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Capturing key energy and emission trends in CGE models:

Assessment of status and remaining challenges

Acknowledgements:

This article is the result of fruitful discussions in the OECD/GTAP workshop "Shaping long-term baselines with CGE models" in OECD, Paris, January 24 - 25 2018, in particular, the break-out session on energy and the environment. We have benefitted greatly from ideas, topics and opinions that were brought up during that session and thank all participants. We would not have been able to assess the modelling and baselining procedures utilised for the various models presented in this article without generous inputs from modellers outside of the author team. Special thanks go to Nick Macaluso, Jim McFarland and Bert Saveyn. All errors are the responsibility of the authors.

1 Introduction

Many of the current modelling and baseline procedures in Computable General Equilibrium (CGE) analysis are motivated by the need to understand potential greenhouse gas (GHG) emission trajectories and possible transition pathways to a decarbonised future. Limiting global warming to below 2°C, or even 1.5°C, in line with the goals in the Paris Agreement will require substantial technological and behavioural transformations (IPCC, 2018). Mid-Century strategies are to be prepared and submitted by all Parties by 2020.[1] The long time horizon of the climate change impacts and technological change makes long-term projections and scenario studies of energy and emissions evolvements necessary.

Our paper provides an assessment of the best practices in CGE modelling when it comes to methodologies and applied modules for representing sectoral energy and environmental characteristics and their projected dynamics over time. It undertakes a review of 15 advanced and regularly used recursive-dynamic CGE models (see Appendix)[2] serving two main purposes. The first is to facilitate that the knowledge frontier on energy technology and emission projections is visible and available for modellers in the research and analysis communities. Sharing knowledge about the state-of-the-art options helps modellers to make better choices in their modelling activities by learning from each other. Second, our assessment informs decision makers and the interested audience about the advantages and limitations of CGE-based projections and current tools. CGE models and results are often perceived as black boxes, and there is a need for contributions like ours to document, explain and evaluate their features.

The main virtue of using CGE models in the study of energy and emissions is that the interaction of energy supply, energy demand and emissions in various economic sectors and regions is placed in an economy-wide context. This enables the accounting for indirect effects and interactions of policies

[1] https://unfccc.int/process/the-paris-agreement/long-term-strategies

[2] All the included CGE models were represented at the GTAP-OECD workshop on "Shaping long-term baselines with CGE models" in OECD, Paris, January 24.-25. 2018.

across markets and across borders as well as technological change. This assessment focuses on the main energy-relevant sectors on both supply and demand sides: power generation, fossil fuel extraction, transport, manufacturing industries and buildings. For each of these sectors, we start by surveying general current and future trends in energy technologies, behaviour and abatement options that state-of-the-art models should capture when used for projections.

Current default modelling of technological change in energy and abatement technologies typically includes a mixture of endogenous substitution of other production factors for energy, induced changes in the energy mix, as well as assumed autonomous factor-specific productivity progress that includes autonomous energy efficiency improvement (AEEI). The cost shares of inputs along with the nesting structure and the elasticities of factor demand dictate how changes in relative prices will affect households' and firms' consumption choices. While energy quantities are typically measured in money-metrics (fixed-price values), physical emissions are commonly linked to the combustion of fossil fuels using fixed emission coefficients observed in the base year or based on chemical contents. CO_2 is represented in most models, other Kyoto greenhouse gases (CH_4, N_2O, SF_6, PFC, HFC and NF_3) are also often included, while local and regional pollutants like NOx, SO_2 and particulate matters are only accounted for in a subset of studies, mostly those focussing on regional air quality. Even more scarce are representations of emissions from processes other than combustion.

After introducing current default characteristics of the specific sector, we visit the most advanced approaches towards capturing technological and behavioural mechanisms. Baseline projections need to represent plausible energy system transitions in the decades to come. Hence, for each sector this assessment starts by examining recent model modifications aimed at improving the description of plausible energy and emissions developments. It then proceeds by discussing challenges with using the models for projecting long-run BaU baselines and other scenarios. We discuss the implications for the base year calibration and the need for and availability of data for parameter quantifications along baselines stretching 20 to 100 years forward in time.

Baselines in this sense are business-as-usual (BaU) projections, i.e., assuming policies already decided upon but allowing for other structural changes in the economic system. Projections rely on three different methodologies – typically in combination – for representing and quantifying the technological development in the baseline,: (a) exploiting novel model characteristics designed for integrating technological bottom-up features and endogenising the responses of investments and utilisation to costs, prices and restrictions, (b) relying on external information sources like GTAP, JRC's Global Energy and Climate Outlook (GECO) balances, IEA's World Energy Outlook (WEO), OECD's Economic Outlook[3], to feed exogenous parameters and variables of the model and (c) linking the model with more technology-rich, partial models in order to provide pathway-consistent values for the parameters and variables.

The purpose is to provide technical insight into recent modelling and quantification advancements and assess their potentials and shortcomings. The paper explains trade-offs in the choice of method. For instance, the approaches have different ambition levels for reconciling bottom-up and top-down, for representing physical energy characteristics and technological detail and for depicting transitional pathways. Finally, the assessment comprises a cross-cutting section on remaining modelling challenges in the environment-energy-economy nexus and considers how the model community is prepared for contemporary, and potentially, upcoming research questions.

[3]See https://www.gtap.agecon.purdue.edu/; https://ec.europa.eu/jrc/en/geco; https://www.iea.org/weo/; http://www.oecd.org/eco/outlook/economic-outlook/.

The experience with these approaches is discussed for each sector in the following subsections. Topical in this context is also calibration of the base year, where national social accounting matrices (SAMs) might need to be supplemented. Having appropriate base-year and baseline values is key to attaining plausible results in subsequent policy analysis. For example, baseline scenario assumptions could significantly influence mitigation costs. A higher energy price in the baseline would reflect higher energy costs share and therefore, normally, higher mitigation costs (Chen et al. 2016). Similarly, how technology and industrial patterns will evolve in the future will be decisive for abatement costs.

Some important lessons can be highlighted from this assessment. The main conclusion is that recent years' advancements in modelling, linking and quantifying allow for a richer and more explicit set of responses to policy and other trends in CGE model analysis. The rapid progress we observe at the research frontier is pivotal for well-informed projections and analysis. The approaches developed recently within the CGE community help to improve the understanding of responses in energy markets and the environment to plausible changes in political and economic conditions in forthcoming decades.

However, there are some caveats. First, input-output information and other economic data are usually not easily accessible at the high resolution that is often preferred. As behavioural and technological modules become more detailed, the data requirements expand beyond national accounts specifications. An additional calibration challenge arises from the fact that some of the specified activities have very small shares in the base year. Then, typical functional forms like Constant Elasticity of Substitution (CES) will not be able to produce plausibly large quantity changes in response to changing surroundings. An alternative is to manipulate the base year shares to be higher than factual data suggest. A difficulty is then how to sum up the input-output matrices, i.e. where to reduce resource use elsewhere in order to inflate the shares of still insignificant but emerging technologies. An alternative is the only later introduction of such technologies, set idle during the calibration period. But, also in this case the modelling of (possibly changing future) input shares and what technologies they actually drive out of the market rely on assumptions that can be contested.

An additional challenge is to account for not yet emerged technologies. The needed information will then not have appeared as data yet, and it will likely deviate from historical trends. One solution is to exploit assessments from experts on energy, technologies or sectors – possibly accumulated in partial models. This approach calls for caution. By nature, such information is subjective and scarce and should be accompanied by sensitivity testing. Further, this kind of information are usually given in technological terms rather than economic and behavioural. A first task is to align economic values with physical energy-related flows (of energy services, transport services, heating services, emissions, etc.). Another, even more challenging issue, is how to translate technological information to behavioural parameters like, e.g., substitution elasticities. These are conventionally perceived as deep, constant economic characteristics that can be based on historical evidence. However, with novel technological opportunities or circumstances, substitution possibilities change, and observations cannot guide us well any longer.

Even if mechanisms that mimic the results of partial models and specific technologies are built into the most advanced CGE models, it will often prove challenging to rely solely on the model's own mechanisms in baseline projections. That will require well-tuned endogenous price and cost movements that, in turn, drive the energy- and emission-related activities. It is a complex task to feed in combinations of inputs producing outcomes consistent with the bottom-up information on which they are based. A common and pragmatic solution is to rely less on endogenous model mechanisms and more on exogenous (or linked) quantitative inputs, while the use of endogenous, bottom-up-informed emulations is rather left for policy shift analysis, where changes in surrounding conditions are usually more limited.

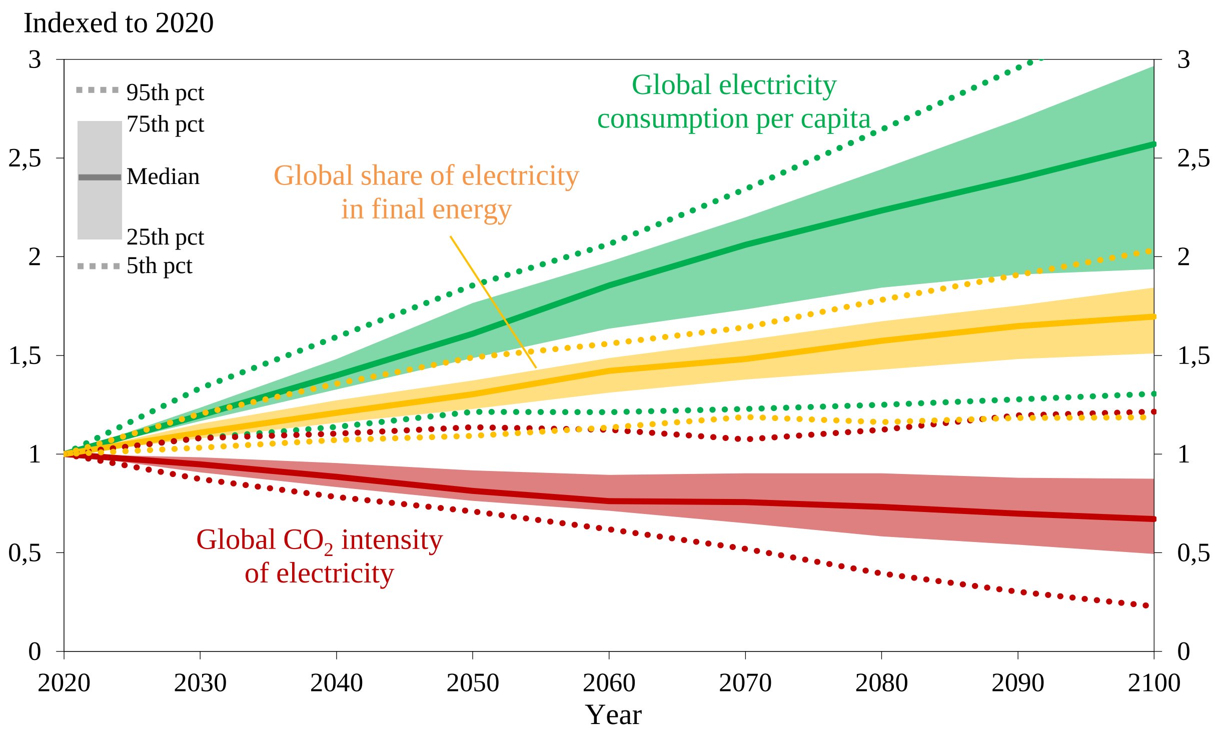
2 Power generation

2.1 General trends in the sector's energy and environment characteristics

Emissions from the electricity generation sector are a key source of global warming and air pollution worldwide. Over the last decade, however, the cost of renewables, particularly solar energy, has fallen substantially. Correspondingly, global investment in the power system is transitioning from fossil fuels to renewables: global investments in renewables have reached a level that more than doubles the investments in fossil fuel-based electricity generation in recent years, while both were at comparable levels ten years earlier (IEA, 2018a).

Based on recent trends, three important evolutions can be anticipated for the following decades. Figure 2.1 illustrates the evolution in electricity consumption and technology mix over the course of the century according to the baseline projections in the IPCC's Fifth Assessment Report Database (IIASA, 2015). First, rising incomes and improved access to energy will contribute to an increase in electricity consumption per capita of roughly 50-75% (25^{th} – 75^{th} percentile) over the 2020-2050 period, with levels in 2100 that are two or three times larger than those in 2020. Second, electricity is expected to increase its share in the overall energy mix. Third, these baseline projections anticipate that electricity generation will imply approximately 8-24% less CO_2 emissions in 2050 (12-51% in 2100) compared to 2020, consistent with further penetration of renewables.

Figure 2.1: Future electricity consumption and technology mix without additional policy measures*



* The figure presents the evolution of the electricity use per capita (n = 240), the share of electricity in final energy consumption (n = 244) and the CO_2 intensity of electricity generation (n = 215) on a global level in the baselines used in the IPCC's Fifth Assessment Report. Data source: AR5 Database, IIASA (2015).

2.2 The modelling of technology and behaviour

CGE models with a focus other than energy and climate would typically not cover electricity generation technologies in a disaggregated way, but rather include an aggregate representation of the electricity sector that covers all production technologies combined with the distribution sector. In this type of setting, the composition of power generation technologies is inflexible and can only be changed through substitutability among production factors. Emissions from each fossil fuel input (usually split into gas, oil and coal) are linked to demand with exogenous coefficients which do not respond to policies or other developments. The options to decarbonize the power system are limited to stylized changes such as a shift from energy to capital inputs. To provide more detail on the implications of the transformation of the power sector, CGE models in the climate and energy field have introduced various improvements, on which we elaborate in the following paragraphs.

2.2.1 Technology disaggregation

Introducing technological detail for power generation is an obvious enhancement of the aggregate approach. As a general recommendation, Krey et al. (2018) highlight the importance of transparency on techno-economic parameters and technology representation. A move towards hybrid modelling (Hourcade et al., 2006, and Böhringer and Rutherford, 2009) brings CGE models one step closer to more engineering-based, bottom-up models. This approach is well on its way to become the mainstream option, as it is applied in, for instance, the GEM-E3, IMACLIM-R, EPPA, ENV-LINKAGES, TEA, AIM/CGE, ADAGE and WEGDYN models. Typically, the detailed technology representation takes the form of a Constant Elasticity of Substitution (CES) function (or Leontief) with explicit emissions of greenhouse gases (and other pollutants) linked in fixed proportions to the use of fossil fuels, with CO_2-coefficients differentiated by the specific carbon content of fuels, and with exogenous assumptions on the evolution of technology costs over time. Technological detail in terms of electricity generation in a hybrid CGE model facilitates the linking between partial and general equilibrium models. The quantification issues of this modelling option are discussed in the context of base-year calibration and baseline building in section 2.3.

With respect to the evolution of costs, we can distinguish models that assume exogenous and endogenous technological progress. The REMIND model (Luderer et al., 2015) provides one example of the latter, including global learning-by-doing curves and internalised spillovers. The DART model (Weitzel, 2017) provides another example, where cost reductions through learning-by-doing apply only to new capital, tracking vintages over time (see 2.2.3 on vintage modelling).

2.2.2 Intermittency of renewables

Going beyond a disaggregated representation of technologies, some models represent additional features of real-world electricity generation, in particular issues related to the integration of intermittency of renewable energy sources (Pietzcker et al., 2017). The EPPA model introduces imperfect substitution between intermittent and non-intermittent electricity generation technologies to reflect the cost of intermittency or models renewables with fixed back-up requirements as perfect substitutes to other sources of electricity (Morris et al., 2010). A similar approach is followed in the USREP model (Tapia-Ahumada et al., 2015). Bachner et al. (2019) include integration costs of intermittent renewables by higher capital costs for wind and solar (grid integration), but also for non-intermittent sources of electricity generation (modified utilization of existing dispatchable power plants). In the AIM/CGE model (Dai et al., 2017), storage and curtailment of variable renewable energy are considered explicitly. Multinomial logit functions determine the shares of power generation sources, depending on the respective costs which are determined by intermediate and primary factor inputs. The share S_r of storage or curtailment in a region r is expressed as a function of the penetration of wind and solar in the electricity generation mix ($Share_r^{wind}$ and $Share_r^{solar}$):

$$S_r = \alpha_r^{wind}(Share_r^{wind})^{\beta_r^{wind}} + \alpha_r^{solar}(Share_r^{solar})^{\beta_r^{solar}},$$

where the parameters α and β are estimated for storage and curtailment separately based on data from a dispatch model using a least squares method. Storage services are then included explicitly as an intermediate input, such that the costs related to intermittency are covered by the model.

Improving interconnections is another way to cope with increasing shares of intermittent renewables in the power mix. Still, cross-border electricity trade is usually represented with standard Armington functions. Although studies point out the potential importance of electricity trade and interconnection capacity (Abrell and Rausch, 2016, and Timilsina and Toman, 2016), particularly with high penetration of intermittent renewable energy sources, a detailed treatment has not (yet) become the mainstream modelling approach.

2.2.3 Capacity investments and vintage capital

In the model approaches described above, the investments in current and new technologies take place smoothly. A realistic assessment of the power system transition could include the time lag to build power plants and their lifetime of operation. Including these details could be facilitated by modelling a vintage capital structure.

In the ENV-LINKAGES model (Chateau et al., 2014), for each good or service, output is produced by different production streams, differentiated by capital vintage (old and new). Capital that is implemented contemporaneously is new – thus investment influences current-period capital, but then becomes old capital (added to the existing stock) in the subsequent period. Each production stream has an identical production structure, but with different technological parameters and substitution elasticities. While new capital is fully malleable across sectors, and derived from an economy-wide investment function, old capital is assumed to be only partially mobile across sectors, reflecting differences in the marketability of capital goods across sectors. There is also homogeneity in the use of old and new capital. The distinction between new and old capital drives results on emissions in ENV-LINKAGES as the two types of capital rely differently on fossil fuel resources and on production inputs. In particular, the elasticities of substitutions for new and old capital reflect the different ease with which the two types of capitals can substitute away from fossil resources towards cleaner inputs.

2.3 Quantifying and parameterising in the base year and baseline

2.3.1 Base-year calibration

As for all input-output and technology structures in CGE models, the social accounts matrices (SAM) provide the basic structure of technologies in the form of base-year cost shares. The calibration is facilitated with improvements on the data side in recent years, with the GTAP-Power database (Peters, 2016) as a clear example. For more detailed representations of power technologies, like in GEM-E3, IMACLIM-R, EPPA, ENV-LINKAGES, TEA, ADAGE and WEGDYN, supplemental data is necessary, typically based on partial equilibrium (PE) models or other detailed bottom-up data studies.

In addition to a monetary representation of energy outputs, some models supplement with energy units by collecting numbers on quantities (e.g. Kilowatt hours) from energy models and inventories. One of the challenges here is that the commonly used CES or CET (Constant Elasticity of Transformation) functions do not preserve additivity, which implies that the sum of the Kilowatt hours generated by specific technologies may not match the total as given by the partial equilibrium energy model. Van der Mensbrugghe and Peters (2016) propose a solution by using a volume preserving CES or CET function, but acknowledge that more work needs to be done to assess the implications of these alternative specifications on model outcomes under a variety of policies.

Also, physical emission units of GHGs must be calibrated. The various fossil fuel flows are associated with fixed unit emissions. A data challenge is that input-output tables provide information on energy market transactions. Emissions data often come from national emissions inventories, which may have emissions other than those accruing from consumption of fuel according to SAMs. One discrepancy can arise as the value of energy reported in the input-output tables may not account for consumption of non-marketed, own-produced energy. This issue is well recognised, and attempts are made to supplement the economic data with the physical energy flow data. In the EPPA and ADAGE models the economic values in energy demand and supply are augmented with accounts in physical terms on energy (exajoules) and emissions (tons). The TEA model follows a linking procedure with the bottom-up model COFFEE that is based on physical flows. The EC-PRO and GEM-E3 models also connect physical flows of energy and emissions with energy technology-based information.

2.3.2 Baseline projections

With the base year as the starting point, the default procedure for undertaking forward projections is to exogenously implement technological change along the baseline through augmenting the total factor productivity term and/or individual factor productivity terms. Among these, the autonomous energy efficiency improvement (AEEI) parameters are particularly useful for targeting energy flows reflected in external projections such as IEA's World Energy Outlook (WEO)[4], or similar.

In order to take into account bottom-up information on expected technological progress in the baseline, CGE models tend to follow one (or a combination) of the three different procedures mentioned in Section 1: (a) Endogenous integration of technological details that emulates bottom-up models, (b) relying on external information, or (c) linking with partial equilibrium models.

The refinements of the power supply modelling described in 2.2. facilitate an emulation of what goes on in more detailed bottom-up models. By projecting exogenous variables like resource constraints, productivity growth and policy interventions, the resulting price and cost impacts, along with the model's endogenous features discussed in Section X, will drive the changes in technological progress and power mix. There are some concerns when relying only on the model's endogenous mechanisms. First, a large variety of assumptions must be consistently estimated, including policies. Already in the base year, a variety of policy measures affect the electricity markets, and more changes might have passed in political processes and would need to be accounted for in a 'current policies' baseline. Another challenge is the small-shares problem pointed out in Section 1. It implies that profound penetration of known and feasible technologies that are not yet implemented (or very minor) in the base year will not take place in a CES structure, which induces relative changes. A similar challenge applies to trade/transmission volumes if transmission infrastructures are expected in the future that are yet non-existing, and trade is based on Armington functions with (nested) CES characteristics. The approach of the AIM/CGE model given in section 2.2 could be considered as a case where certain aspects of the detailed dispatch model – storage and curtailment – are emulated in a top-down CGE model.

Both the small-share problem and the need for reliably projecting many assumptions make inputs of external information – or rather, combinations of the two approaches – more common. The external

[4] https://www.iea.org/weo/

information can come from a variety of sources, such as the WEO and the JRC's energy, emissions, and economic balances published alongside the yearly Global Energy and Climate Outlook[5]. Exogenous resource endowments and productivity parameters are calibrated to give an energy picture consistent with the external sources. AEEIs, technology learning rates, or productivity parameters of inputs can be adjusted over time to match external data sources on cost projections or shares of technologies in electricity generation. As an alternative to changing the energy input efficiency, emission coefficients could evolve over time to reflect technology diffusion or stricter regulation in the future. Typically, elasticity values are obtained from available empirical estimates and kept constant along the baseline, but these are also potential handles for matching external data. Some types of technological change are likely to change substitutability across production factors, including across energy goods.

Baseline projections with the ADAGE model make use of external data (Ross, 2007). Projections of electricity generation by technology are picked from IEA's World Energy Outlook. The energy mix share in the production function in ADAGE is adjusted to capture structural changes, such as the rapid switch of generation from coal to natural gas in the United States in the past few years with the development of lower-cost horizontal fracturing (fracking) technology for oil and gas extraction (see also section 3).

A comparable approach that can go slightly beyond the use of external data is to link CGE models with partial equilibrium energy or power system models. The advantage of connecting to a technology-rich bottom-up model is that more information, in addition to the power mix, can be taken on board in the calibration of the CGE model, such as the evolution of costs and the cost structure of particular technologies. Also, we can be more confident that the inputs are consistent. The established links between the POLES-JRC and the GEM-E3 models (Vandyck et al., 2016), as well as between the COFFEE and TEA models (Garaffa et al., 2018), are good examples of this approach.

To enable the feeding of input from the detailed PE models (POLES-JRC and COFFEE) into the associated CGE models (GEM-E3 and TEA), the latter have implemented disaggregated electricity generation technologies that are combined through a Leontief function. The electricity generation shares are determined by the PE models. This way, relevant economic (overnight costs, fixed and variable operating and maintenance costs, contingency factors, etc.) and technological (discrete investment size, lead time, efficiency, availability, etc.) features of detailed bottom-up models can be accounted for in the CGE models. In addition, the level, evolution, and structure of technology costs feed into the CGE model calibration, and the CGE models incorporate electricity generation in physical units from the PE models. With respect to electricity consumption, the linking between the COFFEE and TEA models is based on energy intensity as a common variable that takes the same values in both models. Thus, in each time-step, the energy intensity parameter endogenously changes in TEA until the ratio between the total energy use (in physical units) and the total production (in monetary units) is the same in both models.

Linking procedures can be more ambitious. As discussed by Delzeit et al. (2019), a *two-way* link will improve consistency between the bottom-up and top-down model baselines in terms of sectoral output or value added linking procedures (Helgesen, 2013; Krook-Riekkola et al., 2017). If necessary, the two-way procedure can be iterated to improve the match across the models. Both the POLES-JRC/GEM-E3 team and the COFFEE/TEA team are in the process of exploring a two-way, iterative approach. When using the baseline as a starting point for a policy study, accuracy can be improved

[5] https://ec.europa.eu/jrc/en/geco

further by simulating the same shift within both models and account for the induced output changes in the iterations.

3 The fossil fuel sector

3.1 General trends in the sector's energy and emissions characteristics

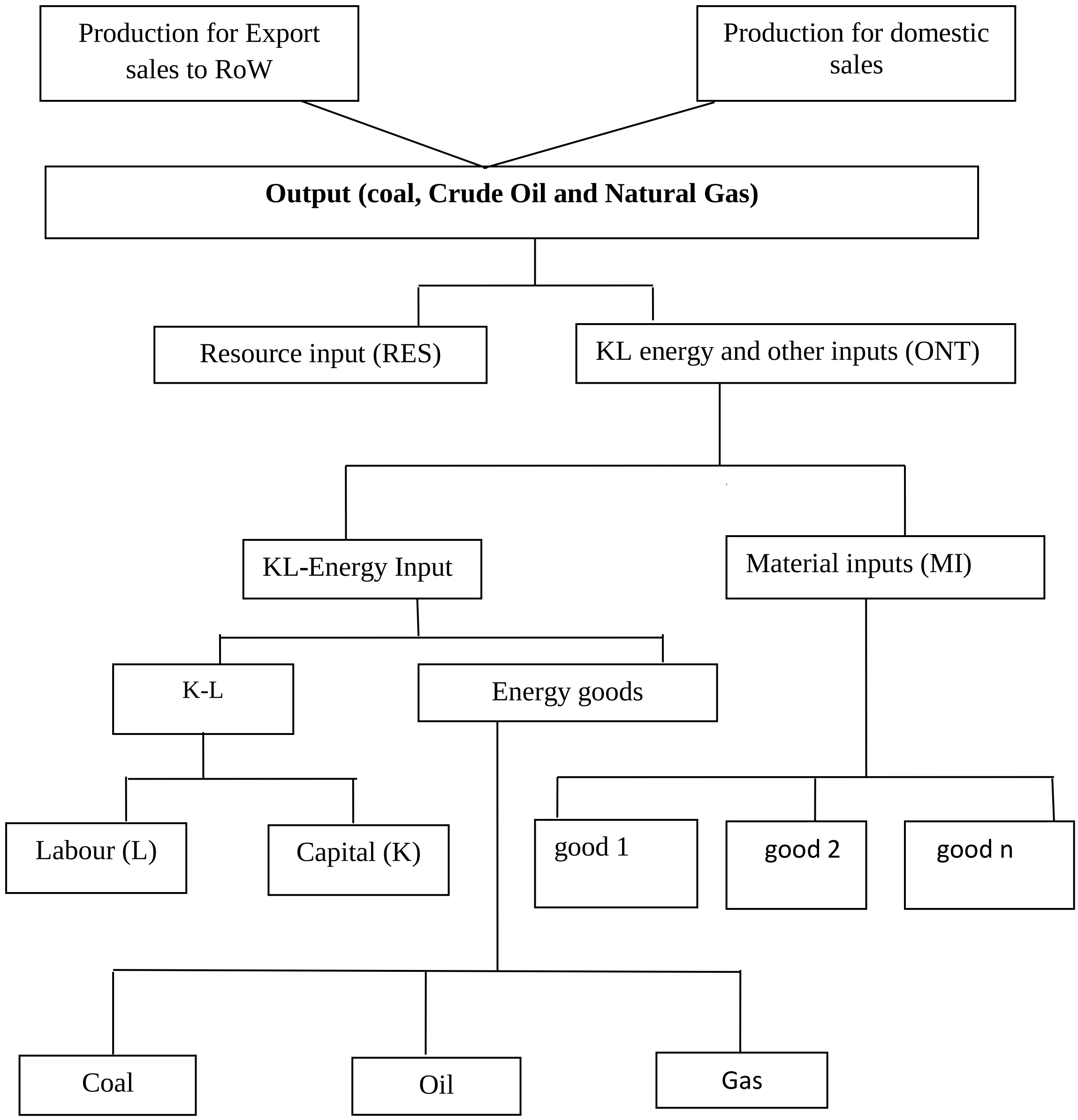
A particularity of the fossil fuel sector is its reliance on natural resources, the proven supply of which is fixed. The cost of extraction of fossil fuels namely, coal oil and gas, rises as these are depleted. However, this sector has been undergoing massive technological innovation in extraction processes over the past decades. For example, the development of hydraulic fracturing (fracking) and horizontal drilling technologies have increased the access to tight oil and shale gas resources and led to increases in supplies of these fuels, not least in the U.S. in recent years. Similarly, in Canada the development of oil sands has spurred along with commercially viable technologies and high oil prices. In Brazil, the pre-salt belt has some of the highest drilling success rates globally and, if effectively exploited, could double Brazil's oil reserves (EPE, 2017). However, despite a North American oil boom, non-OPEC crude oil production is approximately constant because new production roughly balances existing oil field decline which allows OPEC to control the total global oil supply and therefore oil pricing due to their spare production capacity (Cavallo 2016). Arezki et al. (2017) find that shale oil production is more responsive to prices than conventional oil. WEO 2018 reveals that while the historic shift of energy consumption to Asia, there are mixed signals on the pace and direction of change. The demand for natural gas continues to rise due to a period of renewed uncertainty and volatility in oil markets, erasing talk of a glut as China emerges as a giant consumer. The coal demand is projected to decline globally over the next decades as a result of increased competition from gas and renewables.

The future of this sector will be significantly determined by the climate change policies expected by various nations as well as by technological innovations that will take place within extraction technologies and alternatives. The application of artificial intelligence and digital data in this sector is expected to help reduce cost and thus offer prospects in the future (Slav 2018). Although most countries have committed to increase the share of renewable energy generation the production of fossil fuels will still increase for decades (see WEO 2018 and GECO 2017). The pace of energy efficiency improvements and of electrification in end uses like heating, transportation and production processes, the energy mix in the power industry, as well as the extraction sectors' own innovation and adaptation of abatement technologies, will be decisive for the fossil fuel industry's future outlook. It is expected that energy consumption will undertake fundamental change: fossil fuel consumption, coal in particular, will be dramatically reduced.

3.2 The modelling of technology and behaviour

Typically, in CGE models the extraction sectors are represented as a multi-level nested Leontief or CES function with very low elasticity of substitution (Figure 3.1). The functional form at different nest levels may vary slightly between models. At the top level of the nested production function, a sector-specific resource trades off with a composite consisting of labour, capital, energy and other material inputs. At the lowest level, a composite energy bundle is usually represented as a Leontief function of coal, oil and natural gas. Emissions are usually linked to the use of coal, oil and gas at this level.

Figure 3.1: Typical Representation of coal, Crude oil and Natural gas sector



This modelling of a fixed proven resource implies a resource depletion. This aspect is well represented in MIT's Economic Projection and Policy Analysis (EPPA) model (Babiker et al., 2001; Paltsev et al., 2005; Chen et al., 2016). In a recursive-dynamic structure, resource owners do not have perfect foresight. Production in any period is subject to dynamic processes that add reserves from resources and deplete reserves and resources. These features allocate the available resource over time while creating resource rents. The model has estimates of the current rents that are conventionally attributed to three sources: Hotelling, Ricardian, and monopoly (Babiker et al., 2008). The model does not explicitly identify the underlying reason for the rents. The reserve-proving and energy production processes in the model restrict the rate of development and thus create persistent rents.

The resource grade structure with varying quality is reflected by the elasticity of substitution between the resource and the capital-labour-materials bundle in the production function. The elasticities of substitution were then chosen that would generate elasticities of supply that matched the fitted value in the respective supply curves. Production in any one period is limited by substitution and the value share of the resource, i.e., the technical coefficient on the fixed factor in the energy sector production functions. Over time, energy resources R in sector e are subject to depletion based on physical production of fuel F in the previous period. In period t:

$$R_{e,t} = R_{e,\,t\text{-}1} - F_{e,\,t\text{-}1} \qquad (1)$$

This specification implies that fluctuations in the market prices are accommodated by sector specific resource rents. Over the longer-run, the impact is to squeeze out rents and if any production remains it is still priced at long run marginal cost. So, the price drop is limited by the resource rents, and with gradual exhaustion of high rent and low-cost fuels, the underlying marginal cost tends to rise. An importance of resource rents is particularly seen in the effect on oil and coal prices. Since oil has significant rents, and coal has relatively low resource rents, the impact on coal prices is much smaller than the impact on oil prices, but instead there is a bigger impact on the quantity of coal produced than on oil production. A description of modelling these mechanisms in the EPPA model is provided in Babiker et al. (2001), Chan et al. (2012), Paltsev et al. (2005), Paltsev et al. (2011), Paltsev (2012), Chen et al. (2016).

3.2.1 Multiple technologies

While most models do not distinguish between different production technologies, a few models incorporate more detailed technology structures. In Figure 3.2 we represent the crude oil production by technology as in ECCC's EC-PRO model.[6] The crude oil production is disaggregated into 7 technologies. First, Crude-oil subsectors produce either conventional, synthetic or bitumen. Conventional and synthetic crude are treated as imperfect substitutes in the domestic market. Supply response by each technology is controlled by a specific resource factor (lmin, hmin and fmin for conventional and sagd,csss, snds and pnds for non-conventional; see explanation in Figure 3.2). The value share and substitution elasticity with variable inputs determines the price elasticity of supply. The oil refining sector and the coal and natural gas processing sectors use standard nesting structure as in manufacturing sectors, i.e., they do not have resource factors.

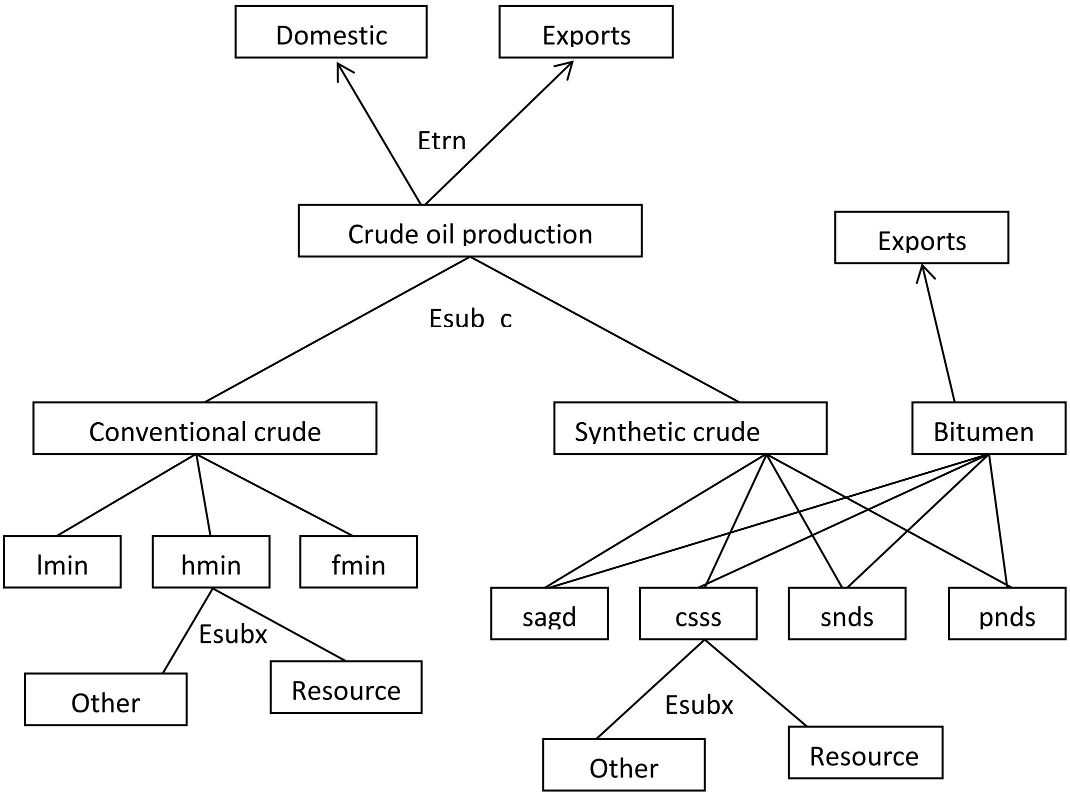
The EPPA model separately represents the conventional and backstop fuel production such as coal gasification and shale oil. In addition, renewable biomass liquids are included as a backstop technology; see 3.2.2. Other models with detailed technology representations are ADAGE, AIM/CGE, MAGNET, TEA and IMACLIM-R.

The IMACLIM-R model deserves more attention. Along with bottom-up details, it explicitly includes depletion and monopolistic behaviour (in the Middle East). As opposed to the formerly mentioned models, CES structures are not used. Inputs are required in fixed proportions irrespective of changes in the relative prices of factors. The model endogenously determines relative prices, physical outputs, demand and the amount of savings in a consistent way and also allow for short-term constraints.

The price is determined by a Leontief function for each region with fixed intermediate inputs and labour intensity. Wages are determined by regional labour markets. Equilibrium prices are directed by a fixed mark-up and decreasing marginal returns of production for each unit of installed productive capital. Based on price signals, the oil and gas bottom-up modules moves the technical frontier between two annual equilibria by adjusting, the mark-up and the productive capacities.

[6] ECCC (Environment and Climate Change Canada) also operates a global CGE model (EC-MSMR) with similar structure.

Figure 3.2: Crude oil production extraction and exports in EC-PRO model



Note: lmin – light oil mining, hmin – heavy oil mining, fmin – frontier oil mining, sagd – steam assisted gravity drainage, csss -cyclic steam stimulation oil sands, snds - oil sands mining (surface), psnd - primary oil sands (in situ), sndu - oil sands upgraders. esub_cru - elasticity of substitution across crude oil types, esubx - elasticity of substitution (supply response).

The oil bottom-up modules of IMACLIM-R seven categories of conventional and five categories of non-conventional oil resources for each region with threshold selling price at which investments in production units are made. The maximum rate of increase of production capacity for an oil category reflects prices as well as geological constraints and follows a bell-shaped profile, depending on the endogenous remaining amount of oil in the field. The function describing this maximum growth rate is calibrated on Rehrl and Friedrich (2006)[7].

The production capacity at date *t* is given by the sum over all oil categories and regions. Non-Middle-East producers are seen as 'fatalistic producers' who do not act strategically on oil markets. Each time an oil category is profitable, they invest in new production capacity given the specific constraint described above. Middle-Eastern producers are 'swing producers', meaning they adjust their production level to apply their market power due to their low costs of production and fluctuation in the rest of the world conventional discovery (Gülen, 1996). As long as they have not reached depletion, they strategically determine their level of investments in order to control oil prices through the payload of their production capacities (Kaufmann et al., 2004). This specific representation allows studying different market power strategies of the Middle-East (see for example Waisman et al. 2012b, Waisman et al. 2013b).

The gas bottom-up module in IMACLIM-R ensures that the evolution of worldwide natural gas production capacities meets demand increases until available reserves enter a depletion process. The

[7] Rehrl and Friedrich (2006) combines the discovery processes (Uhler, 1976) and of the "mineral economy" of (Reynolds, 1999) to model oil production with endogenous bell-shaped profile.

distribution of regional production capacities in the 'gas supply' dynamic module is made with a logit function which captures both reserve availability and the capacity of regional production facilities, using exogenous weights calibrated on the output of the POLES energy model (LEPII-EPE and ENERDATA s.a.s., 2009). Gas markets follow oil markets with an elasticity of 0.68 of gas to oil price. This behaviour is calibrated on the World Energy Model (see WEO 2007) and is valid as long as oil prices remain below a threshold $p_{oil/gas}$.

3.2.2 Endogenous technological change

In addition to fixed-factor specification and autonomous energy efficiency improvements, the ENGAGE model features some aspects of learning curve in the oil and gas extraction sector. An interesting contribution is found in the MAGNET model, which represents endogenous R&D in biofuels (ethanol, biodiesel, 1st and 2nd generation) which implies reduced costs along with profit-induced R&D activity.

3.2.3 Inclusion of renewable fuels

As already mentioned, one of the backstop fuels in EPPA is biomass liquids (together with coal gasification and shale oil). ADAGE introduces eight types of first-generation biofuels and five types of second-generation biofuels. ENVISAGE endogenously brings in new energy commodities such as biofuels that could penetrate under policy scenarios, but this is not allowed for in the baseline simulation.

3.2.4 Emissions and abatement modelling

Most models represent the combustion-related emissions in fixed proportions of energy use, and abatement takes place by energy efficiency or energy mix changes. For process related emissions, particularly the non-CO_2 GHGs, EC-MSMR adapts a simple procedure in which estimates of abatement potentials of non-CO_2 emissions at various technological costs are directly integrated into the model by an activity analysis approach which is similar to that described in Böhringer and Rutherford (2009). By adding realistic future abatement options and their associated economic costs to the model, agents will have a wider range of possibilities than traditional CGE models allow for. These cost curves provide the relationship between the breakeven prices of the carbon for adopting different technologies (see Ghosh et al., 2012 for further detail).

A related procedure is used for including abatement costs in the extraction sector in the model version of SNOW calibrated to the Norwegian economy.[8] The lion's share of emissions from Norwegian offshore petroleum extraction is modelled as process emissions from a variety of activities including flaring, transportation leakages, combustion etc. The emission intensity can be endogenously altered through installation and deployment of abatement technologies. A marginal abatement cost function linking costs of the marginal measures, *c*, to accumulated abatement potentials, *D*:

$$c = f(D) \tag{1}$$

is inserted along with the two following equations, which determine two endogenized variables: μ, the emission intensity of the process, and ε, the total factor productivity (TFP) parameter:[9]

$$\mu = \mu_0 - \frac{D}{X} \tag{2}$$

[8] The original module was introduced in SNOW's predecessor MSG-TECH (Fæhn and Isaksen, 2016).
[9] TFP = 1/ε

$$\varepsilon = \varepsilon_0 + \frac{E}{X} \quad (3$$

Equation (2) represents the benefit of the novel technologies in terms of reduced emission intensity. μ accounts for endogenous abatement, *D*, per unit of output, *X* , *in addition to the exogenous, calibrated base year intensity,* μ_0 . Equation (3) accounts for resources devoted to abatement costs: the higher the abatement costs, *E*, the more resources per output, the higher is ε, i.e. the lower is TFP. In addition, TFP is affected by the *projected exogenous TFP parameter,* ε_0*. E is defined* as the integral of marginal abatement costs, *c*, or, by inserting (1):

$$E = \int f(D)dD \quad (4)$$

This modelling ensures that the actual resource costs of technological abatement are captured, while avoiding the need to insert a new activity in the input-output system. The latter would require recalibration of the model, which complicates updating to new base years, more abatement industries, or novel technological information. Note, however, that the solution implies that abatement costs implicitly assume the same factor mix as output.

3.3 Quantifying and parameterising in the base year and baseline

3.3.1 Base year calibration

The more detailed representations in EC-PRO, ADAGE, AIM/CGE, MAGNET, TEA, EPPA and IMACLIM-R need data sources for the fossil fuel extraction sector beyond national SAMs. Some make use of more detailed, energy models; e.g. AIM/CGE and TEA (see Section 2). The sources for elasticity values are, typically, available empirical studies. For EPPA, for example, supply curves for natural gas were updated as reported in Paltsev et al (2011) and MIT (2011), while supply curves for oil were updated as reported in Chan et al (2012). Another approach is chosen in ECCC's EC-PRO model, where substitution elasticities are estimated based on simulations of a detailed energy technology model called E3MC. Simulations are undertaken for large number of energy price (for coal, oil, gas, electricity) scenarios and the results used to estimate the elasticities. The advantage of this approach is that foreseeable technological progress usually well captured in energy models are fed into the CGE model through the values of the elasticity parameters.

While the input-output tables provide the basic technology characteristics of the production (and consumption), these are values of marketed transactions in money-metric terms. This deviates from data on emissions from countries' emissions inventory systems, which may contain emissions other than those accruing from marketed energy consumption. This inconsistency does in principle apply to all energy-consuming and combusting sectors, also the extraction sector. See Section 2.3 for a more detailed discussion.

3.3.2 Baseline projection

Once the data alignment and calibration of the model for the base year is complete, forward projection of the model is undertaken. The default procedure for projecting technological change is to augment total factor productivity and/or individual factor productivity parameters – cf. Section 2.3.3 for more details. With the more detailed, hybrid modules for the fossil fuel extraction sector described in Section 3.2, technology developments as a response to simulated cost and price changes can be projected more explicitly.

Other approaches are to rely on external sources for the various cost share changes or linking with partial equilibrium models (see Dezeit et al., 2019). For example, the EC-PRO for Canada soft-links with E3MC for projecting oil and gas supply by technology characteristics. The E3MC projection incorporates the potential impacts of policies and measures already taken by federal, provincial and territorial governments. It is also aligned with Canada's historical emissions. The TEA model links its energy intensity to simulated values from the energy model COFFEE in a way that does not modify the general equilibrium effects. In each time-step, the energy efficiency parameter in the oil and gas sectors endogenously changes until the ratio between total energy use (in physical units) and total production (in monetary units) is equal in both models. This way parameters that are normally exogenous, are now endogenous, introducing energy efficiency, technical improvement and/or behaviour change into the model. In both models, fossil fuel quantities are also developed in physical units, as are natural fossil fuel endowments, by accounting for efficiency improvements and resource depletion.

4 Transportation

4.1 General trends in the sector's energy and emissions characteristics

The transportation sector covers different economic activities and is usually split into passenger and freight transportation activities. The demand for passenger transportation services is expected to grow with GDP and income per capita, though may change faster or slower than income per capita depending on the development stage. Historically, the demand for freight transportation services has been historically correlated with economic growth and industry and agriculture production levels, but recent trends in Europe for example prove to show that a decoupling between GDP and freight can operate when a certain level of development is reached (IEA, 2009).

When it comes to energy and environmental issues (whether pollution or climate change), transport is a key sector. It counts, in terms of CO2 emissions for example, no less than 24% of the total global CO2 emissions from fuel combustion. The determinants of carbon emissions in the transportation sector are (i) either technological with the carbon intensity of the fuels and the energy intensity of operating the vehicles, (ii) or behavioural with the modal structure of the mobility and its volume (Chapman, 2007; Schafer, 2012). For a full accounting of all life-cycle emissions of transport activities, vehicle stock and infrastructure, also emission intensity of vehicle and infrastructure production would need to be included. In the usual emission accounting these emissions are not allocated to the transport sector, but to the respective manufacturing sectors or vehicle and infrastructure construction. But even for emissions of the operating phase of vehicles one has to be carefull, if electric vehicles (or electric trains) are concerned. For the energy carrier electricity emissions (pollutants and greenhouse gases) are usually accounted for in the energy supply but not the transport sector.

Energy and CO_2 efficiency of vehicles is increasing fast, especially due to new standards for light duty vehicles and efficiency is expected to continue improving in the future. At the global level, passenger transport energy efficiency has improved with an annual rate of 0.5% between 2000 and 2016, while the annual efficiency improvement rate of trucks in the same period is less than 0.1%. The aviation and shipping past trends are much stronger, enhancing efficiency with annual improvement over these 16 years of about 3.6% and 2.1%, respectively (IEA, 2018a).

In addition to these global efficiency improvements, electrification and biofuels largely contributed to the slowdown in global transport emissions growth. We indeed observe a growth of these global sectoral emissions of 0.6% in 2017 while they used to grow at the annual rate of 1.7% over the past decade. However, despite this positive picture, the IEA estimates that much more efforts[10] are needed to reach the "well below 2°C" target (IEA, 2018b).

Globally, no major changes of the modal structure are expected in a BaU baseline (i.e., when no new policy is implemented) and road transportation is expected to remain the first transportation mode for both passenger and freight transportation in the decades to come (IPCC, 2014b). The evolution of mobility volumes and of modal choices ahead will be closely linked to infrastructure availability, urban forms, and how production and distribution processes are logistically organised (Waisman et al., 2013a).

However, it is worth noting that within road transportation a shift is expected to happen for light duty vehicles with the increasing market penetration of electric-powered vehicles (EVs). Globally, total EV sales have increased from less than 500000 units per year in 2013 to over 3 million units per year in 2017 (IEA, 2018c). In the United States, although adoption rates of EVs are still low, production has been increasing over time and the country represented the largest share of the global EV stock until 2015 (IEA, 2018d). In 2016, the share of production of hybrid vehicles, plug-in hybrid vehicles, and electric vehicles in the U.S. was 1.8%, 0.3% and 0.5% respectively. Preliminary data for 2017 suggests that these production shares increased to 3.3% hybrid vehicles, 0.9% plug-in hybrid vehicles, and 1.0% electric vehicles (EPA, 2018). That same year China had become the country with the largest stock of EVs with more than 30% of the global stock. In terms of leadership, China remains currently on top when the electrification of other transportation modes than private cars is concerned (i.e. more than 200 million two-wheeled electric vehicles, almost 4 million low-speed electric vehicles and more than 300000 electric buses). (IEA, 2018b). Nevertheless, although the market share of EVs is close to 40% in Norway, a country occupying the first position, this market remains quite small in all other countries. China who occupies the 4th position observes its EVs' market share amounting to 2.2% in 2017 and the United-States one to 1.2%. Finally, one can note that as an answer to environmental challenges, EVs are anticipated in many scenarios to represent the bulk of the vehicle fleet by 2050. Needless to say that this electrification of the transport sector – we noted earlier that electricity generation emissions are accounted for outside that transport sector – will only reduce overall emissions to the degree electricity production is emission free.

Beyond electrification of transport we can also highlight the fact that many countries have expanded use of biofuels in recent years. Globally, the IEA estimates that biofuel consumption for transportation increased by over 33% between 2010 and 2016- from about 59 Mtoe in 2010 to about 79 Mtoe in 2016 (IEA, 2018b).

4.2 The modelling of technology and behaviour

The default representation of transport activities in CGE models follows the rules of national accounts. The households primarily demand passenger transportation. This is accounted for in final consumption, where transport services are usually distinguished as a separate activity in the top bundle of the utility function. Typically, transport demand from households is split between services purchased from commercial firms and those supplied by own vehicles in combination with energy demand (petrol and diesel). Only rarely is this same demand structure used for firms (e.g., Heide et al., 2004). It is more common to retain vehicles as part of a capital aggregate, petrol and diesel within

[10] A peak around 2020 and a falling by more than 9% by 2030.

aggregate fossil fuel demand and purchased transport services within intermediates. The utility function in CGE models has traditionally been of the CES type. Other functional forms that allow for income elasticities different from unity are becoming more common; see Lanz and Rutherford (2016). The purchased transport services are supplied by firms in production sectors. Supply of passenger and freight transport services are usually merged. A default solution is that commercial transportation sectors are split in the dimensions water, air and other, the latter covering all land transportation. Production inputs are CES combinations of labour, capital, non-energy intermediates (where commercial transport services are part) and energy (without purpose specified). This aggregation level is available as GTAP data. In all specifications, autonomous energy efficiency parameters (AEEI) are used to implement exogenous, factor augmenting energy efficiency improvement for both private transportations in utility functions and for transport productive sectors in their production function. The following sections exemplify refinements of the modelling of both the behavioural and technological determinants.

4.2.1 Splitting the transport sector

In the transportation industry, technology improvements, represented by decreased energy usage per unit of output, vary significantly by transportation mode. Disaggregation of the transportation sector can improve the representation of energy substitution possibilities among and across transportation modes. Many national accounts also separate between rail and road transportation, as well as domestic and international air and water transport, and these categories can be exploited to grasp substitutability and emission impacts on more detailed levels.

In the ADAGE model, the transportation sector is disaggregated into eight types (light-duty passenger, road freight, road passenger, rail freight, rail passenger, air, water, and all other transportation) (Cai et al, 2018). Transportation service, the monetary value for passenger-miles-travelled for passenger transportation and ton-miles-travelled for freight transportation, is produced within nested CES functions using energy, capital, labour, and materials as inputs. The bottom-up approach used in ADAGE links the physical accounts and monetary accounts together, allowing tracking of fuel economy, vehicle-mile-travelled and price of passenger-mile-travelled for passenger transportation or ton-mile-travelled for freight transportation.

In the WEGDYN single-country model for Austria, special emphasis is placed on the disaggregation of the land transport sector, which is composed of nine different sub-sectors, each one of them being explicitly modelled via different production functions. The model is responding to three main drawbacks of traditional representations, first, by identifying passenger and freight transportation, second, by distinguishing long from short-distance transport and, third, by explicitly modelling infrastructure provision.

As described in Bachner (2017), the WEGDYN model differentiates between the following land transport sectors, which can be summarized as three groups: First, *Motorized Individual Transport* (MIT) is isolated from the generic final demand vector and treated as a separate Leontief type production function, that produces output which is only absorbed as final demand of the representative private household (i.e. individual transport). Second, there are five *land transport service sectors* (rail freight, rail passenger long-range, road freight, short range public transport, rest of transport services (i.e. postal services, warehousing etc.), each one of them modelled as nested CES functions. Third, *land transport infrastructure providers* comprise separate sectors responsible for road infrastructure provision, rail infrastructure provision and the rest of land transport infrastructure provision (pipelines), again modelled as nested CES functions. In addition, the model comprises a water transport and an air transport sector.

The AIM model system adopts a hybrid modelling approach, where results from a separate AIM/Transport model are fed into the AIM/CGE model and the information exchange between them is iterated (Zhang et al., 2018a and 2018b). The AIM/Transport model selects among several modes x technologies endogenously, and the result is that the AIM/CGE model is able to reflect such detailed behavioural choices. All transport sectors are interlinked with the rest of the economy via I-O structures, and each economic sector needs transport service as an intermediate input in order to operate. The transport service sectors, in turn, additionally rely on transport infrastructure in their operation (see Supplementary Material of Bachner (2017) for details on the nesting and elasticities).

4.2.2 Modelling Alternative Fuel Vehicles

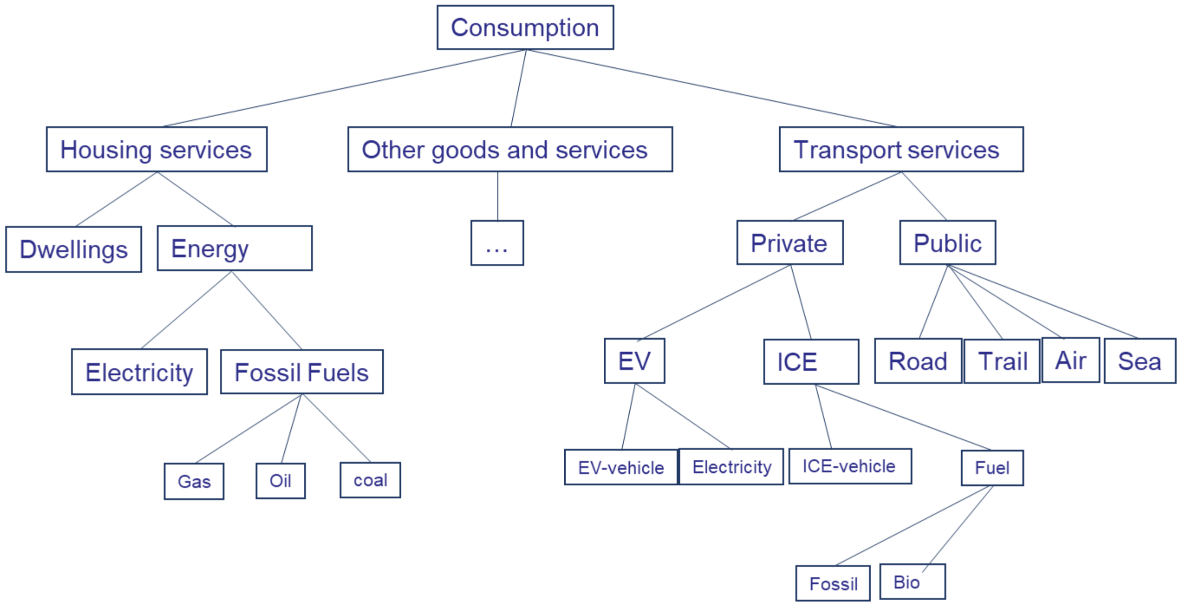
Because of environmental concerns, high oil prices and the potential for peak oil, development of cleaner Alternative Fuel Vehicle technologies (AFVs) with higher fuel economy has become a top priority for many governments and vehicle manufacturers around the world in recent years. Therefore, these technological options are represented in many models.

Typically, the EPPA model (Chen et al., 2016; Paltsev et al., 2018) represents a penetration of AFVs (electric, hydrogen, CNG). When initially adopted, the advanced vehicle technology faces increasing returns to scale to capture the intuition that development and early deployment are more costly per unit produced until large-scale production volumes have been reached, which also affects its cost relative to the Internal Combustion Engine (ICE) vehicle. As ever larger volumes of advanced technology vehicles are introduced, cost of further scaling production will fall accordingly (Karplus et al., 2013; Morris et al., 2014). The model captures the intuition that the cost and pace of deployment should depend on when these vehicles become economically viable, stringency of the fuel economy standard, and the rate at which costs decrease as production is scaled up.

ADAGE includes four categories of AFVs (natural gas , electric battery, oil-electric hybrid -such as plug-in hybrids-, and fuel cell hydrogen drivetrains) for all types of on-road transportation vehicles in the model (light-duty vehicles as well as heavy-duty vehicles such as trucks and buses). Production and consumption of AFVs are defined within the context of the market for transportation services, in terms of passenger mile-travelled for passenger vehicles and ton-mile-travelled for freight vehicles. Both EPPA and ADAGE introduce a fixed factor input and an elasticity of substitution between the fixed factor and the rest of the bundle to the top nest of CES production function. In ADAGE, biofuels can substitute for refined oil in both conventional technologies and AFVs. The transportation services produced by AFVs are modelled as perfect substitutes relative to their counterpart—conventional internal combustion engine technology. The entry of these AFVs is endogenously determined and takes place only when they become economically competitive relative to their conventional transportation counterparts.

In the SNOW version of Norway, the distinction between the technologies of electric vehicles (EV) and ICE vehicles is made in the household's utility function, depicted in Figure 4.1. Also, the model allows for substitutability between fossil fuels and biofuels and separates rail from road transport.

Figure 4.1: The consumption CES structure in SNOW



4.2.3 Behavioural aspects: mobility demand and travel time

In the dynamic, recursive and hybrid IMACLIM-R model (Waisman et al., 2013a), the standard representation of transport technologies is supplemented by an explicit representation of the "behavioural" determinants of mobility. Each representative household maximizes its utility through a trade-off between consumption goods and mobility services. The consumption of goods and services is above a minimum level. For mobility services, these basic needs measure constrained mobility (i.e. the minimum level that households have to satisfy, mainly for commuting and shopping). To provide the mobility service, four transportation modes are considered: terrestrial public transport, air transport, road transport (private vehicles[11]) and non-motorized transport (walking and biking).

Households maximize utility under a twofold constraint that affects transportation decisions. On the one hand, the standard budget constraint captures that transport-related expenditures enter into a trade-off with the consumption of other goods. On the other hand, the demand for transportation services by households and modal share is constrained by a time budget constraint to represent the stability of travel time budget across time and space at a regional or national scale. This constraint allows taking into account congestion effects. Travel time, congested traffic, and trip purpose are typically elements that receive more attention in spatial CGE models. Vandyck and Rutherford (2018), for instance, study dynamic road pricing for commuters with a regional CGE model that includes congestion and agglomeration externalities. Although they do not look into the environmental implications of the studied tolling schemes, reducing traffic congestion can reduce both time lost in traffic and emissions.

The IMACLIM-R representation, in addition to the dialogue between the *top-down* structure and the *bottom-up* modules allows to represent (i) the rebound effect of energy efficiency improvements on mobility, (ii) endogenous mode choices in relation with infrastructure availability, (iii) the impact of investments in infrastructure capacity on the amount of travel, and (iv) the constraints imposed on mobility needs by firms' and households' location (urban forms).

Still in IMACLIM-R, production functions of all the sectors take the form of Leontief specifications, with fixed equipment stocks and fixed intensity of labour, energy and other intermediary inputs in the

[11] Within the personal vehicles market, three types of technologies are represented: Internal combustion engine standard, Efficient internal combustion engine, Electrical vehicles (EVs representing implicitly all types of vehicles that use electricity as service provider, including fuel cells and hydrogen vehicles)

short-term[12]. This means in particular that, at a given point in time, the freight transportation intensity of production is measured by input-outputs coefficients which define a linear dependence of freight mobility in a given mode to production volumes of a given sector. The higher the production volumes, the higher the freight mobility demand. Three freight transportation modes are considered: air, water and terrestrial transport. This input-output representation of freight mobility allows capturing changes in *(i)* the energy efficiency of freight vehicles, *(ii)* the logistic organization of the production/distribution processes, and *(iii)* the modal breakdown

4.2.4 Capital vintage modelling

Instead of relying solely on autonomous energy efficiency improvement (AEEI) parameters to attain technological improvements, some models have introduced endogenous mechanisms. One "semi-endogenous" solution is to split capital use into industry-specific extant capital and new capital. By doing so in the commercial transport sectors, different (exogenous) efficiency assumptions for new and old vintages are allowed for, implying implicit technological change as new (endogenous) investments are made. The vintage solution can also capture that technological change take time, since old vintages are assumed unable to leave the sector, which is for example the case in the IMACLIM-R model. The vintage model is implemented in the ECCC models (both the global *EC-MSMR* and the country model for Canada *EC-PRO*). In ADAGE, a vintage structure is applied to all conventional transportation technologies and aligned to their life expectancy.

Given that the fuel efficiency and CO_2 standards apply only to new model-year vehicles, differentiation between the new and used vehicle fleets is essential, the EPPA model includes a parameterization of the total miles travelled in both new (0 to 5-year-old) and used (6 years and older) vehicles, tracking changes in travel demand in response to income and cost-per-kilometer changes. The EPPA model also represents the ability to substitute between new and used vehicles – another way consumers may respond to changes in relative vehicle and fuel prices as affected by the introduction of vehicle standards, fuel prices, or carbon prices (reflected in fuel prices). Details for representation of fuel and emission standards in the EPPA model are provided in Karplus et al. (2015).

4.2.5 Behavioural modelling: introducing new transport business models

One crucial element to reduce transport emissions is behavioural change, possibly induced by the availability of new organisation forms of transport. In the passenger transport this includes sharing concepts such as car sharing (Prettenthaler and Steininger, 1999). New business models lend themselves particularly well to be analysed by CGE transport models or modules. As a prerequisite the modeller needs to combine a demand structure similar as given in Figure 4.1 with a detailed production structure (and the embodied energy intensity) of vehicles (both the ones used in the new system and the ones substituted for by the new system). As exemplified by Steininger and Bachner (2014), a car-sharing system introduced for commuters, with the vehicle fleet used by the commuters to reach the closest train station and over the day by a standard all-day use such as postal service or mobile health care, can on this basis be analysed for its economic and environmental implications. Based on such BaU modelling and the experiences from a field experiment of a set of commuter and daytime users a roll out to the full nation was possible to be simulated to quantify the emission reduction of both the mode shift of commuters to the major fraction of their trip to electric trains and

[12] These Leontief specifications (with fixed inputs per unit of production) are nevertheless characterized by flexible utilization rates of installed production capacities.

the reduction in the car fleet, with the CGE approach also acknowledging for the indirect and aggregate market effects.

4.3 Quantifying and parameterising in the base year and baseline

The disaggregate representations of consumption shares, production shares, trade shares, and production cost shares in many of the models (see 4.2.1) exploit different data sources.[13] In the case of ADAGE, for instance, input/output data from Global Change Assessment Model (GCAM), national I/O accounts data, GTAP data and the six transportation sectors (road, rail, air, water, pipeline, and other) in the World Energy Outlook database are used.

The quantification of the competition between AFVs and ICE in projections is challenging, because the penetration and the technological features of future AFVs likely deviate significantly from the current status. Thus, historical data can be of minor relevance for the technologies and preferences for the decades ahead. The SNOW model version for Norway relies on forward-looking projections from MDIR (2016), which has calculated the costs of phasing in EVs to meet different targets for the share of EVs in the fleet in 2030 (and subsequent emissions levels of CO_2). The costs of a larger EV share in 2030 are in MDIR's data related to compensating the consumer for the increased user-cost of the 2030 fleet. Their user-cost estimates also account for the value of the consumer's disadvantage when using an EV instead of an ICE related to weaker technological performance of EVs. Thus, one can interpret the costs of increasing the EV share of the fleet as how much the consumer must be compensated for being willing to take on these larger costs. This is exactly what we need to calculate the CES parameter between the two technologies, which represents the inclination to increase the relative use of EVs to ICEs for each percent increase in the relative user-cost of ICEs to that of EVs for a given demand for transport services; see Figure 4.1.[14]. The result of the calculation is an elasticity of 2.7 by 2030.

In EPPA and ADAGE, another approach is used to quantify the competition between AFVs and ICE The elasticity of substitution in ADAGE is obtained from an econometric estimation based on historical observed data while the mark up factor, defined as the relative cost ratio between AFVs and ICE, measures the dynamic technological advancement.

5 Manufacturing industries

5.1 General trends in the sector's energy and emissions characteristics

Manufacturing industries are often energy intensive and are large consumers of fossil fuels for combustion. In addition, the production *processes* themselves often emit CO_2 or other gases, termed "industrial process emissions." The most important process emitting manufacturing sectors in absolute terms are the production sectors of metals, minerals and basic chemicals (Lechtenböhmer et al., 2016). A quantitatively quite prominent source of process CO_2 emissions is cleaning of iron ore from oxygen by means of coke in steel production. CO_2 is also released as a by-product of transforming the intermediate product clinker to lime, a component of some types of cement. Also, the GHG N_2O is a process emission from production of fertilizers, and emissions of the GHG PFC results from certain aluminium production processes.

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[13] Because of space limitation, only some illustrative examples are given here. The reader can refer to each model documentation for specific details

[14] The other substitution elasticities are estimated on historical data (Aurland-Bredesen (2017); Aasness and Holtsmark (1996); Elkadi (2017). The substitutability between fossil and bio fuels is not activated (elasticity set to 0). A reason for this is that bio fuel in Norway is promoted by blending mandates, implying fixed shares.

As opposed to energy or combustion related GHG emissions, process emissions are more difficult to abate. Efficiency measures can help here, but are not sufficient for deep decarbonization, as emission reduction is limited by chemistry, i.e. stoichiometric principles. For a deep decarbonization there are basically three ways for reducing process emissions: First, by reducing the sectoral activity and replacing emission-intensive materials (e.g. substituting steel by bio based polymers in car production), second, by changing the whole production process to maintain the production activity (e.g. switching to "electrowinning" in steel production, where renewable electricity is used to substitute for carbon-based processes) and third, by using end-of-pipe technologies (essentially carbon capture and storage or use (CCS or CCU); see Lechtenböhmer et al., 2016). Another issue that complicates the reduction of process emissions on a global scale is the fact that process emission-intensive sectors are heavily involved in international trade and thus leakage prone (Bednar-Friedl et al., 2012; Schinko et al., 2014, Mayer et al., 2019).

When looking at the recent development of the steel and cement sectors, the importance of tackling process emission from these sectors becomes even more evident. Between 1980 and 2010 emissions from these two sectors have increased sharply, with annual growth rates between 2-4%. Driven by a strong increase in demand, global steel production has doubled and cement production more than tripled, within the same period. The corresponding annual CO_2 emissions in 2010 from the steel and cement sectors amounted 3.3 Gt and 3 Gt, respectively (van Ruijven et al., 2016) with at least half of that from process emissions. Regarding the basic chemical industries, we see a similar picture, with growth in physical output (measured in tonnes) having even exceeded the one of steel since 1989, with current annual CO2 emissions of 1.7 Gt (Broeren et al., 2014).

Other topics that are related to reducing process emission reductions are recycling, or more generally, the "circular economy", as well as new material research, aiming at the substitution of process emission intensive products. We will come back to these subjects in Section 7.

5.2 The modelling of technology and behaviour

The combustion-induced emissions from industries, including manufacturing, are adequately modelled in most models. The modelling of process emissions in CGE models is scarcer. If process emissions are accounted for, they are typically modelled *proportional to sectoral output at the top level of the nested production functions*. Examples for this default inclusion are the ENV-Linkages model (Château et al., 2014), the MIT EPPA model (Paltsev et al., 2005) or SNOW (Bye et al., 2018). The default when it comes to abatement modelling, is to include the usual endogenous substitutability of other factors for energy and across energy forms, else AEEI, substitution elasticities and emission coefficients are exogenous. Among models accounting for process emissions, the default is, thus, *exogenous emission factors* that can be adjusted in projections to account for anticipated abatement.

5.2.1 Emission-reducing technology specification

A few models specify endogenous process emission reduction. In SNOW and GEM-E3, marginal abatement cost (MAC) curves are included for selected process-emitting sectors (see Fæhn and Isaksen, 2016 and Capros et al., 2013, respectively). The WEGDYN model allows for new production technologies options based on (renewable) electrification for iron and steel (Mayer et al., 2019; Schinko et al., 2014). A similar modelling is used in the MAP-CGE model for cement (Jun et al., 2014).

Inserting marginal abatement cost curves implies that change in the costs of emitting can endogenously alter process emissions through deployment of abatement technologies. Potential technology options are exogenously specified, but endogenously chosen by the firms. In SNOW, the abatement and related costs in the industries producing cement, chemicals, metals and pulp and paper are modelled analogously to what is described for the Oil and Gas sector in section 2.2.4. Induced abatement changes parameters of existing technologies via i) changed emission intensity and ii) changed total factor productivity to account for additional costs of abatement. Note, that since abatement technologies are not modelled explicitly, the cost structures of abatement measures have the same unit costs as the technologies which are equipped with these abatement measures.

Also, GEM-E3 models non-combustion CO_2 and the non-CO_2 emissions as proportional to output with abatement following a MAC curve. The approach used in GEM-E3 is comparable to the activity analysis described in Kiuila and Rutherford (2013). Abatement in GEM-E3 requires additional intermediate inputs, delivered by other sectors (such as construction), hence capture general equilibrium mechanisms of changed unit cost structures (as opposed to the approach in SNOW).

In the WEGDYN model, the approach of modelling abatement Is different, here exemplified for the iron and steel sector. Abatement is not based on a MAC curve, which alters existing technologies, but is modelled by the introduction of a completely new production technology (activity) explicitly, thus closer to the actual technological development for process emission abatement, ultimately dependent on switching technologies. In WEGDYN one can switch from the current conventional process-emission intensive technology (blast furnace-basic oxygen furnace, BF-BOF) to a hydrogen-based process-emission-free technology, which is calibrated to bottom-up cost information provided by stakeholders from the steel industry (Bachner et al., 2018; Mayer et al., 2019). This switch is introduced exogenously and represents a more fundamental switch of production technology, not just marginal improvements, as is the case with MAC-curve-based approaches. Note that the approach used in WEGDYN deals with the issue that in process industries emission reduction of existing technologies is limited by chemistry, which is given by stoichiometric principles. This implies that when following a MAC curve approach a modeller should take care when going to very high abatement levels in these industries, as the MAC curve actually must show jumps at the point where chemistry limits further marginal improvements, requiring a sudden switch of the whole production process.

5.3 Quantifying and parameterising in the base year and baseline

By default, process emissions, if represented, are calibrated based on national accounts and emission inventory data (e.g. UNFCCC, 2017) in the base year, and the emission coefficients are exogenously prolonged into the future. To represent changes over time, the GEM-E3 model use baseline emission coefficients calculated in IIASA's bottom-up GAINS model, where process emissions are abatable by end-of-pipe options. That is, even if GEM-E3 has modelled MAC curves that endogenise abatement of process emissions in manufacturing, only the policy scenarios, not the baseline projections, rely on these mechanisms. The emissions are available for different scenarios of GAINS that reflect three different policy stringency levels for the GEM-E3 baselines. Similarly, WEGDYN prolongs base year emission coefficients in the baseline, with the switch to a new process emission-free alternative only taking place in the policy scenarios.

In SNOW, two options for baseline construction are available: Either exogenous emission coefficients as in GEM-E3 or using the endogenous MAC curve to endogenise the coefficient and the related costs. The bottom-up information used to estimate the MACs involves various substitutions in processes of bio (e.g. bioanodes instead of carbon anodes, bio-blended composites in ferro-silicon and silicon production), as well as CCS/CCU. See Fæhn and Isaksen (2016) for details and data sources.

6 Buildings

6.1 General trends in the sector's energy and emissions characteristics

The building sector, when termed in the energy research field, usually includes two kinds of sectors, namely *residential* and *commercial* sectors. The energy consumption in the building sector accounted for 32% of final energy consumption that is 32.4 PWh in 2010 ((IPCC, 2014a). The energy consumption in the residential sector is about three times higher than that in the commercial sector. The space heating represented 32-34% of energy consumption in these sectors. Developed countries consume more residential energy per capita than developing countries. Globally, the energy consumption in the commercial sector has increased while that in the residential sector has been almost stable during the last decades. The energy carrier composition has changed, particularly in developing countries where we have seen a shift from traditional biomass and coal to cleaner energy such as gas and electricity.

Globally, the GHG emissions from the building sectors reached 9.18 GtCO2eq in 2010 which is around 19% of total emissions. This number accounts for direct as well as indirect emissions, the latter constituting around two thirds of the total. From 1970, the total emissions have increased by around two times, whereas direct emissions have almost stagnated.

Along with the historical trend, the energy consumption within the building sector in developing countries is often projected to increase dramatically, particularly in South Asia; see, e.g., IPCC (2014a). A main driver is income growth that enables many people with currently poor energy access the access to modern energy options.

6.2 The modelling of technology and behaviour

The energy consumption in residential sector is a part of the energy consuming activities made by household in the CGE or SAM context. Usually, energy for cooling, heating, water, lighting and use of other electric appliances corresponds to the residential energy use category in energy system accounting such as energy balance table. The energy consumption associated with private car usage is not accounted in this category (cf. Section 4). The commercial sector includes various kinds of so-called tertiary industrial activities (retail, education, hospital, private and public services and so on) which should have homogenous energy service and consumption patterns, whereas the representations in the current CGEs or even energy system models rarely distinguish these individual commercial sector's energy behaviours.

Almost all models use CES production function for the commercial sector with a slight variety in the nesting structure, substitution elasticity parameters and future technological parameter assumptions.[15] A typical CES structure would resemble the one depicted for the oil and gas sector in Figure 3.1., except for the reliance on resource input (RES). Typically, energy use in buildings is not explicitly separated from other energy use in firms, and buildings are part of capital input. Regarding the future technological assumption, most models assume non-price induced technological progress in energy consumption represented as exogenous AEEIs. The electricity consumption is generally assumed to be more preferred along with the economic growth.

For the residential (household) sector, various functional forms are used, including CDE (Constant-differences-in-elasticities), LES (Linear Expenditure System), ELES (Extended LES) and CES. See

[15] One exception is the IGEM model which uses translog cost function for the commercial sector's production function.

Figure 4.1 for a typical CES structure. The alternatives give the possibility to depart from an income elasticity of 1, which does not match well with evidence.

6.2.1 More detailed representation of energy use in buildings

Many models use multi-nesting structure beyond the above-mentioned function by using CES. Typically, total energy consumption is nested by individual energy carriers similar to the production function structure.

The AIM/CGE model has a version explicitly representing individual energy services (e.g. space cooling, lighting and so on) and technological selections (e.g. high efficient air conditioner, traditional biomass cooking device and so on). The energy service is associated with activity levels, which are household income and commercial sector's output, and logit functions are used for the technological selections. The details are described in Fujimori et al. (2014). This rich technological representation provides more detailed and realistic insights in studies of both emissions mitigation analysis and climate change impacts, the latter in terms of capturing energy demand changes associated with space cooling and warming (Hasegawa et al., 2016 and Park et al., 2018).

6.2.2 Linking energy efficiency to physical characteristics of buildings

The IMACLIM-R model couple an energy submodule with the CGE model. Energy consumption in households is driven and constrained by the ownership of square meters of housing (depends on housing capital price).

6.3 Quantifying and parameterising in the base year and baseline

In order to quantify substitutability between building capital and energy use, SNOW's CES substitution parameter between building capital and energy use in projections is based on bottom-up information provided by an TIMES energy system model (Rosenberg and Espegren, 2014). The motivation for this approach rather than ex-post estimations is that energy efficiency improvements is subject to increasing political and societal attention, arguably rendering historical evidence less relevant. See Bye et al. (2018) for the calibration procedure.

7 Remaining challenges and research questions

Recent modelling improvements have moved us far in getting insights into mechanisms of technological change, abatement options, and linking economic activities to emissions of greenhouse gases. However, there are still challenges ahead. In particular, improvements can be made within three main issues: (i) emission data and modelling; (iii) scenario assumptions; and (iii) policy instruments and new technologies.

7.1 Emission data and modelling

As shown in the previous sections, most emission sources for CO_2 are currently covered in state-of-the-art CGE models. There are however emission sources that are more rarely included, such as emissions from venting and flaring, resource extraction, and forest fires. These require a large effort to be incorporated properly in models and sometimes, such as the case of forest fires, it is challenging to robustly project how emissions will develop in the future as they vary year by year.

Emission sources from transportation also need further improvement, especially as transport is one of the main sources of GHGs. In the existing literature, CGE models have been developed recently to include the emergence of low-carbon technologies either by including/emulating bottom-up information or by linking with technology-rich models. Low- and zero-GHG technology options for passenger transport on land, including electric vehicles, are represented in some models. Notwithstanding, key areas of technological and behavioural abatement potentials are still insufficiently explored. Aviation emissions should be better modelled, as they are projected to increase in absence of further policy action and as they are often regulated for certain types of airplanes and certain distances, only, as in the case of the EU emission trading scheme. Global shipping is another very large and rising source of GHG emissions that is not necessarily well captured in many models. Emissions from national ferries and fishing boats are also rarely treated in detail, while being relevant for climate change as well as local health impacts and having abatement options that should be accounted for in scenarios.

One recurring challenge in modelling emissions is the mismatch between the aggregate nature of CGE models and the local nature of air-pollution-related emissions and the environmental and health consequences they have. One solution for approaching this can be to split the household sector in the urban-rural dimension as in Beck et al. (2016). A more ambitious advance for the future would be to improve the modelling of spatial issues, possibly matching CGE models and their aggregate databases with more detailed grid-based spatial databases and models. This has already been done by different teams when assessing for instance the economic consequences of climate change or air pollution in CGE models (see OECD, 2016 and Vandyck et al., 2018). In these reports the emissions from the GEM-E3 and ENV-LINKAGES were matched to the TM5-FASST biophysical model to calculate concentration of air pollutants at the local level, taking into consideration GHG emissions and climate change. Another similar example is to split the aggregated emissions obtained from a CGE model (Fujimori et al., 2018) by means of spatially detailed outputs of an air quality model CMAQ, eventually translated into CGE model as labour loss (Xie et al., 2018).

Similar approaches could be undertaken in the future to better take into consideration land use changes, ecosystem services as well as the consequences of demographic trends and urbanisation on emissions and energy use. A better matching between spatial and CGE models would also allow studying the development of urban infrastructures and emission reductions in cities, which are central in the policy discussions, given the large contribution of cities to overall emission reductions. The AIM/CGE and EPPA models take into consideration land-use change emissions (Fujimori et al., 2014; Gurgel et al., 2016). Still, most models do not endogenise land use changes but rely on separate partial analysis or couple with other external land use model (e.g. AIM/Spatial land use model; Hasegawa et al. 2016).

7.2 Scenario assumptions

The resulting emissions and energy use in CGE model projections are heavily dependent on baseline assumptions. This paper has concentrated on BaU scenarios. Policy assumptions and developments in a baseline setting are important as they could potentially have large impacts on GHG emissions and other environmental and economic variables. In particular, the emerging interest by governments in improving resource efficiency and facilitating the transition to a circular economy, may lead to more policies and economic changes be put in place. A circular economy transition will mean a higher share of secondary materials instead of primary ones, the re-use, extended life and repairing of products which will lower production in some sectors as well as a lower use of resources in general. All these changes will affect production processes, energy use and emissions and will, thus, be important to take into account.

Similarly, in the coming decades new economic trends may affect energy use and emissions. The servitisation of the economy projected to take place in most countries will likely lead to lower emissions as services are less emission-intensive. But it remains unclear how the emergence of certain types of services, such as those linked to the sharing economy, will affect emissions. Car sharing is a clear example. In principle it should lead to diminish car use of those needing to travel, but the lower price of its service compared to other means of transport may instead increase demand and finally lead to higher emissions. Similarly, digitalisation will imply the reduction of some emission sources (e.g. production of paper, commuting and travelling for work, which can be replaced by telework) but also the increase of other emission sources (e.g. digital storage needs, use of electric appliances). Self-driving cars is also emerging, which can affect mobility and emissions in indefinite ways.

Changes in mind-sets and preferences may also affect energy use and emissions both within households and firms. Even in the absence of new price or policy incentives, a higher awareness of external environmental consequences can lead to a lower use of energy by households. Another key area, which mostly falls outside the scope of our review, is food consumption and GHG emissions from agriculture (see also Delzeit et al, 2019). On the production side, there is increasing interest for using greener inputs, for instance substituting for plastic use, putting weight on carbon footprints etc. This can be seen as self-regulation and shift in the attitudes towards larger corporate social responsibility (CSR).

Several models allow substitution elasticities to adjust along a baseline and even across scenarios to capture new ways of relating to options. However, it is not obvious how to empirically distinguish between changes in attitudes to options and changes in the scope and costs of technological options. More empirical evidence is pivotal for calibrating or endogenizing such changes in CGE models. There is an emerging literature on empirical and experimental studies of how attitudes and preferences are affected, including what role policies like promoting education, awareness campaigns, nudging and also price signals, can play. The still premature empirical literature on CSR shows ambiguous results on whether greening signals are accompanied by real behavioural adjustments and whether action reflects more than profitability considerations that account for anticipated future regulations or demand shifts (see, e.g., Schmidt and Schrader, 2015; Servaes and Tamayo, 2017).

Most CGE models used for energy and climate policy analysis have the limited ambition of endogenously modelling impacts of economy on GHG emissions but exclude the impacts of emissions on the economy via climate change. Integrated Assessment Models (IAMs) (see Nordhaus, 1991 and Nordhaus and Yang, 1996 for seminal work on the first IAMs) include the climate modelling to have a full loop between the economic development, the climate change impacts, and their costs on the economy. IAMs are generally very aggregated and consider a much more stylised representation of the economy than CGEs. However, some CGE models have been expanded to become IAMs and to include the full climate loop. There is an increasing empirical literature on the consequences of climate change on energy use, which can be useful in calibrating climate change consequences in CGE models (OECD, 2015; Bosello et al., 2012; Roson and van der Mensbrugghe, 2012). These assessments include the impact of climate change on energy demand. Energy supply is also likely affected by climate change. Wind, solar and hydro power plants are vulnerable to weather conditions. Fossil fuel and nuclear power plants need cooling and will therefore become less efficient in the case of warming. Biomass and biofuel energy are dependent on crop yields, while extreme weather events can damage extraction facilities, power plants and transmission lines. Numerical information at global level is still lacking for CGE models to include energy supply as part of the climate damage categories.

As highlighted throughout this paper, when setting up a baseline scenario, technology assumptions are fundamental. Current CGE often lack a robust modelling of low-carbon technologies, such as CCS/CCU and emission changes through Land Use, Land-Use Change and Forestry (LULUCF).

Geoengineering technologies, which could also help limit climate change though large-scale projects, could also change projections of GHGs. However, it is hard to create future projections of technologies that are not yet well developed and for which the emission reduction potentials and costs are not yet clear.

In the context of baseline projections, the need to represent future uncertainties is particularly strong. The modelling community has greatly improved in this subject moving from presenting a single baseline projection, to better highlighting future economic uncertainties in the context of the Shared Socio-Economic Pathway (SSPs) scenarios (O'Neill et al., 2016, Dellink et al., 2016). The SSPs work could be further enhanced developing Monte-Carlo analysis on scenario explorations. Further improvements in highlighting the role of uncertainty can also be made on sensitivity of emission projections to key parameters and modelling assumptions. Modelling comparison exercises, such as those of the Energy Modelling Forum (EMF), are also useful to understand the role of modelling assumptions in creating emission projections. Finally, to understand the robustness of modelling projections, hindcasting could be used more frequently (Fujimori et al, 2016; Snyder et al., 2017). Unfortunately, this is a time-consuming process and for baseline projections not very validating if technologies, sectoral patterns or preferences are expectedly very different from history.

7.3 A richer context for policy analysis

CGE models have been the workhorse to assess the economic costs and benefits of carbon markets and emission taxation since the first works on including GHG emissions in CGE models (see e.g. Burniaux et al, 1992; Burniaux and Troung, 2002). Effects of carbon taxes and emission caps are well understood thanks to a large literature using CGE models. However, with the policy discussion having moved from climate policy, towards green growth and circular economy, there is a strong need to model other types of policy instruments. For instance, in the recent EU FP7 project POLFREE, different modelling teams have developed a policy package with different instruments to achieve a circular economy, including recycling, re-use, energy efficiency, etc. (see e.g. Hu et al., 2015). More work is needed to robustly model the consequences of policy instruments other than carbon taxes and markets, especially through modelling comparison exercises that can help clarify the role of modelling assumptions.

Similarly, CGE models can be used to understand the interlinkages between different environmental issues and consequences of policies on various indicators, clarifying the interplay between climate, sustainability and equity with reference to the Sustainable Development Goals (SDGs). OECD (2016) contributed to the discussion of interconnections between scarce resources by highlighting the nexus between land, water and energy. The multi-model CD-Link project addressed the interlinkages between climate change goals and sustainable development (see e.g. McCollum et al., 2018). This literature is likely going to gain increasing attention and can be further developed by improving the modelling of equality, labour markets and beyond-GDP economic indicators.

Under stringent climate policies such aiming at well below 2 °C or 1.5°C, the global CO_2 emissions likely need to be zero or negative by mid of this century (Rogelj et al., 2018). To attain these conditions, some negative emissions are inevitably necessary, since there are some emissions sources which are hard to completely decarbonise. Afforestation and bioenergy combined with CCS (BECCS) are considered as possible efforts for large-scale negative emissions. These technologies are obviously related to land-use and moreover, bioenergy crop may have interactions with forestry activity which includes reforestation and afforestation. As mentioned above, modelling advancements are needed for good representations of such scenarios.

Development of new technologies, especially as linked to policy supports such as R&D subsidies, would also help improving deep de-carbonization pathways, which aim at limiting the rise of global temperature due to global warming to 2 °C or less. Some CGE models approach induced productivity change in energy and abatement technologies by means of learning curves. Another source of productivity growth is the role of profit-driven R&D policy. The topic has mainly been addressed in aggregate general equilibrium settings (reviewed in Löschel, 2004; see early contributions by e.g., Goulder and Schneider, 1999; and more recent by e.g., Acemoglu et al., 2012). While some sector-disaggregated, country models address endogenous R&D impacts (e.g., Bretschger et al., 2011; Popp, 2004, Bye and Jacobsen, 2011), regionalised global models with knowledge spillovers are rare (see Bretschger et al., 2017 for an example). The MAGNET model includes endogenous R&D in biofuels; see also the ICES model (Parrado and De Cian, 2014).

Other discussions that would need further modelling efforts to be addressed adequately concern how climate policies introduced in the presence of alternative behavioural models or market imperfections should be formed. The evolvement of behavioural economics has shed light on aspects of consumption that also affect the optimal choice of policy instruments in the energy and climate nexus. People may not behave as traditionally assumed when searching for information, responding to social networks and situations or planning for the future.

Market imperfections can include network externalities for new mobility modes to penetrate, infrastructural public goods that are prerequisites for impacts of policies, commitment problems that impede responses to announced policies, credit market imperfections that hamper optimal investment behaviour or market power. While OPEC's market power in the oil market is described in some models, CGE-based analyses that include barriers to free entry of firms in the electricity market remain scarce, although substantial market power may exist in some countries, and may be relevant for assessing electricity market design reforms (Akkemik and Oğuz, 2011).

Progress in these fields would greatly contribute to better understanding baseline emission projections under future uncertainties, as well the benefits of policy actions in different environmental fields in terms of emission reductions, limitations to climate change and more generally sustainable development. Like in other research fields, empirical evidence to support simulations and model calibration is crucial to obtain reliable projections. Similarly, improvements in scientific models, which address for example technology development, the climate cycle, and other environmental issues, can help provide more reliable input data for CGE models and thus make CGE projections more reliable.

8 Concluding remarks

CGE modelling provides an important contribution to climate and energy scenarios and policy analysis. Structural relationships between different economic sectors in an economy-wide setting make CGE models a unique tool for investigating regional and global energy markets, technological compositions in different scenarios and their implications for the resulting GHG and air pollution emissions. For given external surroundings, CGE models provide consistent projections of induced investments in different sectors and technologies, the speed of technology adoption and resulting changes in inputs, outputs and their prices. By introducing different policy assumptions, the economic costs, benefits and trade-offs of different strategic choices can be obtained. These outputs are useful for government and industry decision makers.

Our paper provides an assessment of the best practices in CGE modelling of baselines and alternative scenarios. Building and maintaining largescale numerical models are costly, and the need for sophistications and data details should be carefully considered. Sharing knowledge about the state-of-the-art options helps provide the modelling community with better and less costly choices. This is a low-hanging fruit for better research and analysis. Better understanding of the mechanisms by which energy and emissions are incorporated in CGE models and projected into the future, and the pros and cons of different solutions, would help decision makers and academic researchers to interpret adequately the modelling results and to make better research and more informed policies.

Reliable findings require that the CGE studies reflect main technological and behavioural mechanisms, well-estimated empirical relationships and plausible future scenarios. The research activities in the fields of CGE modelling and projections within the energy and climate field have advanced rapidly. Modern approaches in modelling and quantifying power generation, fossil fuel production, transportation, manufacturing industries and buildings offer valuable tools for projection and analysis.

The advances include a considerable detailing of the power generation sector, including vintaging structures (i.e., tracking power generation fleets of different ages and their corresponding capital costs), backup requirements for intermittent generation from wind and solar resources, transmission constraints, and endogenous cost reductions due to learning-by-doing and other technological advances.

To understand the pathways for low-carbon energy development, it is important to represent fossil fuel extraction in an adequate fashion, because advanced energy options have to compete with fossil-based energy options. Both fossil fuel and low-carbon energy supply are subject to technological improvements that are represented in the modelling.

Passenger and freight transportation is a significant energy-consuming sector. State-of-the-art CGE models offer descriptions of current and future vehicle technology, such as improvement in efficiency of internal combustion engine-based vehicles, adoption of plug-in hybrids, battery electric, hydrogen fuel cell vehicles. The models also incorporate different fuel choices, such as biofuels, natural gas, electricity, and hydrogen. Modelling of marine and air transport is also advancing. Some CGE models incorporate consumer preference changes towards different modes of transportation. These choices are particularly important when considering the future evolvement or car sharing and ride sharing, and their impacts on transportation service demand.

Another main energy-intensive sector are the manufacturing industries. Besides considerable GHG emissions from combustion, many manufacturing industries emit CO_2 and other Kyoto gases from other processes. These emissions require different approaches to modelling in a CGE setting because they are tied to sectoral outputs instead of fuel use. Modelling process-related abatement opportunities involves a representation of abatement costs and/or creating the emission-free technologies that are perfect substitutes to the existing production processes. Advanced CGE models offer explicit treatments of options for several sectors including cement, metals, chemicals, fertilisers, pulp and paper.

Modelling energy consumption in buildings creates certain challenges because the underlying input data to CGE models do not distinguish buildings as a separate category but they are rather allocated to the corresponding economic sectors (retail, education, services, industrial, etc.). Energy use in residential buildings is accounted in household consumption part of the input data. Advanced CGE models represent energy use for heating and cooling needs and their evolvement under different income growth scenarios and energy efficiency improvement patterns.

This assessment addresses approaches to constructing long-term baseline scenarios from a calibrated base year. For all, sophisticated modules of energy supply, demand and market features, as those summed up above, are prerequisites for the projections to be reliable and explicit on the technological setting. Model characteristics have implications for the base year calibration and the need for and availability of data for parameter quantifications along baselines stretching 20 to 100 years forward in time.

We distinguish between three different approaches to baseline quantification. A first approach is to feed in plausible values on exogenous variables and simulate the model forward. The richer and more accurate the model is in its technological refinement, the more is its potential for emulating bottom-up expert opinion or model results. However, the more exogenous information is required – information that can be inconsistent or induce unexpected impacts on key outputs. Another approach is therefore often combined with the first, namely to track key outputs by calibrating the values of parameters and exogenous variables. This paper assesses handles to select and provide the most common data sources, including the publications of the International Energy Agency, The World Bank, International Monetary Fund and others.

The third approach is to use bottom-up sector models, like PE models of the energy markets, in tandem with the CGE model by establishing linking procedures and adapting the models to each other. This means that the PE model results replace external data sources like those mentioned above. For example, significant progress has been demonstrated in the attempts of linking CGE models with more detailed electricity sector models that can provide finer temporal and technological resolution, including a better representation of intermittency constrains that are especially important for an analysis of low-carbon options. For consistency across data sources, linking monetary flows with physical flows of energy allow an assessment of production, consumption and international energy trade flows both in monetary and physical units.

Though the three approaches can be seen as complementary and can be combined, awareness must be given to the risk of double-counting by including forward-looking trends both as a parameter value (e.g., productivity parameter) and in an endogenous emulating mechanism (e.g., learning-by-doing).

The last part of our assessment is devoted to several challenges related to the need of the better and more disaggregated data, baseline creation, and more concise representation of policy instruments and advanced technologies related to energy, industrial processes and land use. The resulting emissions and energy use in CGE model projections are heavily dependent on baseline assumptions. This paper has concentrated on BaU scenarios that usually take into consideration only policies that are already in place. When picking assumptions for long-term BaU baselines uncertainty is inevitably large. Disruptive technologies may emerge and businesses that we do not know today may appear. Our discussion touches upon many alternative assumptions and point to the need for addressing such uncertainties by means of sensitivity analysis, scenario approaches (SSP reference) or hindcasting.

We also sketch some areas of research and policy analysis that are relevant to and likely to influence the energy and climate nexus, including the study of the circular economy, induced environmental R&D, behavioural economics and spatial modelling. The CGE modelling community steadily makes progress in addressing novel challenges. Our paper provides an opportunity for a better understanding of the efforts needed to make CGE modelling even more relevant.

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Appendix: Energy and emissions: model characteristics and baseline sources of represented CGE models

Energy and emissions: model characteristics and baseline sources of represente

Model	General scope and features	Fuel supply
Default	Global - recursive dynamic - 1-year-steps Monetary input-output structures	CES factor demand Aggregate production function also including Transmission/distribution Resource input energy: coal, oil, gas exogenous factor-augmenting productivity growth

Supplem

Represented model (Organisation)	General scope and features	Fuel supply
ADAGE (RTI International/EPA)	Also intertemporal version 5-year steps Physical accounting of energy, land use and agriculture, transport services	Multiple technologies Dynamic resource depletion Renewable fuels
AIM/CGE (National Institute for Environmental Studies)	In a linked system with AIM/Energy, AIM/Transport and AIM/Spatial and use	Multiple technologies
DART-BIO (Kiel institute of the world economy)		Learning by doing Renewable fuels
EC-PRO/EC-MSMR (Environment and Climate Change Canada)	SOE Canada and global, respectively Soft-link to energy model (E3MC)	Multiple technologies
ENGAGE		Learning by doing
ENVISAGE		Renewable fuels
ENV-LINKAGES (OECD)		
EPPA (MIT)	Physical accounting of energy	Multiple technologies

		Dynamic resource depletion Renewable fuels
GEM-E3 (Joint Research Centre)	Linked with energy model (POLES-JRC) Physical accounting of energy	
IMACLIM-R (CIRED)		Multiple technologies Dynamic resource depletion
MAGNET (Thünen Institute of Market Analysis)		Multiple technologies R&D in biofuels
REMIND (PIK)		
SNOW (Statistics Norway)	SOE Norway or global (SNOW-GLO) SOE Norway intertemporal (SNOW-DYN)	MAC curve
TEA (Univ	Linked to energy model (COFFEE) Physical accounting of energy	Multiple technologies
WEGDYN (WEG-Centre, University of Graz)	SOE Austria (also static version 5 year steps)	

d CGE models

Default:

Power supply	Energy demand	Emissions
CES factor demand	*In households:*	CO_2 and often also non-CO_2 Kyoto gases
Aggregate production function	Energy use split between transport and housing in CES demand systems usually in composites with vehicles and buildings, resepctively	Physical units (t CO_2-equivalent)
	In firms:	Linked to demand/combustion of coal, oil, gas in all sectors
energy: coal, oil, gas	Standard CES factor demand where energy use for transport, buildings and processes usually are merged, as is capital.	Fixed emission coefficients
exogenous factor-augmenting productivity growth	Transport sector split into air, water and other, but freight and passenger transport merged.	
	Exogenous factor-augmenting technical change	

ents and advancements of represented models:

Power supply	Energy demand	Emissions
	Transport in households: Multiple types of vehicle and associated fuel demand. Vintage transport capital *Commercial transportation:* Disaggregated. Vintage transport capital	Endogenous abatement
Multiple technologies Intermittent renewables Bioenergy potential linked to spatial land use model	*Buildings in households:* A version with energy services demand modelling and detailed technology selection	
Vintage capital Learning by doing Renewable Energies		
Multiple technologies Physical accounting of energy	*Commercial transportation:* Vintage transport capital	endogenous abatement
Multiple technologies Capital vintages		Process emissions in Manufacturing
Multiple technologies	*Transport in households:* Multiple types of vehicle and associated fuel demand	

Intermittent renewables	*Commercial transportation:* Disaggregate, physical accounting, vintage transport capital	
		Endogenous abatement (sector-wise MAC curves) Process emissions in Manufacturing
Multiple technologies	*Transport in households:* Multiple types of vehicle and associated fuel demand, minimum mobility consumption, travel time and congestion *Commercial transportation:* Infrastucture capacity, vintage transport capital *Buildings in households:* Physical accounting og square meters that determine energy demand	
Learning by doing		
	Transport in households: Multiple types of vehicle and associated fuel demand	Process emissions in Manufacturing and Fossil fuel extraction Endogenous abatement (sector-wise MAC curves)
Multiple technologies		
Exogenous portfolios of technologies	*Transport in households:* exogenous technology switch *Commercial transportation:* Disaggregate land transport, incl. infrastructure services *Manufacturing:* Exogenous technology switch	Process emissions in Manufacturing

Markets	Central data sources
Competitive	GTAP incl. GTAP-Power, I EA/WEO, Enerdata, OECD/EO, GECO, econometric studies National SAMs, emission inventories

Markets	Central data sources	Model documentation
Land-use change	US DOE Energy Information Administration GCAM model	Ross (2009) Cai et al. (2018)
Land-use change	EDGAR, RCP, IMAGE, own database reconciling international statistics, FAOSTAT/GAEZ AIM/Energy, AIM/Transport models	
	E3MC model	Ghosh et al. (2017), Böhringer et al. (2016) Ghosh et al (2012), Zhu et al. (2017)
		Chateau et al., 2014)
Land-use change		Paltsev et al. (2005)

Market power in oil market		Chen et ak. (2016)
	GAINS model	
Market power in oil market	POLES-JRC model, World Energy Model	Waisman et al. (2012a)
Land-use change Blending targets	FAOSTAT & IMAGE	
		Luderer et al. (2015)
	MDIR (2010), MDIR (2016)	Bye et al. (2018) Fæhn, T., Isaksen, E.T. (2016) Rosnes et al. (2019)
	COFFEE model	
	EnergyDatasheets: EU-28 Countries (EC, DG ENER)	Mayer et al. (2019); Schinko et al (2014) Bednar-Friedl et al., 2012; Bachner et al. (2018)