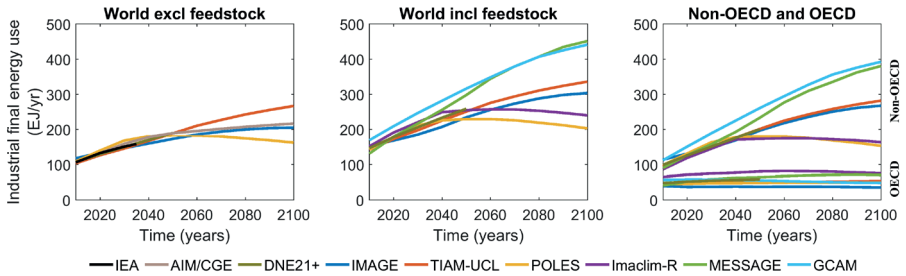


Figure 8-2: Baseline final energy demand projections in the industry sector up to 2100: a) Global excl. feedstock, b) Global incl. feedstock and c) Non OECD and OECD countries incl. feedstock.

The different levels of transport passenger energy demand can partly be traced back to different projected travel volume and the expected magnitude of energy efficiency improvements. In Chapter 3 future energy consumption pathways of passenger transport of different models are compared. Baseline energy transport demand varies in 2050 from 93 to 121 EJ and in 2100 from 130 to 206 EJ (for comparison: in 2010 the energy use is 47-55 EJ). Although the annual growth rates of passenger travel cover a relatively small range compared to what has been observed historically, over the longer term this can lead to a significant spread in projected demand (see Figure 8-3). Transport demand increases across the models by a factor two to five compared to current values. In physical terms LDV global demands ranges from travelling 68.000 to 123.000 billion passenger kilometres in 2100, compared to on average 22.000 billion passenger kilometres[46] in 2010, clearly affecting the energy requirements.

44 The values are rounded to nearest ten.
45 This is equal the energy use per GDP.
46 Average value across models with a spread of 17.000-26.000 billion kilometers in 2010.

Chapter 3 also shows that the average passenger transport energy efficiency decreases to 0.5–1 MJ/passenger kilometre in 2100. The inclusion of energy service demand projections enables us to compare projected energy efficiency improvements to those estimated by bottom up studies. The model projections show that energy efficiency improvements are an important factor to decrease emissions from passenger transport. In 2100 the energy used per passenger kilometre improves with 46–72%. From a bottom up technical perspective already in 2030 fuel consumption could reduce with 30–50%, while switching to alternative driving mechanisms like electric vehicles could reduce fuel consumption even further. Although switching to more energy efficient modes, such as the train, could also contribute to reduced energy use, the IAM modal shares remain close to current modal shares or switch limitedly to faster, less energy efficient modes such as cars and planes.

The cement sector model comparison in Chapter 2 shows that baseline energy efficiency improvements are within the technical potential. In order to evaluate whether energy efficiency improvements are realistic, industrial subsector detail needs to be included. Accounting for energy service demand requires modelling specific subsectors of the industry sector. Several models have included material and technology detail to represent cement sector dynamics. Baseline projections are compared in Chapter 2. The specific energy consumption (GJ/tonne product) for cement and clinker making is generally projected to decline driven by technology development. Literature suggests that the energy use for clinker making can drop to 2.9 GJ/tonne clinker and when improved equipment for cement making and lower clinker to cement ratios are used the energy use could drop further to 2.1–2.7 GJ/tonne cement. The baseline model projections are well within the technical potential. In fact, considerable improvement of the energy efficiency would still be possible in the mitigation scenarios compared to the baseline projections. Modelling industrial energy service demand could in addition provide the opportunity to relate the consumption of materials to non-economic drivers such as infrastructure or buildings stock development and possibly better evaluate demand saturation scenarios.

8.2.2 How do energy demand sectors in IAMs respond to climate policy?

Energy efficiency and fuel switching (including electrification) play both an important role in emission mitigation. In the short-term, both terms are important while in the long-run fuel switching is more dominant. There a several strategies to mitigate demand sector emissions that can be categorized at a higher level into: 1) increasing energy efficiency 2) changing fuel mix and 3) reducing or changing energy service demand (i.e. kilometres driven, floor space requirements, steel production). This categorization is used to discuss the projected mitigation pathways in the demand sectors.

1. Energy efficiency

Energy efficiency improvements are required in all demand sectors in mitigation scenarios. The improvement stays within potential from technical studies. Chapter 7 shows that to remain within 2 °C temperature rise, in each sector energy use per capita is reduced, measured relatively to baseline. In the middle of the road SSP2 scenario this leads to respectively 0.4 (0.0-0.7), 1.1 (0.2-2.0), 1.3 (0.0-2.5)[47] Gt CO_2 reduction in the buildings, industry and transport sector in 2030. Although the IAM reductions are well within the potential estimated by a sector by sector literature review, these bottom-up estimates show that there is still significantly more room for energy efficiency improvements (Table 8-2).

Table 8-2: Comparison of average 2030 avoided emissions in the IAMs under a SSP2 2 °C pathway in Gt CO_2 with the emission reduction potentials found in the sector-by-sector analysis bottom up analysis. The negative sign in the ranges indicates increased emissions instead of avoided.

	Buildings	Industry	Transport
Integrated assessment models	*0.7 (0.3 to 1.0)*	*2.6 (0.9 to 3.2)*	*1.7 (0.9 to 2.7)*
Efficiency	*0.4 (0.0 to 0.7)*	*1.1 (0.2 to 2.0)*	*1.3 (0.0 to 2.5)*
Electrification	*0.0 (-0.1 to 0.0)*	*0.0 (0.0 to 0.2)*	*0.0 (0.0 to 0.3)*
Fuel switch	*0.3 (0.2 to 0.4)*	*1.4 (0.6 to 1.9)*	*0.3 (0.0 to 0.8)*
Technology-oriented assessment	*1.6-2.1*	*2.1-3.3 (incl. CCS 3.3 – 4.6)*	*4.1 – 5.3*
Efficiency	*1.2 - 1.8*	*1.6 – 2.8*	*3.0 – 4.9*
Electrification			
Fuel switch	*0.4 – 0.9*	*0.4 – 0.6 + 0.9 – 1.5 (CCS)*	*0.6 – 0.8*

2. Fuel switching

Fuel switching is central to meeting stringent climate targets and increasingly important over time. The global scenarios show that to mitigate emissions in the energy demand sectors switching to low carbon fuels is the most effective strategy. There are different pathways to do so, depending also on the sector, energy service requirements and technology options. In the buildings sector the electrification trends seen in the last decades are projected to continue reaching 43-49% in 2050 and 57-69% (model range) in 2100 under no climate policy assumptions. These would increase further to 45-53% in 2050 and 73-93% in 2100 in response to climate policy as shown in Chapter 7. This means that by far the largest share the buildings sector emissions are not emitted directly but indirectly during the electricity production. The cross sector perspective of integrated assessment models is particularly suitable to analyse the effectiveness of fuel switching to decarbonize

47 On average with between brackets average model range.

emissions. In the near term incentives to switch fuels can be limited because electricity for example may still be carbon intensive, while in the longer term energy reductions will have less effect if fuel sources such as electricity and liquid fuels have been decarbonized. Indeed, we find that fuel switching, as measure to mitigate emissions, in the demand sectors increases over time.

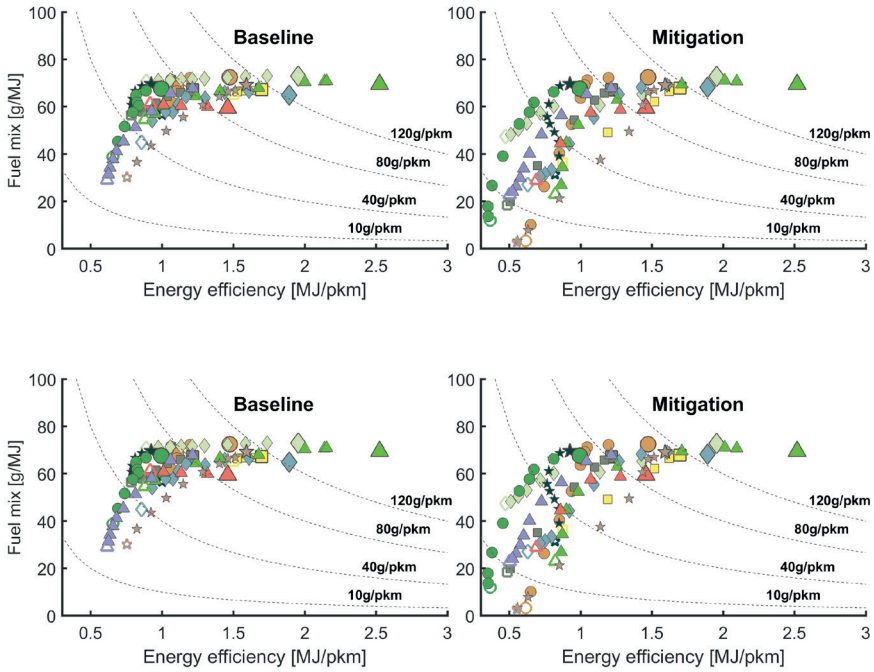


Figure 8-3: Top: Global passenger transport activity per capita (x-axis) compared to CO_2 intensity (y-axis) development over time. The CO_2 emissions per capita are indicated by the plotted isolines. The left panel shows baseline and right mitigation scenario. DNE21+ and GEM-E3 model projections run to 2050, Imaclim-R to 2070 and the rest until 2100. Bottom: Global passenger transport energy intensity (x-axis) compared to fuel mix (y-axis) development in top figures. The isolines indicate emissions per passenger kilometre.

Models show different fuel switching strategies in the passenger transport sector. The passenger transport comparison in Chapter 3 shows different pathways of fuel transition, with different fuel types being deployed and different rates of deployment. The uncertainty of technology development is reflected in the range of electric as well as fuel cell vehicle capital cost projected by the models in Chapter 3, but does not explain the different choices

made by the models fully. Other important aspects are as fuel price, non-financial factors or calibration factors, model solution methods (as seen in Chapter 4). The transport sector has in recent decades been dominated by oil use but large scale decarbonisation of fuel is required to meet climate targets (see Figure 8-3) – in some projections the passenger transport fuel market shares need to increase to 80 % of electricity or hydrogen or in others reaching 50% of biofuels by the end of the century globally – which would imply a clear break with historical trends.

In the industry sector, similarly, switching from coal to electricity is an important a measure to reduce emissions. Interestingly, models that explicitly include industrial technologies seem to be more constrained in the flexibility to switch to alternative fuels. In Chapter 2 there is a reasonably high agreement of future fuel shares in the baseline, remaining close to current shares. Most models project a slight increase in electricity use and a decrease in fossil fuel use, both between 10 and 20% change, while in a 2 °C scenario the fuel share respond strongly (see Figure 8-4). Mitigating emissions occurs through a combination of fuel switching and energy intensity improvements. The percentage reduction in industrial final energy use remains fairly constant after 2040 in all models compared to baseline, although it spans a range of 10-50%. In this set of models, and a similar division is seen in Chapter 4, the more technology detailed model are less flexible to fuel switching and see more potential in energy efficiency improvements. An issue here could be that the energy efficiency improvements are constrained to current knowledge of technology developments. Some industrial processes are suitable to apply carbon capture and storage measures to reduce emissions. The representation of this in the global models has however not been studied specifically during this research.

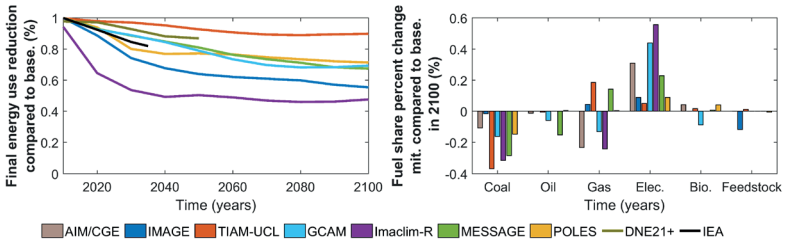


Figure 8-4: Left panel) Mitigation scenario final energy demand as a portion of the baseline scenario final energy demand. Right panel) Percent change in fuel share mitigation scenario compared to baseline.

3. Demand for energy services

The projected demand for energy services is not so responsive to climate policy. The potential of energy service demand change to mitigate emissions is in the current representation not well understood. As mentioned, not all IAMs explicitly account for energy service demand driving energy demand. In those cases, that it was possible to analyse energy service demand projections, such as in Chapter 3 and 4, for the transport sector, and in Chapter 7 for all three demand sectors using the IMAGE model results we find that energy service demand is hardly responsive to climate mitigation policy or similarly not elastic to fuel price change. Besides reduction of energy service, also, modifying energy service demand, for example shifting to alternative low carbon transport modes is hardly responsive. The common way to represent climate policy is through a carbon tax affecting fuel price. In some models service demand is related only to exogenous GDP assumptions and therefore is cannot be affected by fuel price change. In other models alternative mitigation measures are more attractive which are less reliant on behavioural change, which is commonly represented by a factor to fit model outcome to historic data. Place based transport studies emphasize the mitigation potential of infrastructure and behavioural change especially in the urban environment, leading also to local co-benefits. These studies indicate that the cost optimization perspective of IAMs might underestimate the potential of energy service demand change, which could complement the radical fuel switching required in current projections.

8.2.3 How do IAMs currently perform in their energy demand representation?

Two different methods have been used to compare the future transport sector projections to historic indicators. Although other evaluation methods have been applied to all three demand sectors, discussed in the sections above, this question is addressed by analysing specifically the transport sector dynamics. Projected future trends in the transport energy demand sector are generally comparable to historical indicators concerning activity growth, modal shift, energy intensity, energy and income price elasticities. Fuel switching trends however go beyond historical measurements, as the transport sector has for the last decades been largely (>90%) dependent on oil.

The transport models' activity growth and energy intensity projections are well within the historic range, reported in between 1973 and 2007 in several OECD countries. In fact, the variation reported historically in this set countries is larger than the range across models. In Chapter 3 activity growth, energy intensity, modal shift and fuel mix developments contributing to the projected greenhouse gas emissions are untangled through the Laspeyres index decomposition analysis. The same method has

been used in energy research in recent decades to understand historical trends of the first three components. Fuel mix was not examined historically as this remained more or less dominated by oil. While energy intensity in all models decrease, historically this has not always been the case. In the mitigation scenario the energy intensity reduction increases further, moving toward the low end of the range reported historically. Consistent with historical trends, modal shift generally leads to increasing emissions in the baseline, although this effect in the model projections is small and unresponsive to climate policy.

LDV energy demand elasticities to oil and gas prices are projected to range from –0.2 to –0.5 in 2030, close to the range described in the empirical literature. In the very long term (30–40 years), LDV energy demand elasticity values vary -0.4 and -2.1, showing either continuous demand or increased demand responses over time. The energy demand to income elasticity values range between 0.3 and 1.4 This is within the range reported in the literature. Key model drivers are income, generally expressed in GDP, and fuel price levels. In Chapter 4 the transport models' fuel demand elasticities are explored, by comparing demand sector responses to various fuel price and income trajectories. Historic price and income elasticities have been reported extensively in the literature. Efficiency and service demand elasticities to fuel price are within the range of values found empirically, and very close to each other in the medium term. In 2060, the models show more diverging patterns, and elasticity values cover a broader range due to fuel substitution, increased efficiency, reduced service demand growth and feedback effects on the price shocks applied. The energy service demand projections are found to be more responsive to income level than to fuel prices, which corresponds to findings in the literature. Saturation effects of service demand over time or with increasing income are not clearly visible. Even so, the relatively small range between models has a large impact on the projected transport demand, and could explain the varying transport demand growth projections which have been seen in Chapter 3.

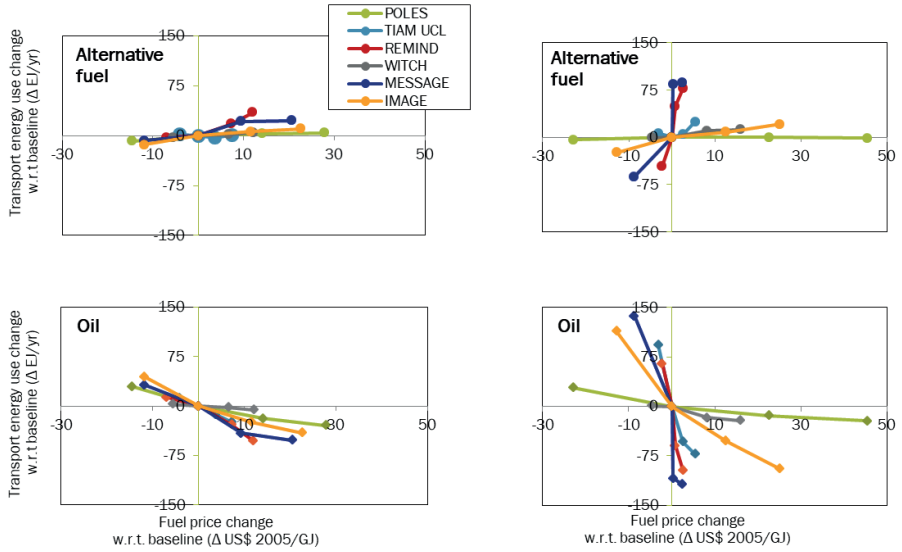


Figure 8-5: The oil (bottom) and alternative fuel (AF) (top) energy demand response to -50%, +50% and + 100% oil and gas price shocks in 2030 (left) and 2060 (right). Alternative fuel is defined as any fuel other than oil.

8.2.4. How can complicated demand processes such as technology transitions be represented in global models?

The demand sector is complex in many ways. Here we focus on specifically on developments affecting a transition to electric vehicles in the transport sector. The energy demand sector is not one sector but many sectors and subsectors with their own specifics, depending also on the location. Within this complexity the challenge is include not too much detail but also not too little, and identifying those relationships that affect demand development and response. Maintaining sub sector and regional detail is rather data intensive and keeping up with technology development is challenging. Realizing that in this thesis we cannot provide a complete overview of the demand side modelling challenge we focus specifically on the complexities associated with modelling a technology transition to electric vehicles. The recent growth of electric vehicles, with two million electric cars on the road globally in 2016 – doubling the 1 million threshold passed in 2015 -, and the rapid reduction of battery cost, indicates that this market is evolving. A technology transition to electric vehicles could offer an attractive solution to mitigate LDV emissions if electricity generation is decarbonized.

Sensitivity analysis shows that battery size and battery cost largely determine the success of the future transition to electric vehicles. The recent fall of battery costs has initiated a rise in current sales, however the key issue for the long term is the lower limit of battery costs. Over the last years the costs of electric vehicle batteries have dropped significantly. This is happening faster than expected and the debate of how this development will continue is very topical. An important question is how this impacts future transport electrification. Interestingly, in Chapter 5 we find that for long term models understanding the lower limit of battery costs is more relevant than the rate of cost reduction. Only when battery costs reach 100$/kWh do battery electric vehicles take up a considerable (15%) market share. Besides the costs per kWh, the sensitivity of the extent to which a transition to battery-electric vehicles takes place to battery capacity assumptions is examined. Currently regional differences in battery capacity are observed, where in China and Japan smaller battery sized electric vehicles that have gained a foothold, in the USA vehicles with a larger battery capacities have a gained a market share. How will this evolve over the future, affected also by advances in speed up charging and for example further urbanization, is shown to be a key uncertainty impacting the projected technology transition (see Figure 8-6). The analysis shows the importance of sensitivity analysis on uncertain input assumptions, in this case on electric vehicle cost and battery size, to untangle the robustness of future projections.

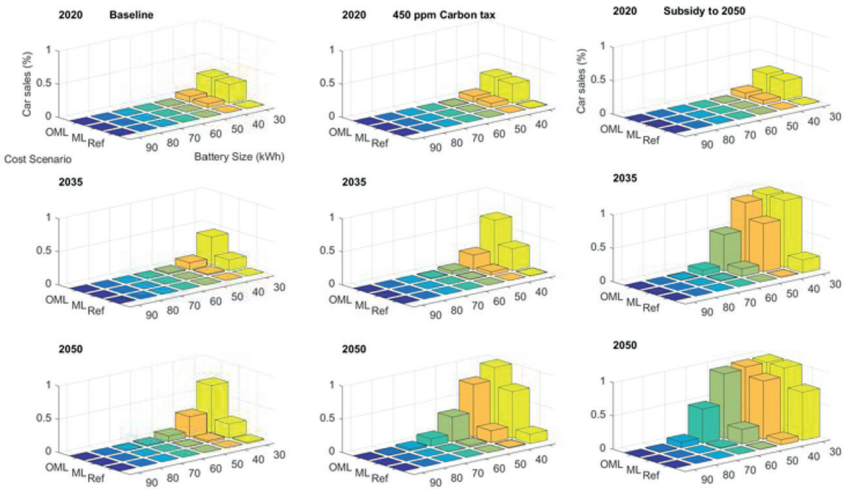


Figure 8-6: Global BEV share in the vehicle fleet for three scenarios under varying assumptions of average battery capacity and battery cost scenarios: 1) OML: battery cost reduction following the optimistic market leader statements, 2) ML: battery cost reduction following the market leader statements, 3) Ref: Reference battery cost reduction based on the literature.

The challenge of demand side modelling within global models is finding the right level of detail and distinguishing robust patterns that explain the sector dynamics. In modelling a technology transition therefore, the key elements technology learning, behaviour, social learning and user heterogeneity and how they relate to each other should be included. Technology choice depends, besides technology costs, on non-financial (i.e., behavioural) factors, such as preference for aesthetics and performance, or social norms. These factors, however, will be different per person, and are therefore heterogeneous. The heterogeneity of users itself can play an important role in a technology transition. When early adopters, are attracted to new technologies this impacts others' decision making processes, for example changing perspectives on status, reliability and safety of a certain vehicle. This is called social influence or social learning. Through this process behavioural considerations are dynamic, respond to their environment, affected by market heterogeneity. Technology cost and performance similarly is affected by the market heterogeneity through technology learning. By capturing the cause-effect relationships between these process the phases of a technology transition can be better understood.

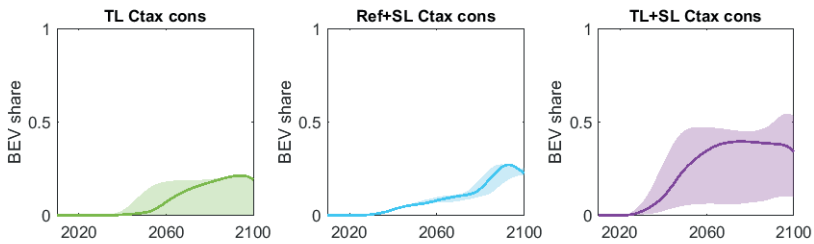


Figure 8-7: The BEV market shares at the global level under an exponential carbon tax for the scenario: TL: Technological learning 2) SL: Social learning and 3) TL+SL: Technological and Social learning scenario. The shaded colour indicates the scenario range.

Social learning and technological learning jointly explain technology diffusion and can mutually reinforce each other. This shows the importance market heterogeneity and targeted policy to initiate a technology transition. Chapter 6 explores how social learning, technological learning can be included in an IAM in a simple manner, based on empirically derived relationships. The new model formulation shows that if the learning processes work in the same direction they can mutually reinforce each other. In particular, the dynamic interaction between social and technology learning, triggered by market heterogeneity is very interesting. In the initial phase of a technology transition improved technology performance and reduction of production cost are essential processes to become competitive to conventional practices, driven by use of early adopters. The effect of

social learning can be seen in the diffusion of BEVs from early adopters to the later adopter groups. This modelling exercise shows that information on social dynamics is needed in addition to technology information to understand the potential for future demand side transitions.

8.3. Discussion and steps ahead

In this thesis, we have provided an overview of the current state of projecting future energy demand using global models. We discussed the current methods, the results (baseline and potential for mitigation) and indicated possible improvements.

We identified future activity as a key uncertainty impacting demand sector emissions and mitigation challenges. Models projections are, relative to historically observed ranges, often quite comparable to each other. Short-term projections are similar across the various models. In the long-term much larger differences can be seen mostly based on saturation dynamics and efficiency improvements. The differences across models cannot be easily traced to model type. So while the models show an uncertain future, how this future is affected is not so well understood.

We conclude that there is a need to better understand the development of future energy demand response and the relationship with future activity levels. This is very relevant as is also illustrated by the large differences in energy demand between SSP1 and SSP3. Some models use exogenous assumptions on activity levels and technology development. These can obviously limit the potential for mitigation. Chapter 6, describing electric vehicle technology transition modelling, shows the added value of identifying simple cause-effect relationships based on empirical data to better understand energy demand response. This approach allows to dynamically model complex demand-side processes in a transparent manner while keeping the model relatively simple. It must be kept in mind that models are always a simplification of reality and therefore limited in what they can represent. This is also because they need to be transparent. Models are also limited by the data and limited by the ability to catch all relevant processes in formal equations. Therefore, using multiple scenarios, such as through the SSP framework, and sensitivity analysis are important tools to improve our understanding of energy demand response. It also remains important to use model results in combination with other tools (as done in Chapter 7).

Our results are limited by the subset of models that we have assessed, but also the level of debt by which the sectoral models have been studied. While we have addressed several issues for all sectors, we have studied one specific case study in detail, namely modelling

a technology transition to electric vehicles to reflect on how demand models can be improved. Based on this work, and the limitations in our current activities, we would finally like to briefly discuss some key areas of progress in the field of energy demand modelling.

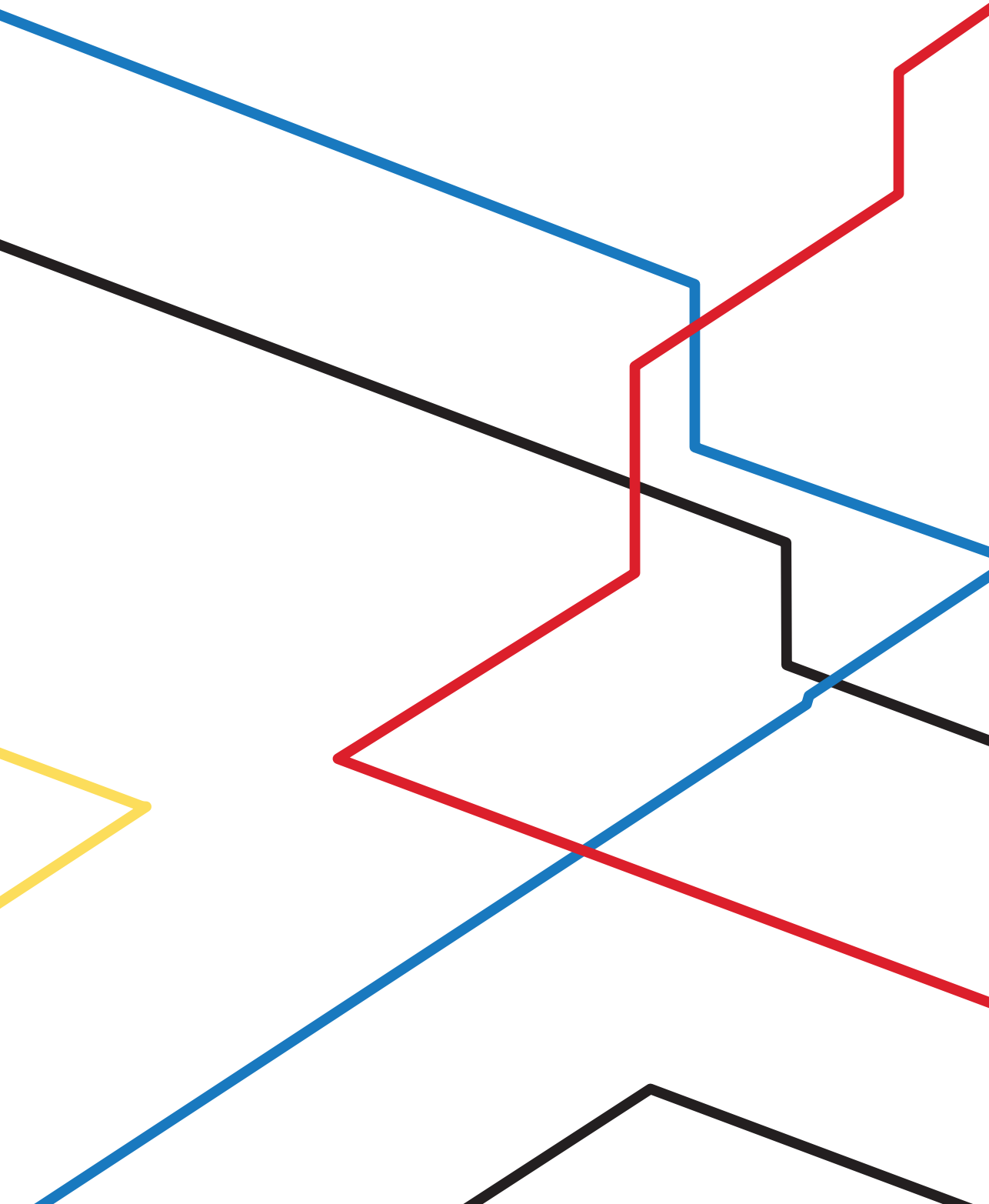
Behaviour change. Behavioural factors are difficult to quantify. Still their influence cannot be ignored. By calibrating model outcomes to historic data behavioural factors, such as technology or lifestyle preferences, behaviour factors are often implicitly included, but this allows only for limited interpretation of the effect of behaviour and behavioural change in energy demand decisions. Possible next steps would be to more explicitly include empirically found relationships in the model dynamically (see Chapter 6) or if quantification fails by assessing uncertainties and possible effects through qualitative scenario design.

Physical demand. Currently, the growth of the transport, industry and buildings sector is often directly related to exogenous economic projections. Including physical energy service demand projections, such as kilometres travelled or tonnes of steel produced, could allow us to compare energy efficiency improvements to technical bottom-up studies as shown at multiple occasions in thesis. The demand sector developments are also related to each other. Including physical demand projections can also be used to make cross sector relationships more explicit. Increased usage of cars for example would likely affect industrial sectors that provide for the materials to builds cars and roads. These cross linkages between sectors relations would be very relevant to further explore. Moreover, this might enable to better understand physical limits and possible energy demand saturation.

Representation of climate policy. The more sustainable developments assumed by SSP1 such as faster or improved technology development affecting energy efficiency, or car sharing and material recycling reducing the demand for energy services can be affected by policy. Similarly, structural economic change, such as moving to a more service sector oriented economy, can reduce energy requirements. However, these developments show little response to the representation of climate policy in IAMs by a carbon tax. Sector specific studies emphasize the importance of these SSP1 types of measures and indicate that they might be able to contribute more to energy demand reduction as a measure to mitigate emissions than currently accounted for under cost optimizing assumptions. Findings a way to better evaluate these types of measures in global long term models is an important next step.

Barriers. There are promising opportunities to reduce energy demand through behavioural change, sustainable developments, demand side oriented policies. However, there are –certainly in the demand sector – also many factors that prevent using this available potential. The existing infrastructure, buildings stock, involved actors and governance structures are examples of factors that create a barrier to a possible transition. These barriers affect the energy demand sector response and are a key part of the story. Therefore, models should not only look at the available potential but also better understand and represent the barriers that need to be overcome.

Short term and long term dynamics. So-far, global models have mostly been used to show the general characteristics of response strategies. . After Paris, there is an increasing interest in detailed policy advise. This requires greater detail, also on the demand side. Models could follow two strategies. A group could choose to include a richer amount of technology options and/or sector details. These models would be particularly "good" in analysing short-term mitigation potentials and can be compared to sector specific studies. A second group could remain using a less detailed representation. This means that they will also be less bounded by characterization of specific technologies and more flexible in the long term. Based on our findings we conclude that there is not a preferred method, as they each have their value and can learn from each other, and the type of model applied will depend on the question addressed. Both types of models are informative and it will be useful to combining and communicate the results together. Chapter 4 shows how looking at elasticities can do this – but also how aggregated models could use model-based elasticities of detailed models instead of empirical elasticities. The former might be more useful for the future than the latter. Even more so, as countries have started to implement climate policies, the translation between short term measures and long-term trends, is as relevant as ever.



Chapter 9

Samenvatting en Conclusies

Toekomstige energievraag volgens mondiale modellen

Projecties van een complex systeem

9.1 Focus van het proefschrift en hoofdvragen

De energievraag-sectoren industrie, transport en gebouwde omgeving zijn gezamenlijk direct[1] verantwoordelijk voor zo'n 51% van de mondiale energiegerelateerde CO_2 emissies. Daarbij zijn deze sectoren ook indirect verantwoordelijk voor de emissies uit de energieaanbod-sectoren[2] via de vraag naar elektriciteit en warmte. Ontwikkelingen in de energievraag in deze sectoren spelen daarom een grote rol in de toekomstige CO_2 emissies.

De energievraag-sectoren zijn complexe systemen, gekarakteriseerd door veel subsectoren, veel verschillende technologieën en heterogene gebruikers met verschillende voorkeuren en behoeften. Daarbij vinden in deze sectoren vaak snelle veranderingen plaats. Deze diversiteit is niet gemakkelijk te vangen in mondiale, lange termijn modellen die gebruikt worden om emissie-mitigatiepaden te bestuderen. Daar komt nog bij dat de relevante actoren in deze sectoren vaak beïnvloed worden door diverse overwegingen die vaak minder goed definieerbaar of kwantificeerbaar zijn dan de "rationele" kostenoptimalisatie die in de modellen wordt aangenomen (en die beter past bij de investeringsbeslissingen in energieaanbod-sectoren). Om hier mee om te gaan en deze complexiteiten te vermijden, kiezen modelleurs er vaak voor om de energievraagontwikkelingen op een geaggregeerde, simplistische manier te beschrijven. Dit betekent dat de energievraag wordt beschreven als functie van een activiteitontwikkeling, en een inkomens- en prijselasticiteit. Een indirect gevolg hiervan is echter dat er veel minder aandacht uitgaat naar het gebruik van energie en de rol van energiebesparing binnen de modelanalyse om klimaatdoelen te behalen.

Met de toenemende focus op klimaatbeleid is op dit moment sprake van een toenemende interesse naar de effecten van concrete beleidsmaatregelen. Hierdoor zijn geaggregeerde beschrijvingen minder bruikbaar. Meer gedetailleerde informatie is bijvoorbeeld nodig om beleid te ondersteunen gericht op de implementatie van het akkoord van Parijs. Meer details bieden de mogelijkheid om modelresultaten beter te relateren aan sectorspecifiek beleid, maar ook aan sectorspecifieke studies. Nu is de vergelijking tussen modelresultaten en concrete mitigatiemaatregelen niet altijd eenvoudig.

1 Direct refereert hier aan de emissies fysiek in de vraagsectoren uitgestoten worden.
2 Energyaanbod-sectoren is hier gedefinieerd als alle energie extractie, conversie, opslag, transmissie en distributie processen, met uitzondering van die processen waar (finale) energie wordt gebruikt om energie diensten in de energievraag-sectoren te leveren (industrie, transport, gebouwde omgeving, landbouw en bosbouw).

Er zijn echter ook nadelen verbonden aan een meer gedetailleerde beschrijving. Bij het maken van lange termijn projecties betekent meer detail namelijk niet per definitie accuratere resultaten. Details verliezen betekenis als de onzekerheid over de tijd groter wordt. Gegeven de complexiteit van het systeem en de snelle verandering leidt het toevoegen van een meer gedetailleerde beschrijving daarom niet per sé tot een betere beschrijving van de sectordynamiek.

Binnen dit kader wordt er in dit proefschrift getracht een antwoord te geven op de volgende vraag:

Hoe kan de representatie van energievraag-dynamiek verbeterd worden in mondiale modellen die lange termijn klimaatverandering bestuderen?

Om dit doen kijken we eerst naar de weergave van de energievraag in "*integrated assessment modellen*" (IAMs). We onderzoeken daarvoor de mondiale projecties van de industrie, transport en gebouwde omgeving, en bekijken de modeluitkomsten in combinatie met modelaannames. In het proefschrift gebruiken we hiervoor diverse methoden, en vergelijken we modeluitkomsten met historische data, sectorspecifieke studies en andere modellen. Deze vergelijkingen helpen ons algemene trends te herkennen maar ook onzekerheden tussen de modellen bloot te leggen. Op basis hiervan kunnen we ook een beschouwing geven over hoe "goed" de modellen presteren. Het eerste deel van het proefschrift richt zich voornamelijk op de eerste drie van de vragen die hieronder zijn geformuleerd. Daarna duiken we dieper in specifieke processen en bestuderen we de invloed van technologieontwikkeling, consumentheterogeniteit en gedrag bij sectortransities.

Van de hoofdvraag zijn de volgende vier vragen afgeleid:

- Hoe wordt de mondiale energievraag in IAMs gerepresenteerd en welke resultaten en inzichten levert dit op?
- Wat vertellen IAMs over klimaatstrategieën in energievraag-sectoren?
- Hoe goed zijn de modellen in de weergave van energievraag?
- Hoe kunnen gecompliceerde processen bepalend voor de energievraag, zoals technologieontwikkeling of sociaal leren, worden weergegeven in mondiale modellen?

9.2 Hoofdbevindingen van het proefschrift

9.2.1 Hoe wordt de mondiale energievraag in IAMs gerepresenteerd en welke resultaten en inzichten levert dit op?

De wereldwijde vraag naar energie zal de komende decennia blijven groeien als de huidige trends doorzetten. Een toenemende energie-efficiëntie zal de snel toenemende vraag gedeeltelijk compenseren. Hoofdstukken 2, 3 en 7 laten zien hoe door de blijvende groei van de wereldbevolking en de economie het toekomstige energieverbruik zal blijven toenemen in lijn met historische ontwikkelingen. Sommige modellen berekenen de energievraag direct op basis economische en demografische trends. Anderen modellen berekenen eerst de vraag naar energiediensten, zoals de vraag naar materialen, industriële producten of afgelegde kilometers. De vraag naar energiediensten wordt dan vervolgens verder uitgewerkt per sector, zoals de vraag naar auto's of busvervoer, of in de industriesector, bijvoorbeeld de cement- en staalvraag. De mate waarin dit onderliggende detail wordt beschreven verschilt per model. De structuur van de sector (zoals het aandeel per vervoerstype), wordt in sommige modellen exogeen aangenomen, maar in andere modellen intern beschreven, inclusief prijs- en verzadigingsaannames. De meeste modellen bevatten een weergave van de huidige en toekomstige technologieën om aan de nodige vraag voor diensten te voldoen, maar opnieuw varieert het detailniveau aanzienlijk per model. Modellen nemen vrijwel altijd aan dat de technologiekeuze wordt gemaakt op basis van de relatieve kosten: wanneer brandstofprijzen stijgen leidt dit dus tot verbeteringen van de energie-efficiëntie of het overstappen naar een ander type brandstof. In veel modellen wordt technologieontwikkeling aangedreven door exogene aannames, terwijl enkele modellen leercurves gebruiken. Een belangrijk verschil tussen de modellen is ook de gebruikte oplossingsmethode: de modellen die in dit proefschrift zijn geanalyseerd zijn óf (intertemporele) optimalisatiemodellen óf simulatiemodellen.

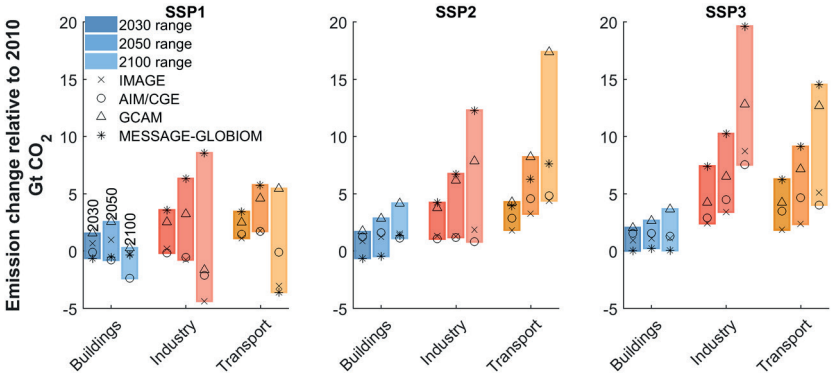
Op de korte termijn zijn de trends tussen de modellen vaak vergelijkbaar terwijl lange termijn projecties veel meer van elkaar verschillen. Het is geen verrassing dat de wereldwijde vraag naar energie over meerdere decennia steeds onzekerder wordt. De verschillende modelprojecties tonen een breed scala aan mogelijke toekomsten. Deze hangen af van de veronderstelde technologieontwikkeling, demografische veranderingen, beleid, veranderingen in levensstijl, structurele veranderingen en de beschikbaarheid van natuurlijke hulpbronnen. Waarschijnlijk is de echte onzekerheid nog veel groter dan wordt gevangen door de modellen. IAMs bevatten een weergave van hoe de verschillende ontwikkelingen tussen sectoren zich tot elkaar verhouden en hoe deze van invloed zijn op de wereldwijde vraag naar energie. De verschillende energievraag-paden zijn dus ook afhankelijk van de onzekerheid in de onderliggende ontwikkelingen. Zullen er steeds meer

wegen en huizen worden gebouwd? Zal de wens om meer te reizen en gebruik te maken van snellere vervoersmiddelen blijven groeien? Zullen de kosten van elektrische voertuigen blijven dalen? Worden auto's efficiënter? Op basis van historische gegevens kunnen relaties worden vastgesteld, die in modellen worden geëxtrapoleerd naar de toekomst. Een belangrijk vraag daarbij is óf er verzadiging van de energievraag zal plaatsvinden en wanneer dat gebeurt. Historisch hebben we een dergelijke verzadiging in bepaalde sectoren gezien, maar niet in alle. Het is voorstelbaar dat er bijvoorbeeld een maximum aantal wegen of huizen gebouwd kan worden, al is het maar door een beperking van de beschikbare ruimte. Ook zou er ook een bovengrens kunnen zijn aan het aantal kilometers dat een persoon aflegt. Er bestaat in ieder geval een (theoretische) limiet in de mogelijke verbeteringen van de energie-efficiëntie. Voor de komende 10 of 20 jaar hebben we een redelijk idee van wat technisch haalbaar is, maar wat daarna gebeurt is een open vraag. Deze overwegingen verklaren de resultaten van de modellen: veel overeenkomsten in de komende 10-30 jaar en sterke divergentie daarna.

In SSP2 (het basisscenario) neemt de jaarlijkse directe CO_2-uitstoot met -0.4-2.9, 1.2-6.7 en 3.3-8.2 Gt CO_2 toe in 2050 voor respectievelijk de gebouwde omgeving, de industrie en de transportsector, volgens de modelprojecties. De onzekerheid is echter groot. In alternatieve scenario's worden een lage CO_2 uitstoot (SSP1, het duurzame ontwikkeling scenario) of een hogere uitstoot (SSP3, het gefragmenteerde wereld scenario) geprojecteerd. Het laatste hoofdstuk van dit proefschrift vergelijkt modellen en verschillende scenario's voor alle drie de vraagsectoren. Belangrijke onzekerheden die de toekomstige CO_2 emissies van de eindgebruikssectoren bepalen zijn de bevolkingsgroei en de groei van de finale energie per hoofd van de bevolking. Tabel 9-1 toont de projecties van de finale energievraag in de gebouwde omgeving, de industrie en de transportsector in 2010 en voor 2050 en 2100. Al in 2010 is er een aanzienlijk verschil in de aangenomen industriële energievraag tussen de modellen. Dit is deels het gevolg van sectordefinities. Het gebruik van industriële grondstoffen draagt bijvoorbeeld bij voor 17% van het totale industriële energiegebruik (zie Figuur 9-2), en modellen gaan verschillend met deze emissies om. Het verschil tussen modellen in 2010 benadrukt vooral het belang van duidelijke definities bij het vergelijken van modelprojecties. Hetzelfde hoofdstuk laat ook zien hoe de alternatieve scenario's SSP1 en SSP3 het energieverbruik en de nodige emissiereductie om een klimaatdoel te bereiken sterk beïnvloeden. Modelverschillen zijn echter vaak meer uitgesproken dan scenarioverschillen (zie Figuur 9-1). Dit laatste heeft veel te maken met de eerdere discussie over modelaannames rond verzadiging.

Tabel 9-1. Finale energie vraag in EJ in de gebouwde omgeving, industry en transport sector in 2010, 2050 en 2100. De model resultaten zijn afgerond op tientallen.

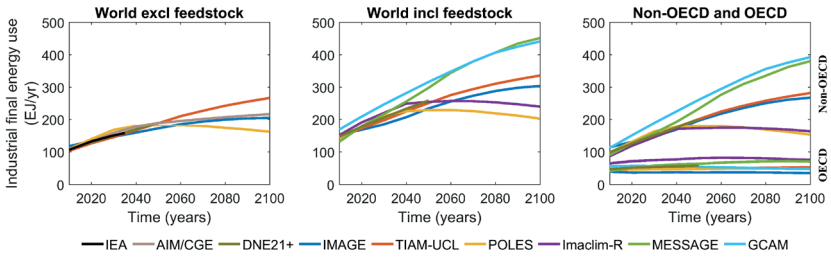
2010			
Buildings	120-130		
Industry	120-140		
Transport	90-100		
2050	**SSP1**	**SSP2**	**SSP3**
Buildings	170-190	180-220	190-240
Industry	150-270	190-240	210-300
Transport	120-190	160-190	150-230
2100	**SSP1**	**SSP2**	**SSP3**
Buildings	160-250	240-360	200-370
Industry	120-280	210-350	300-460
Transport	110-180	200-300	200-360



Figuur 9-1: De verandering in jaarlijkse CO_2 emission in 2030, 2050 and 2100 vergeleken met 2010 in de SSP1, SSP2 en SSP3 scenarios als er geen klimaatbeleid wordt ingevoerd. De staven geven de bandbreedte tussen modellen weer terwijl de iconen de model specifieke resultaten aanduiden.

De groei van de wereldwijde industrie-energievraag wordt grotendeels bepaald door ontwikkelingen in niet-OESO-landen, terwijl de vraag in de OESO-landen min of meer constant blijft. De industriële energievraag in 2100 in niet-OESO-landen varieert volgens de modelprojecties tussen 150 tot 400 EJ. Hoofdstuk 2 vergelijkt

de projecties van industriële energieconsumptie van acht modellen. Dit proefschrift concentreert zich op het mondiale niveau, al liggen regionale ontwikkelingen hierbij aan de basis. De jaarlijkse reductie van de industriële energie-intensiteit[3] varieert van 1.8 tot 2.2% in niet-OESO-landen. Dit is aanzienlijk sneller dan de historisch waargenomen reductie en zou betekenen dat deze regio's zich sneller in de richting van het niveau van OESO-landen ontwikkelen. Hoewel de modellen het hierover eens lijken te zijn, leidt de range van deze reductie tot grote verschillen in energieverbruik op de lange termijn (zie Figuur 9-2). De modellen verschillen sterk in detailniveau wat betreft activiteits- en technologie-representatie van de industriesector. De resultaten van Hoofdstuk 2 tonen echter geen systematisch verschil tussen modellen met of zonder sectordetail.



Figuur 9-2: Finale energievraag projecties van de industriesector: a) Mondiaal zonder grondstof gebruik, b) Mondial inclusief grondstof gebruik en c) OESO en Niet OESO landen inclusief grondstof gebruik.

De verschillende projecties van de transport-energievraag zijn deels te herleiden naar verschillende verwachte reisvolumes en naar de grootte van de energie-efficiëntie verbetering. In Hoofdstuk 3 worden de toekomstige energievraag-paden als gevolg van personenvervoer tussen verschillende modellen vergeleken. De geprojecteerde vraag varieert in 2050 van 93 tot 121 EJ en in 2100 van 130 tot 206 EJ in een scenario zonder klimaatbeleid (ter vergelijking: het niveau in 2010 is 47-55 EJ). Hoewel de jaarlijkse groeipercentages van afgelegde kilometers een relatief dicht bij elkaar liggen in vergelijking met wat in het verleden is waargenomen, kan dit op langere termijn leiden tot een aanzienlijke spreiding van de verwachte vraag (zie Figuur 9-3), de groei variërend van een factor twee tot vijf ten opzichte van 2010. Het aantal afgelegde passagierskilometers met de auto varieert bijvoorbeeld van 68.000 tot 123.000 miljard in 2100, vergeleken met gemiddeld 22.000 miljard passagierskilometers in 2010[4], wat een aanzienlijk effect heeft op de energie vraag.

3 Dit is de energiegebruik per BBP.
4 Gemiddelde van een range van 17.000-26.000 miljard kilometers in 2010.

Hoofdstuk 3 toont ook aan dat de gemiddelde energie-efficiëntie van het passagiersvervoer afneemt tot 0.5-1 MJ/passagierskilometer in 2100. Door de vraag voor energiediensten, zoals de hoeveelheid afgelegde kilometers, expliciet mee te nemen kan er een betere vergelijking gemaakt worden met energie-efficiëntieramingen van bottom-up studies. Uit de modelprojecties blijkt dat verbeteringen van de energie-efficiëntie een belangrijke middel zijn om emissies van passagiersvervoer te verminderen. Zelfs in een scenario zonder klimaatbeleid zou aan het eind van de eeuw de gebruikte energie per passagierskilometer aanzienlijk verbeteren (46-72%). Bottom-up studies laten zien dat in 2030 al een daling van 30-50% in 2030 mogelijk is. In de model projecties beïnvloedt, naast ontwikkelingen in energie-efficiëntie, het overschakelen op alternatieve aandrijfmechanismen zoals elektrische voertuigen het gerapporteerde brandstofverbruik sterk. Hoewel meer gebruik van energie-efficiënte vervoersmiddelen zoals de trein ook zou kunnen bijdragen aan een lager energieverbruik, blijft de sector structuur van de passagiersvervoer in IAM projecties dichtbij de huidige situatie.

De vergelijking van de cementsectorprojecties (Hoofdstuk 2) laat zien dat in scenarios zonder klimaat beleid verbeteringen van de energie-efficiëntie in de IAM projecties ruim binnen het verwachte technisch potentieel liggen. Om te beoordelen of de verbeteringen van de energie-efficiëntie realistisch zijn, is het belangrijk voldoende details van de industriële subsector te projecteren. Verschillende modellen hebben een gedetailleerde beschrijving van de materiaalvraag en technologieopties in de cementsector. In Hoofdstuk 2 vergelijken we deze modelprojecties. Het specifieke energieverbruik (GJ/ton-product) voor het maken van cement en klinker zal naar verwachting dalen als gevolg van technologische ontwikkeling. De literatuur suggereert dat het energieverbruik voor het maken van klinker kan dalen tot 2.9 GJ/ton klinker. Met verbeterde technologie zou voor het maken van cement een lagere klinker/cementverhoudingen kunnen worden gebruikt waarmee het energieverbruik verder kan dalen tot 2.1-2.7 GJ/ton cement. De projecties vallen ruim binnen het technisch potentieel en er zou nog aanzienlijke verbetering van de energie-efficiëntie mogelijk zijn in een scenario met klimaatbeleid. Het modelleren van de vraag naar industriële energiediensten biedt de mogelijkheid om het verbruik van materialen te relateren aan de ontwikkeling van infrastructuur of gebouwen en daarmee de discussie rond vraagverzadiging beter te evalueren.

9.2.2 Wat vertellen IAMs over klimaatstrategieën in energievraag-sectoren?

Energie-efficiëntie en het gebruik van alternatieve brandstoffen (inclusief elektrificatie) spelen beide een belangrijke rol bij de reductie van emissies afkomstig van vraagsectoren. Op de korte termijn zijn deze processen volgens de modellen

vergelijkbaar in hun bijdrage. Op lange termijn wordt het overstappen naar alternatieve brandstoffen belangrijker. Er zijn verschillende strategieën om emissies van de vraagsector te mitigeren: 1) verbetering van de energie-efficiëntie 2) gebruik van andere brandstoffen en 3) vermindering of verandering van vraag naar energiediensten (zoals bijvoorbeeld gereden kilometers, nodige vloeroppervlak, staalproductie). Deze indeling wordt hieronder gebruikt om de geprojecteerde mitigatiepaden van de vraagsectoren te bespreken.

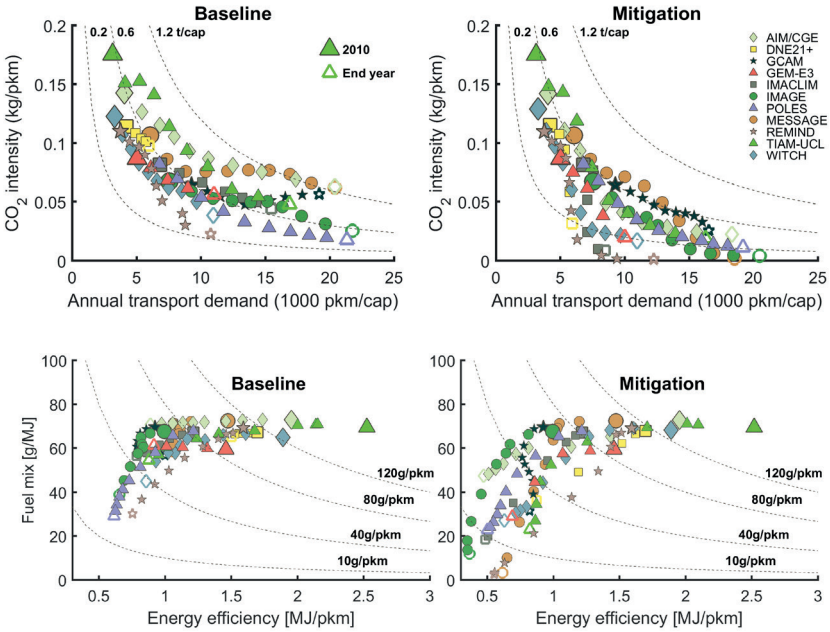
1 Verbetering energie-efficiëntie

Energie-efficiëntieverbeteringen zijn in alle vraagsectoren nodig om emissies te mitigeren. De in de modellen geprojecteerde energie-efficiëntieverbetering blijft ruim binnen het potentieel van technische studies. Hoofdstuk 7 laat zien dat om de temperatuurstijging te beperken tot 2 °C, de modellen in elke sector een daling van het energiegebruik per hoofd laten zien ten opzichte van de referentie scenario's (SSP1, SSP2 en SSP3). In het basis SSP2-scenario leidt dit in 2030 tot respectievelijk 0.4 (0.0-0.7), 1.1 (0.2-2.0), 1.3 (0.0-2.5)[5] Gt CO_2-reductie in respectievelijk de gebouwde omgeving, de industrie- en de transportsector. Deze emissiereducties vallen ruimschoots binnen het potentieel geraamd in sectorale literatuurstudies. In feite suggereren deze bottom-up schattingen dat er nog meer ruimte is voor verbetering van de energie-efficiëntie (Tabel 9-2).

Tabel 9-2: Vergelijking tussen de in 2030 vermeden emissies in een SSP2 2 °C scenario met de sector specifieke emissiereductie potentialen volgens de technische bottom-up studies in Gt CO_2. De negatieve waardes geven een emissive toename in plaats van afname aan.

	Buildings	Industry	Transport
Integrated assessment models	*0.7 (0.3 to 1.0)*	*2.6 (0.9 to 3.2)*	*1.7 (0.9 to 2.7)*
Efficiency	*0.4 (0.0 to 0.7)*	*1.1 (0.2 to 2.0)*	*1.3 (0.0 to 2.5)*
Electrification	*0.0 (-0.1 to 0.0)*	*0.0 (0.0 to 0.2)*	*0.0 (0.0 to 0.3)*
Fuel switch	*0.3 (0.2 to 0.4)*	*1.4 (0.6 to 1.9)*	*0.3 (0.0 to 0.8)*
Technology-oriented assessment	*1.6-2.1*	*2.1-3.3 (incl. CCS 3.3 – 4.6)*	*4.1 – 5.3*
Efficiency	*1.2 - 1.8*	*1.6 – 2.8*	*3.0 – 4.9*
Electrification			
Fuel switch	*0.4 – 0.9*	*0.4 – 0.6 + 0.9 – 1.5 (CCS)*	*0.6 – 0.8*

5 Gemiddelde met tussen haakjes de model range.



Figuur 9-3: Boven: Projecties van personenvervoer activiteit (x-as) vergeleken met de CO_2 intensiteit (y-as) ontwikkelingen, op mondiale schaal. De totale CO_2 emissies per person worden aangegeven door de isolijnen. Het linkerdeel geeft een scenario zonder klimaatbeleid en het rechterdeel een scenario met aangenomen klimaatbeleid weer. De modellen DNE21+ and GEM-E3 maken projecties tot 2050, Imaclim-R tot 2070 en de andere modellen tot 2100. Onder: Projecties van personenvervoer energie intenstiteit (x-as) vergeleken met brandstof mix (y-as) ontwikkeling, op mondiale schaal. De isolijnen geven de totale emissies per persoonkilometer aan.

2 Gebruik van andere brandstoffen

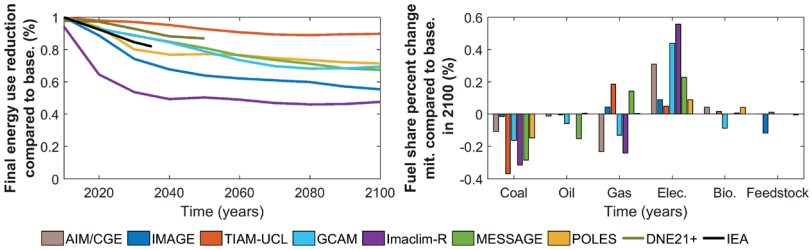
Het gebruik van alternatieve brandstoffen is essentieel voor het halen van strenge klimaatdoelstellingen en wordt in de loop van de tijd steeds belangrijker. IAMs zijn met name geschikt om de effectiviteit van ander brandstofgebruik als mitigatiemaatregel te analyseren. Op de korte termijn kunnen de voordelen van het overstappen naar alternatieve brandstof nog beperkt zijn omdat elektriciteit bijvoorbeeld nog koolstofintensief is. Op langere termijn kan dit echter veranderen en dan hebben verdere energiebesparingen ook minder effect. De modellen laten inderdaad zien dat het overstappen naar een ander type brandstof, als maatregel om emissies te verminderen, in de vraagsectoren met de tijd toeneemt. Er zijn verschillende routes om dit te doen, afhankelijk van de sector, de specifieke energiedienst en technologische opties. In de gebouwde omgeving projecteren

modellen dat de elektrificatietrends van de afgelopen decennia blijft doorzetten en een aandeel hebben van 43 tot 49% in 2050 en van 57 tot 69% in 2100 (modelrange) in het basis SSP2 scenario zonder klimaatbeleid. Deze zou kunnen toenemen tot 45-53% in 2050 en 73-93% in 2100 in een streng klimaatbeleid scenario (Hoofdstuk 7). Dit betekent dat veruit het grootste deel van de emissies in de gebouwde omgeving niet direct maar indirect tijdens de elektriciteitsproductie wordt uitgestoten.

Modellen hebben verschillende strategieën voor het gebruik van alternatieve brandstoffen in de personenvervoer sector. De modelvergelijking over de personenvervoer sector in Hoofdstuk 3 toont verschillende mogelijke routes van een brandstoftransitie: routes verschillen qua inzet van brandstoftypes en ook wat betreft de omvang van de transitie. De onzekerheid van toekomstige technologieontwikkeling kan terug worden gezien in de uiteenlopende verwachtingen van de kosten van de elektrische en brandstofcel in de komende decennia. Deze verschillen verklaren echter niet volledig de verschillende keuzes die in de modellen gemaakt worden. Andere belangrijke factoren zijn de brandstofprijs, diverse methoden die gebruikt worden om tot een modeloplossing te komen, zoals te zien is in Hoofstuk 4 en andere niet-financiële factoren. In de transportsector was de afgelopen decennia olie dominant, maar een grootschalige transitie naar koolstofarme brandstoffen is nodig om de klimaatdoelstellingen te halen (zie Figuur 9-3): in sommige projecties stijgt het aandeel elektriciteit en/of waterstof tot 80%, terwijl andere projecties een sterke stijging van biobrandstoffen laten zien (tot een aandeel van 50%). In beide gevallen is dit een duidelijke trendbreuk met historische ontwikkelingen.

In de industriesector is eveneens het overschakelen van kolen op elektriciteit een belangrijke maatregel om emissies te verminderen. Interessant genoeg lijken modellen die expliciet industriële technologieën meenemen minder geneigd te zijn om over te stappen op alternatieve brandstoffen. Hoofdstuk 2 laat zien dat er een redelijk hoge overeenkomst is tussen modellen wat betreft de brandstofmix in de scenario's zonder klimaatbeleid (baseline) in de industriesector. De meeste modellen voorspellen een lichte toename van het elektriciteitsverbruik en een afname van het gebruik van fossiele brandstoffen (een verandering van ongeveer 10 en 20 procentpunten). Voor een 2 °C scenario laten de modellen echter een sterke verschuiving van het brandstofaandeel zien (zie Figuur 9-4). Emissiemitigatie vindt plaats door een combinatie van de overstap op alternatieve brandstoffen en de verbetering van de energie-intensiteit. De reductie van finale energie ten opzichte van de "baseline" varieert van 10-50% tussen de modellen, en blijft in alle modellen redelijk constant na 2040. Opvallend is dat in de bestudeerde modellen (Hoofdstukken 2 en 4) de modellen met meer technologiedetail minder flexibel zijn in het overstappen naar alternatieve brandstoffen en daarmee energie-efficiëntie

een belangrijkere rol geven. Verbeteringen van de energie-efficiëntie worden echter vaak beperkt tot de huidige kennis van technologische ontwikkelingen en kunnen daardoor in de verloop van tijd stagneren. Sommige industriële processen zijn geschikt voor het toepassen van maatregelen voor het afvangen en opslaan van koolstof om de uitstoot te verminderen. De weergave hiervan in de globale modellen is echter niet specifiek bestudeerd tijdens dit onderzoek.



Figuur 9-4: Links) Finale energievraag in de industrie sector in een mitigatie scenario vergeleken met een scenario zonder klimaatbeleid. Rechts) Verandering in de industriesector brandstofaandelen in een mitigatie scenario vergeleken met een scenario zonder klimaatbeleid.

3 Vermindering vraag naar energiediensten

De verwachte vraag naar energiediensten is, volgens de modelprojecties, niet zo gevoelig voor het klimaatbeleid. Het potentieel om emissies te verminderen door vraagvermindering wordt in de huidige scenario's dus nauwelijks bestudeerd. Zoals eerder genoemd, wordt de vraag naar energiediensten niet in alle IAMs expliciet meegenomen. In gevallen dat het wel mogelijk was om projecties voor energiedienstvraag te analyseren, zoals in Hoofdstukken 3 en 4 voor de transportsector, en in Hoofdstuk 7 voor alle drie de vraagsectoren gebruikmakend van het IMAGE-model, vinden we dat de vraag naar energiediensten nauwelijks reageert op het klimaatmitigatiebeleid of niet elastisch is ten opzichte van verandering van de brandstofprijs. Naast vermindering van de vraag naar energiediensten, wordt ook het veranderen van de vraag naar energiediensten, bijvoorbeeld door over te stappen naar alternatieve koolstofarme transportmodi, nauwelijks benut in de scenario's. Hierbij moet worden begrepen dat het klimaatbeleid in deze modellen gebruikelijk wordt gerepresenteerd door middel van een CO_2-belasting die de brandstofprijs beïnvloedt. In sommige modellen is de vraag naar diensten alleen gerelateerd aan exogene GDP-aannames, waardoor deze niet kan worden beïnvloed door de verandering van de brandstofprijs. In andere modellen zijn alternatieve maatregelen, die minder afhankelijk zijn van gedragsverandering, aantrekkelijker. In tegenstelling tot de modelprojecties

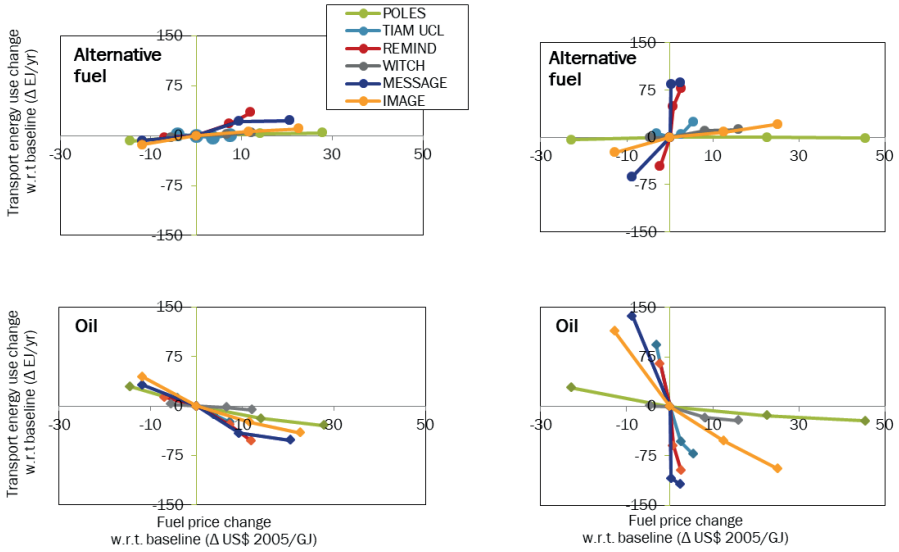
benadrukken bottom-up en lokale transportstudies wel het belang van infrastructuur- en gedragsverandering, vooral in de stedelijke omgeving, wat ook leidt tot andere lokale bijkomende voordelen, zoals verbetering van de luchtkwaliteit. Deze studies geven aan dat het kostenoptimalisatieperspectief van IAMs het potentieel van de veranderde vraag naar energiediensten zou kunnen onderschatten. Verandering van de energiedienstenvraag zou een belangrijke aanvulling kunnen zijn op de snelle en drastische overstap naar alternatieve brandstoffen die in de huidige projecties vereist is om klimaatdoelen te halen.

9.2.3 Hoe goed zijn de modellen in de weergave van energievraag?

Door middels van decompositie analyse en het berekenen van de impliciete modelelasticiteiten zijn de toekomstige transportsector projecties vergeleken met historische indicatoren. Alhoewel andere evaluatiemethoden zijn toegepast op alle drie de vraagsectoren, zoals besproken in de bovenstaande secties, wordt de vraag over de mate van model-prestatie hier beantwoord door specifiek de dynamiek van de transportsector te analyseren. De vergelijking van de projecties met historische gegevens laat zien dat de verwachte toekomstige trends in de transportsector over het algemeen vergelijkbaar zijn met historische observaties van activiteitgroei, verschuiving in de wijze van vervoer, energie-intensiteit en prijs- en inkomenselasticiteiten. De verwachte overstap naar alternatieve brandstoftypes gaat echter verder dan historische observaties, aangezien de transportsector de afgelopen decennia grotendeels (> 90%) afhankelijk is geweest van olie.

De activiteitgroei- en energie-intensiteitprojecties van de transportmodellen vallen binnen de historisch gemeten range, gerapporteerd tussen 1973 en 2007 in verschillende OESO-landen. De variatie die historisch wordt gerapporteerd is zelfs een stuk ruimer dan de verschillen tussen modellen. In Hoofdstuk 3 worden de componenten activiteitgroei, energie-intensiteit, *"modal shift"*[6] en brandstofmix-ontwikkelingen die bijdragen aan de verwachte uitstoot van broeikasgassen uit elkaar gehaald door de Laspeyres-index decompositie-analyse. Dezelfde methode is de afgelopen decennia gebruikt in energieonderzoek om historische trends van de eerste drie componenten te begrijpen. We hebben niet gekeken naar de historische verandering in brandstofmix omdat deze min of meer werd gedomineerd door olie. Terwijl de energie-intensiteit in alle modellen afneemt, is dit historisch gezien niet altijd het geval geweest. In het mitigatiescenario neemt de vermindering van de energie-intensiteit verder toe, richting de meest optimistische waarden in historische observaties. In overeenstemming met historische trends leidt *"modal shift"* (verschuiving tussen transporttypen) in het algemeen tot toenemende emissies in de baseline, hoewel dit effect in de modelprojecties klein is en nauwelijks reageert op het klimaatbeleid.

6 Het overstappen naar een ander type vervoer.



Figuur 9-5: De olie (onder) en alternatieve brandstof (boven) energievraag reactie naar aanleiding van een -50%, +50% and + 100% olie en gas prijs schok in 2030 (links) en 2060 (rechts). Alternatieve brandstof is gedefinieerd als anders dan olie.

9

De olie- en gasprijselasticiteit voor de energievraag van personenauto's (inclusief busjes) varieert van -0.2 tot -0.5 in 2030, vergelijkbaar met de empirisch gevonden waarden. Op de zeer lange termijn (30-40 jaar) variëren de elasticiteitswaarden van -0.4 tot -2.1. Dit is voor sommige modellen dus een toegenomen vraagrespons in de tijd. De inkomenselasticiteit van de energievraag van personenvervoer ligt tussen 0.3 en 1.4. Factoren die een grote invloed hebben op modelprojecties zijn inkomen, meestal uitgedrukt in het bbp, en brandstofprijzen. In Hoofdstuk 4 worden de elasticiteitswaarden van de transportenergievraag in relatie tot deze factoren in IAMs onderzocht. Historische prijs- en inkomenselasticiteiten zijn uitgebreid gerapporteerd in de literatuur. Brandstofprijselasticiteiten van efficiëntie en energiediensten van de modellen liggen op middellange termijn zeer dicht bij elkaar (-0.2 tot -0.5) en vallen binnen de empirisch gevonden waarden. In 2060 laten de modellen meer divergerende patronen zien en bestrijken de elasticiteitswaarden een veel breder bereik (-0.4 tot -2.1). Dit kan verschillende oorzaken hebben zoals verschuiving naar andere type brandstof, verhoogde efficiëntie, verminderde groei van de vraag naar diensten en feedbackeffecten op de toegepaste prijsschokken. De vraagprojecties naar energiediensten blijken sterker te reageren op inkomensverschillen dan op de brandstofprijzen, wat overeenkomt met de

bevindingen in de literatuur. Verzadigingseffecten van de energiediensten over de tijd of met een toenemend inkomen zijn niet duidelijk zichtbaar. Desalniettemin hebben de relatief kleine verschillen tussen de modellen een grote invloed op de verwachte transportvraag op de korte termijn, wat ook tot uiting komt in de transportvraag projecties in Hoofdstuk 3.

9.2.4 Hoe kunnen gecompliceerde processen die bepalend zijn voor de energievraag zoals technologieontwikkeling of sociaal leren worden weergegeven in mondiale modellen?

De vraagsector is op veel manieren complex. Hier richten we ons specifiek op ontwikkelingen die van invloed zijn op een transitie naar elektrische voertuigen. De energievraagsector is niet één sector, maar veel sectoren en subsectoren met hun eigen specifieke kenmerken, die bijvoorbeeld ook heel verschillend zijn per locatie. Het is een uitdaging om niet al te veel detail mee te nemen in mondiale modellen (voor de transparantie), maar ook niet te weinig (voor de relevantie). Het bijhouden van subsector- en regionale kernmerken en bijblijven met de laatste technologieontwikkeling is data-intensief. Het is daarom vooral van belang om relaties te identificeren die geldig zijn over een lange tijdsperiode en een duidelijk effect hebben op de dynamiek van de vraagsector. Natuurlijk kunnen we in dit proefschrift geen volledig overzicht van de mogelijkheden en uitdagingen in het modelleren van de energievraag. Daarom richten we ons specifiek op de complexiteit van het modelleren van een transitie naar elektrische voertuigen. De recente groei van elektrische voertuigen, met wereldwijd twee miljoen elektrische auto's op de weg in 2016 - een verdubbeling ten opzichte van 2015 - en de snelle daling van batterijkosten geven aan dat deze markt in beweging is. Een transitie naar elektrische voertuigen zou een aantrekkelijke oplossing kunnen bieden om de emissies van auto's te verminderen, als ook de elektriciteitsopwekking koolstofarm wordt.

De gevoeligheidsanalyse laat zien dat de grootte en kosten van de batterij een belangrijke factor zijn bij het mogelijke succes van een transitie naar elektrische voertuigen. De recente daling van batterijkosten heeft bijgedragen aan een kostendaling van elektrische auto's, maar de belangrijkste overweging voor een lange termijn transitie is de ondergrens van de kosten van de batterij. De afgelopen jaren zijn de kosten van batterijen voor elektrische voertuigen aanzienlijk gedaald. Dit gebeurde veel sneller dan verwacht en het debat over hoe deze ontwikkeling zich verder zal voortzetten en de mogelijke consequenties hiervan is dan ook zeer actueel. In Hoofdstuk 5 zien we, interessant genoeg, dat het voor lange-termijn modellen vooral relevant is om te begrijpen wat de ondergrens van batterijkosten zijn, meer dan de snelheid van de kostenreductie. Alleen wanneer de batterijkosten tot onder de 100 $/kWh dalen, stijgen batterij elektrische voertuigen zonder verdere overheidsstimulering tot een aanzienlijk

(15%) marktaandeel. Naast de kosten per kWh is ook de benodigde batterijcapaciteit van belang. Momenteel zijn duidelijke regionale verschillen in batterijcapaciteit zichtbaar: waar in China en Japan vooral kleinere elektrische auto's met een kleinere batterijcapaciteit voet aan de grond krijgen, hebben in de VS voertuigen met een grotere batterijcapaciteit aan marktaandeel gewonnen. Hoe dit in de toekomst verder gaat hangt mede samen met technologieontwikkelingen rondom het opladen van de batterij en verdere verstedelijking. Dit heeft veel invloed op een mogelijke transitie (zie Figuur 9.6). Deze analyse laat dus zien dat het model gevoelig is voor onzekere modelaannames, zoals de kosten van elektrische voertuigen en de grootte van de batterij. Onzekerheidsanalyse is dus belangrijk om te testen hoe robuust de toekomstige projecties zijn.

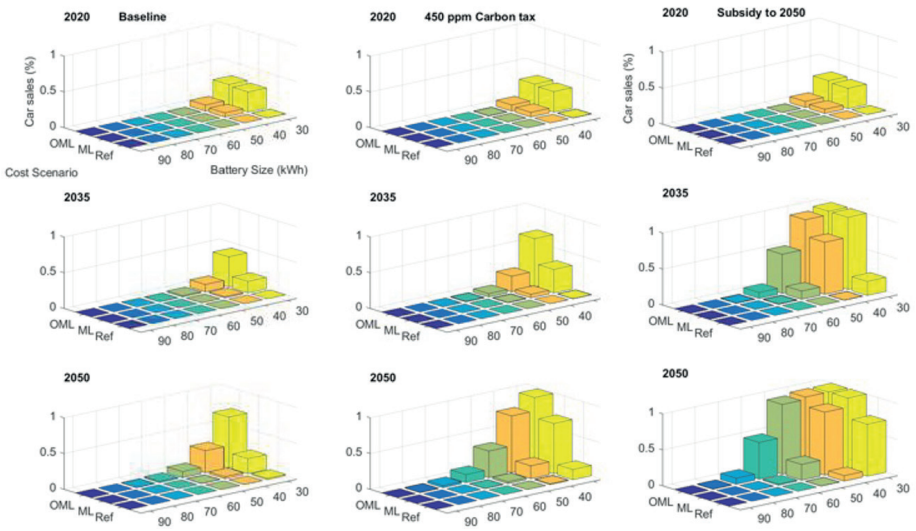
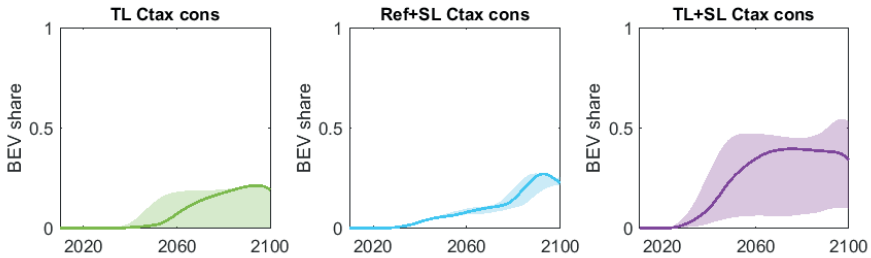


Figure 9-6: Mondiaal aandeel van de elektrische auto in het wagenpark voor drie scenario die variëren in aannames voor gemiddelde batterijcapaciteit en batterijkosten: 1) OML: batterijkosten reductie volgt de optimistische verwachtingen van vooroplopende marktpartijen, 2) ML: batterijkosten reductie volgens vooroplopende marktpartijen, 3) Ref: batterijkosten reductie op basis van de literatuur.

Dé grote uitdaging voor mondiale modellen is het onderscheiden van robuuste patronen en het vinden van het juiste detailniveau. Hier laten we zien dat de technologietransitie beter te begrijpen is bij weergave van de belangrijke elementen technologieleren, gedrag, sociaal leren en heterogeniteit van gebruikers en hun interactie. In de keuze voor een bepaalde technologie zijn naast de kosten ook niet-financiële (d.w.z. gedrags-) factoren belangrijk, zoals voorkeur voor esthetiek en prestaties, of sociale normen. Deze factoren verschillen echter per persoon en zijn daarom heterogeen.

De heterogeniteit van gebruikers kan een belangrijke rol spelen in een technologische transitie. Wanneer koplopers zich aangetrokken voelen tot nieuwe technologieën, beïnvloedt dit de besluitvormingsprocessen van anderen, bijvoorbeeld door het veranderen van het perspectief op status, betrouwbaarheid en veiligheid. Dit wordt sociale invloed of sociaal leren genoemd. Door dit proces zijn gedragsoverwegingen dynamisch: mensen reageren op hun omgeving, beïnvloed onder andere door de heterogeniteit van de markt. Technologiekosten kunnen ook "leren" en worden op een vergelijkbare manier beïnvloed door de heterogeniteit van de markt. Door de oorzaak-gevolg relaties tussen deze processen vast te leggen, kunnen de fasen van een technologietransitie beter worden begrepen.

Sociaal leren en technologisch leren kunnen elkaar wederzijds versterken en gezamenlijk een verklaring geven voor diffusie van een technologie. Dit laat zien dat de heterogeniteit een belangrijke rol kan spelen bij het beschrijven van toekomstige transities en daarmee ook bij het maken van gericht beleid om een technologische transitie te initiëren. Hoofdstuk 6 onderzoekt hoe sociaal leren en technologisch leren op een eenvoudige manier kan worden meegenomen in een IAM, op basis van empirisch gevonden relaties. De nieuwe modelformulering laat zien dat als de leerprocessen in dezelfde richting werken, ze elkaar wederzijds kunnen versterken. Interessant is de dynamische interactie tussen sociaal en technologisch leren, die wordt bevorderd door de marktheterogeniteit. In de beginfase van een transitie spelen vooral koplopers een rol. Het gebruik van technologie door deze groep kan helpen bij de verbetering van de technologie en verlaging van de productiekosten. Door de daling van de kosten kan de technologie vervolgens ook interessant worden voor anderen. Deze analyse laat zien dat naast kennis over technologie ontwikkeling, kennis over sociale dynamieken nodig is om het potentieel voor toekomstige transities aan de vraagkant goed te begrijpen.



Figuur 9-7: Het marktaandeel van elektrische auto's als gevolg van een exponentiële CO_2 belasting onder verschillende "leer" aannames: TL: Technologisch leren 2) SL: Sociaal leren 3) TL+SL: Technologisch en Sociaal leren. Het gekleurde vlak geeft de range van uitkomsten aan.

9.3 Discussie en volgende stappen

In dit proefschrift hebben we een overzicht gegeven van de huidige stand van zaken in mondiale toekomstige energievraagprojecties. We bespraken de huidige methoden, de resultaten (scenario's met en zonder klimaatbeleid) en hebben mogelijke verbeteringen geïdentificeerd.

De toekomstige vraag naar energiediensten is geïdentificeerd als een belangrijke onzekerheid die een cruciale invloed heeft op de toekomstige energievraag. De projecties van modellen zijn vooral op de korte termijn behoorlijk vergelijkbaar met elkaar, ook ten opzichte van historische observaties. Op de lange termijn zijn veel grotere verschillen te zien, meestal ten gevolge van aannames over verzadiging, technologie-ontwikkeling en mogelijke efficiëntieverbeteringen. De verschillen tussen modellen kunnen niet eenvoudig worden herleid tot het modeltype en hangen dus af van aannames rond modelparameters. Dus hoewel de modellen een onzekere toekomst laten zien, is het niet eenvoudig te herleiden waar dit van afhangt.

We concluderen dan ook dat er behoefte is aan een beter begrip van de ontwikkeling van de toekomstige energievraag en de relatie met toekomstige activiteitenniveaus. De relevantie hiervan wordt ook geïllustreerd door de grote verschillen in energievraag tussen SSP1 en SSP3 scenario's. Sommige modellen gebruiken vooral exogene aannames over activiteitenniveaus en technologieontwikkeling. Dit betekent dat deze factoren dus ook geen invloed hebben op het potentieel voor emissiereductie. Hoofdstuk 6 beschrijft de transitie-modellering van elektrische voertuigen en toont de toegevoegde waarde aan van het identificeren van eenvoudige oorzaak-gevolg relaties op basis van empirische gegevens om de energievraagrespons beter te begrijpen. Deze aanpak maakt het mogelijk om complexe vraagzijdeprocessen dynamisch en op een transparante manier te modelleren, terwijl het model relatief eenvoudig blijft. Toch moet er rekening mee worden gehouden dat modellen altijd een vereenvoudiging van de werkelijkheid blijven en daarom beperkt zijn in wat ze kunnen weergeven. Dit komt vooral omdat modellen transparant moeten zijn en omdat veel ontwikkelingen uiteindelijk fundamenteel onzeker zijn. Daarom is het gebruik van meerdere scenario's, zoals via het SSP-framework, en gevoeligheidsanalyse belangrijke hulpmiddelen om ons begrip van de energievraag te verbeteren. Het blijft ook belangrijk om modelresultaten te gebruiken in combinatie met andere onderzoekstechnieken (zoals gedaan in Hoofdstuk 7).

Natuurlijk worden de resultaten hier beperkt door de subset van modellen die we hebben bestudeerd, maar ook door de mate van diepte van de analyse. We hebben om na te gaan hoe vraagmodellen kunnen worden verbeterd een specifieke casus beter bekeken,

namelijk het modelleren van een transitie richting elektrische voertuigen. Op basis van dit werk en de beperkingen in onze huidige activiteiten, willen we kort ingaan op enkele belangrijke terreinen die de modellering van de energievraag in mondiale modellen zou kunnen verbeteren.

Gedragsverandering. Gedrag is moeilijk te kwantificeren, maar toch kan de invloed van gedrag op keuzes niet worden genegeerd. Door modeluitkomsten te kalibreren naar historische gegevens worden gedragsfactoren, zoals technologie of levensstijlvoorkeuren, vaak impliciet meegenomen in modellen, maar dit zorgt voor een beperkte interpretatie van het effect van gedrag en gedragsverandering. Mogelijke volgende stappen zijn om empirisch gevonden relaties in het model explicieter op te nemen (zie Hoofdstuk 6) of, als kwantificering niet mogelijk is, door onzekerheden en mogelijke effecten te analyseren met behulp van scenario analyse.

Fysieke vraag. Momenteel is de geprojecteerde groei van de transport-, industrie- en gebouwensectoren in IAMs vaak direct gerelateerd aan exogene economische aannames. Door de fysieke vraag voor energiediensten, zoals afgelegde kilometers of staal, expliciet in de modellen mee te nemen, zouden energie-efficiëntie aannames direct kunnen worden vergeleken met inschattingen van technische *bottom-up* studies. Dit is in dit proefschrift meerdere keren gedaan. De ontwikkelingen in de vraagsectoren houden ook verband met elkaar en door de fysieke vraag expliciet mee te nemen kunnen ook sectoroverschrijdende relaties explicieter worden gemaakt. Een toename van het autogebruik heeft naast de directe invloed op energievraag in de transport ook invloed op de industriële vraag voor materialen om auto's en wegen te bouwen. Deze verbanden tussen sectoren kunnen zeer relevant zijn voor verdere verkenning. Bovendien zou dit het mogelijk kunnen maken om de fysieke grenzen en mogelijke verzadiging van de energievraag beter te begrijpen.

Klimaatbeleid. De meer duurzame ontwikkeling die wordt aangenomen in SSP1, zoals een snellere of verbeterde technologieontwikkeling, het delen van auto's of het hergebruik van materialen, kunnen door beleid worden beïnvloed. Net zo goed kan structurele economische verandering, zoals een verschuiving naar een meer op de dienstensector gerichte economie, de energiebehoeften verminderen. Dit soort factoren spelen echter nauwelijks een rol in de standaardanalyse van klimaatbeleid in IAMs, die vooral via een CO_2 belasting loopt. Sectorspecifieke studies benadrukken het belang van deze "SSP1-type" maatregelen en geven aan dat zij mogelijk een grotere bijdrage kunnen leveren aan de vermindering van de vraag naar energie dan momenteel wordt aangenomen onder kostenoptimalisatie. Het zoeken van manieren

om dit soort maatregelen beter te evalueren in wereldwijde lange termijn modellen is een belangrijke volgende stap.

Barrières. Veelbelovende mogelijkheden om de energievraag te verminderen zijn door middel van gedragsverandering, duurzame ontwikkelingen en op de vraagzijde gericht beleid. Er zijn echter - zeker in de vraagsector - ook veel factoren die beletten dat dit beschikbare potentieel wordt gebruikt. Bestaande infrastructuur, gebouwen, betrokken actoren en bestuursstructuren zijn voorbeelden van factoren die een belemmering vormen voor een mogelijke transitie. Deze barrières zijn van invloed op de respons van de energievraagsector en vormen een belangrijk onderdeel van het verhaal. Modellen moeten daarom niet alleen naar het beschikbare potentieel kijken, maar ook belemmeringen die moeten worden overwonnen beter begrijpen en representeren.

Korte en lange termijn dynamiek. Tot nu toe worden mondiale modellen vooral gebruikt om de algemene kenmerken van mitigatiestrategieën te bestuderen. Na het akkoord van Parijs is er toenemende belangstelling voor specifieker beleidsadvies. Dit vereist meer detail, ook aan de vraagzijde. Modellen kunnen twee strategieën volgen. Modelleurs (of een deel hiervan) kunnen ervoor kiezen om een rijker aantal technologische opties en / of sectordetails toe te voegen. Deze modellen zouden met name geschikt zijn in het analyseren van korte termijn mitigatiepotentialen en kunnen worden vergeleken met sectorspecifieke studies. Modelleurs kunnen ook een minder gedetailleerde weergave blijven gebruiken. Het voordeel is dat zij ook minder gebonden zullen zijn aan de karakterisering van specifieke technologieën en op de lange termijn flexibeler zijn. Op basis van onze bevindingen concluderen we dat er geen voorkeursmethode is: beide methoden hebben hun waarde en kunnen van elkaar aanvullen. Het type model dat wordt toegepast zal afhangen van de vraag die wordt behandeld. Beide typen modellen zijn informatief en is nuttig om de resultaten samen te voegen en te communiceren. Hoofdstuk 4 laat bijvoorbeeld zien dat verschillende type modellen vergeleken kunnen worden met behulp van elasticiteiten. Het laat ook zien hoe meer geaggregeerde modellen elasticiteiten van gedetailleerde modellen zouden kunnen gebruiken. Modelgebaseerde elasticiteiten zijn mogelijk nuttiger voor de toekomst dan empirische elasticiteiten. Nu landen zijn begonnen met het implementeren van klimaatbeleid is de vertaling van korte termijn maatregelen naar lange termijn trends zeer relevant.

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Curriculum Vitae

Oreane Edelenbosch was born on 26th of December 1986 in Islamabad, Pakistan. She spent a part of her childhood in Pakistan and Kenia, and then moved to the Netherlands. After graduating from secondary school (VWO) in 2005 in the Hague, she went to Amsterdam for the B.Sc. Bèta-Gamma, and majored in Physics at the University of Amsterdam. She then pursued an M.Sc. degree Energy Science at Utrecht University, performing her master thesis research on lumiscent solar concentrators at the Physics Department of the Imperial College London. Her master internship on energy and air pollution co-benefits was carried out at the PBL Netherlands Environmental Assessment Agency where she after graduating in 2012 continued to work. Her main topic of interest is energy demand modelling and energy consumption reduction in the energy intensive sectors (such as transport and industry). During this period, she visited the International Institute of Applied System Analysis in Vienna for three months. The work carried out at PBL has been combined into a PhD thesis at Utrecht University in 2017. Currently she is working at the Politecnico di Milano as a postdoc analyzing the impacts of behavior change on efficient energy use and aiming to represent these dynamics in energy system models.

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