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Capturing Key Energy and Emission Trends in CGE Models: Assessment of Status and Remaining Challenges

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Limiting global warming in line with the goals in the Paris Agreement will require substantial technological and behavioural transformations. This challenge drives many of the current modelling trends. This article undertakes a review of 17 state-of-the-art recursive-dynamic computable general equilibrium (CGE) models and assesses the key methodologies and applied modules they use for representing sectoral energy and emission characteristics and dynamics. The purpose is to provide technical insight into recent advances in the modelling of current and future energy and abatement technologies and how they can be used to make baseline projections and scenarios 20-80 years ahead. Numerical illustrations are provided. In order to represent likely energy system transitions in the decades to come, modern CGE tools have learned from bottom-up studies. Three different approaches to baseline quantification can be distinguished: (a) exploiting bottom-up model characteristics to endogenize responses of technological investment and utilization, (b) relying on external information sources to feed the exogenous parameters and variables of the model, and (c) linking the model with more technology-rich, partial models to obtain bottom-up- and pathway-consistent parameters.

JEL codes: C68, O13, O18, Q43, Q54.

Keywords: Computable general equilibrium models, Long-term economic projections, Energy, Emissions, Greenhouse gases.

1. Introduction and background

The world's production, handling and use of energy have a strong bearing on the environment. Especially greenhouse gas (GHG) emissions, but also other polluting compounds, are regarded as major concerns on global, regional and local scales, as environmental impacts feedback on economic activity and well-being. Limiting global warming to below 2°C, or even 1.5°C, compared with pre-industrial level, in line with the goals in the Paris Agreement, will require substantial technological and behavioural transformations (International Panel on Climate Change, IPCC, 2018). By 2020, all parties are requested to prepare and submit mid-century strategies, in which these transformations should be reflected.[1]

One important motivation for many of the recent developments in computable general equilibrium (CGE) models and projections has been to understand emissions, particularly GHG emissions, and to sketch possible transition pathways that can limit climate change. Abating energy-related GHG emissions also has potential environmental co-benefits in terms of limiting local and regional pollution. Among early CGE models adapted for these purposes was the GREEN model (Lee et al., 1994), developed and maintained by the Organisation for

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

Economic Co-operation and Development (OECD).[2] Since the 1990s, the demand for CGE models as analytical tools has increased. Many of the modern CGE models are based on the core model structure from GREEN.

The long time horizon for climate change impacts and technological change makes long-term projections and scenario studies of energy and emissions necessary. For that purpose, the main virtue of using global CGE models is that the interaction of energy supply, energy demand and emissions in various economic sectors and regions are placed in an economy-wide context. This enables the accounting of the indirect effects and interactions of policies and other economically relevant drivers across markets and across borders. An obvious example is that electrification taking place in several sectors with the aim of reducing GHG emissions from the combustion of fossil fuels will not have the desired abatement impact if the increase in power generation is based on fossil fuels. Another example is expansion of bioenergy, where the net GHG-mitigating effects of replacing fossil fuels with bioenergy depend heavily on the specific feedstock used, regional productivity and production practices, as well as resulting land use change. Agriculture, forestry, and land use have become increasingly important components of energy and environment-focused CGE models as the expansion of bioenergy and other policies has tightened their linkages to the energy sector. CGE-based analysis is also able to identify emission leakages and other transboundary impacts of domestic or regional mitigation efforts or other market trends.

This article provides an assessment of best practices in CGE modelling when it comes to methodologies and applied modules for representing emissions and their projected dynamics over time. It focuses on recent developments in the modelling of the main energy-related sectors: fossil fuel extraction, power generation, transportation, energy-intensive manufacturing industry and buildings as well as the agriculture and forestry sectors. The review includes not only carbon dioxide (CO_2) from combustion, but also other major sources of CO_2 and non-CO_2 GHGs. As can be seen from Figure 1, which shows the 2010 allocation of global GHG emissions by sector, agriculture and land use constitute significant shares. The majority of emissions from these sectors are not directly energy-related; they consist of methane (CH_4) and nitrous oxide (N_2O) emissions as well as changes in carbon sequestration in agricultural land and forestry. This article covers these large GHG sources in a separate section, as they are linked to developments in the energy sector through their provision of feedstocks for bioenergy production.

[2] For explanations of all the model names mentioned in this article, see Appendix A.

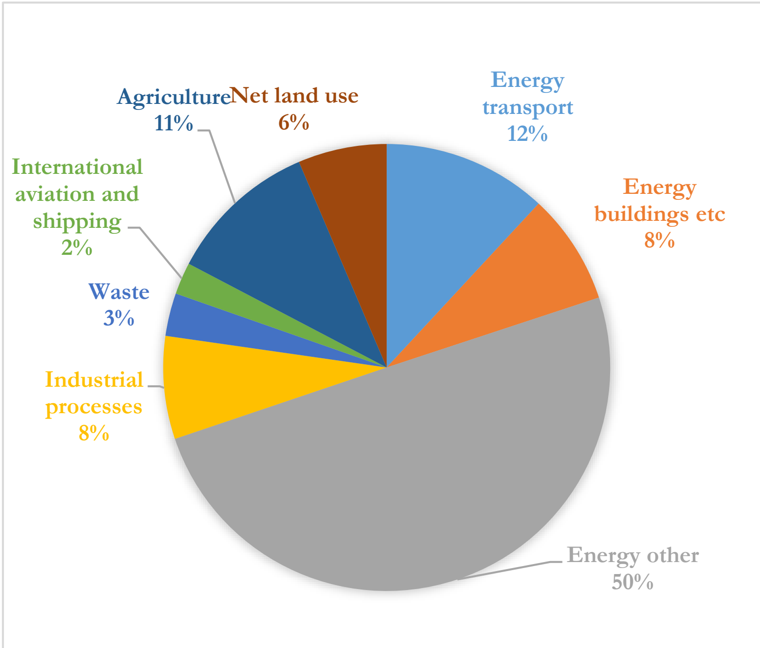

Figure 1. Global greenhouse gas emissions by sector, 2010

Source: Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) http://www.fao.org/faostat/en/#data/EM

A review of 17 established recursive-dynamic CGE models is undertaken.[3] The models included in this review are listed and briefly described in Appendix B, which also provides references to the main documentations for these models. The intention is to provide technical insight into recent modelling and quantification advances, assess their potential and shortcomings and explain trade-offs in the choice of methods. 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.

The review serves two main purposes. The first is to make the knowledge frontier of energy technology and emission projections more visible and available for modellers in the research and analysis communities. Sharing knowledge about state-of-the-art options helps modellers to make better choices in their modelling activities by learning from each other. Second, the assessment informs decision-makers and the interested audiences about the advantages and limitations of CGE-based analyses and current tools. CGE models and results are often perceived as

[3] 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.

black boxes, and there is a need for contributions like the present to document, explain and evaluate their features.

Since the trends and options for behavioural and technological adjustments in the coming decades will tend to be sector-specific (though with feedback and indirect effects to other sectors), the challenges and practices of modelling and projecting developments look quite different from sector to sector. Therefore, after an sector-overarching overview in Section 2 that consolidates the main common findings across sectors, sectoral detail is scrutinised in the subsequent sections: Sections 3 and 4 report on the main energy-supplying sectors (fossil fuel extraction and power generation), Sections 5, 6, and 7 address the main energy-consuming sectors (transport, manufacturing industries and buildings), while projection methods for agriculture and forestry are reviewed in Section 8.

Each of the sector sections starts by describing general current and future trends in energy technologies, behaviour and abatement options that state-of-the-art models should capture for use in projections. After introducing the current default characteristics of the specific sector, the survey visits the most advanced approaches. Baseline projections need to represent plausible energy-system and technological 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 emission developments. It then proceeds by discussing challenges involved in using the models for projecting long-run baselines and other scenarios. Baselines in this sense are business-as-usual (BAU) projections, i.e., incorporating expected structural changes in the economic system, but keeping policies as already implemented or decided upon. Implications are discussed for base year calibration and the need for and availability of data for parameter quantifications along baselines stretching 20 to 100 years forward in time. Numerical illustrations are provided. For further quantitative insight into the projections, a visit is recommended to the interactive website http://www.icio.oecd.org:3838/GMRO2018.

Many current and future energy- and/or emission-relevant trends, topics and challenges that are not within the scope of this assessment, will be briefly visited in Section 9. Section 10 concludes.

2. Overview of main findings

2.1 State of the art

Recent advances in modelling, computerization, linking and quantification procedures have facilitated more effective baselining routines in the CGE community. They have ensured a better informed and more consistent understanding of how energy markets, land use and emissions can plausibly change in response to political and economic conditions ahead. The observed trends within energy markets and land use are to a large extent driven by climate policies and novel technological solutions in the fields of abatement and energy efficiency as well as in more generic technologies like artificial intelligence and digitization.

Introducing technological detail has improved CGE modelling. Krey et al. (2018) highlight the importance of transparency for techno-economic parameters and technology representation. A move towards hybrid modelling (Böhringer, 1998; Hourcade et al., 2006) brings CGE models one step closer to more detailed, engineering-based, bottom-up models, enabling modellers to use the best of both modelling worlds: the comprehensiveness of CGE models, and the technological detail of bottom-up models. This approach is well on its way to becoming the mainstream option.

Essentially, baseline projections rely on three different methodologies – typically in combination – for representing and quantifying energy and emissions developments: (a) exploiting novel model characteristics designed for integrating technological bottom-up features and endogenizing the responses of investment and utilization of technologies to costs, prices and restrictions, (b) relying on external information sources to feed the exogenous parameters and variables of the model and (c) linking the model to more technology-rich, partial equilibrium (PE) models in order to provide pathway-consistent values for the parameters and variables.

Best practices will generally depend on the purpose of the projections and what input and output are regarded as most important for a given application. CGE baseline projections are used to present consistent information about the future impacts of policies that are currently in place or that have been approved and will come into effect during the projection in interplay with expected trends. In a macroeconomic overview of long-term trends, the level of abstraction can be relatively high and energy goods and technologies fairly aggregated. If sectoral energy and emissions information are sought, more specific representations are needed. In particular, the purpose of constructing baselines is often that they serve as reference paths for analysis of alternative assumptions about energy and emissions policies and emerging technologies. This will call for more refined and detailed representations of technological mechanisms and how emissions respond endogenously to the altered drivers. The reference path must then reflect details accordingly. In the most advanced models used for such analysis, specific technologies are modelled directly to mimic bottom-up information from PE models or other expert knowledge. Linking procedures between CGE and PE models will also benefit from comparable levels of detail.

When constructing the baseline, it often proves challenging to rely solely on the model's own mechanisms. This requires well-tuned endogenous price and cost movements which, in their turn, drive energy- and emission-related activities. It is a complex task to feed in combinations of inputs capable of reproducing 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 in baseline construction and more on exogenous inputs, while full use of endogenous, bottom-up-informed emulations is left for policy shift analysis.

2.2 Modelling technology and behaviour

When projecting technological and behavioural change, the default practice includes a mixture of endogenous substitution of other production factors and consumer goods for energy, induced changes in the energy mix, as well as assumed autonomous total factor productivity (TFP) growth and factor-specific productivity progress, including autonomous energy efficiency improvement (AEEI). These autonomous parameters are typically calibrated to target some of the main expected trends in the production, trade and use of energy indicated by existing bottom-up projections.

Typically, the technological representation of production in CGE models takes the form of a multi-level constant elasticity of substitution (CES) function (or Leontief functions without substitutability); see example in Figure 2. Default modelling of household behaviour often relies on the linear expenditure system (LES) or CES; see Figure 7 for a typical structure. Other options are the extended linear expenditure system (ELES) and constant-differences-in-elasticities (CDE), which give the possibility to depart from an income elasticity of 1, an assumption that does not match well with the evidence (Lanz and Rutherford, 2016).

CO_2 from combustion is represented in all models used for climate policy studies and emission projections. CO_2 is linked in fixed proportions to the use of fossil fuels. If other Kyoto energy-related GHGs are included, they are also linked with base-year coefficients of energy use. Kyoto GHGs include CH_4, N_2O, sulphur hexafluoride (SF_6), perfluorinated compounds (PFCs), hydrofluoro-carbons (HFCs) and nitrious fluoride (NF_3). Representations of emissions from non-energy-related processes are scarcer. When included, they are typically linked to output, resources or capital use.

The recent progress within modelling differs from sector to sector, but some common features are evident. First and foremost, the technology representations have become more detailed. Extraction processes for fossil fuels and novel renewable, intermittent sources of electricity generation have driven this progress. More recently, emerging transportation options have been included and some models have refined the details of manufacturing processes.

Such disaggregation lightens the task of linking CGE models with bottom-up models like energy system models, land use models and transport models. With a view to using bottom-up information or linking CGE and PE models, physical accounts have been harmonized with monetary accounts and included in the CGE models. This also facilitates a better link between energy/resources, energy services and resource and emission flows.

In order to capture endogenous technological growth other than energy efficiency or energy mix changes, a few models have included induced technological change, usually in the form of learning-by-doing curves. Another "semi-endogenous" solution is to split capital use into industry-specific extant capital and new capital. In contrast to the default approach, where investment in current and new technologies takes place smoothly, such vintage modelling captures a more realistic transition where it takes time to build and phase out technologies. Capital that is implemented contemporaneously is new and may be more productive and/or flexible than already installed capital. 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.

Finally, some models represent technological progress within emission abatement by including marginal abatement cost (MAC) curves that allow for endogenous emission coefficients and investment costs. 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 permit. This method can be applied on a sectoral basis and is particularly suitable for process emissions, for instance in manufacturing industries, fossil fuel extraction and agriculture. Harmsen et al. (2019), for example, provide a systematic review of sources of non-CO_2 emissions and the methodological steps involved in constructing source-specific, non-CO_2 MAC curves. Their estimates reflect baseline correction and barriers to implementation extending beyond the technical feasibility of adopting abatement technologies. This review is a valuable novel tool for including non-CO_2 emissions and abatement options in CGE models. Complementing these methodological advances, recent work illustrates how detailed bottom-up information on discrete abatement options can be integrated and preserved in a CGE model (Weitzel et al., 2019a).

2.3 Calibration in the base year and the baseline

The social accounts matrices (SAM) provide the basic structure of technologies in the form of base-year cost shares. Lately, emerging energy technologies and goods have inspired the formation and launching of more detailed input-output databases, with the Global Trade Analysis Project, GTAP-Power Data Base (Peters, 2016) as a clear example. Elasticities of substitution are also available in the GTAP Data Base (Aguiar et al., 2016; Aguiar et al., 2019) at sectoral and regional levels. At even more detailed levels, data may need to be collected from various sources. Frequent sources are bottom-up models, other detailed bottom-up studies or stakeholder and expert knowledge. Along with the emergence of new trends and markets, the increasing possibilities offered by data processing and sharing are promising.

As mentioned above, linking procedures call for keeping track not only of monetary flows, but also of physical flows in the CGE model. One challenge is that the commonly used CES or constant elasticity of transformation (CET) functions do not preserve additivity, which implies that the sum of physical quantities (e.g. 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 for using CES or CET functions that preserves volumes 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.

Input-output data on physical energy pave the way for assigning physical emission units to combustion of energy. Data on energy prices and on fuel qualities are needed for good physical calibration. Another data-related challenge is that monetary input-output values in SAMs provide information only on marketed energy transactions. Emission data often come from national emission inventories, which may include emissions other than those accruing from fuel consumption according to SAMs. The GTAP Data Base has made the alignment task significantly easier by including energy balances in physical units (million tonnes of oil equivalent, Mtoe).

Emissions of energy-related CO_2 are accessible in several databases and also linked to energy use by means of the physical carbon content of fuels, e.g., in the GTAP Data Base. An alternative is to use the ratio of base-year emissions to base-year energy. This provides average emission coefficients, i.e., less specific information.

Emission Database for Global Atmospheric Research (EDGAR) is a rich source of emission data. Currently, the GTAP Data Base is also incorporating local air pollutants as well as non-CO_2 GHGs and how they are linked to economic activity. Once the data alignment and calibration of the model for the base year are complete, forward projection of the model is performed for the next 2 to 10 decades (typically). Usually, a mixed approach is used that partly relies on the model mechanisms (approach (a) – see section 2.1) and partly calibrates productivity parameters to target certain output values (approach (b)). These values are chosen from other bottom-up projections, typically from the International Energy Agency (IEA)'s *World Energy Outlooks (WEO)* the OECD's *Economic Outlooks*, the Joint Research Centre (JRC)'s GHG and energy balances in *Global Energy and Climate Outlooks (GECO)* of and *Annual Energy Outlooks* from the Energy Information Administration (EIA), or from common scenarios such as the Shared Socioeconomic Pathways (SSPs); see O'Neill et al. (2014).[4]

One example of a baseline calibration is documented in OECD (2019). It includes projections to 2060 of GHG emissions with a focus on environmental

[4]See https://www.iea.org/weo/; http://www.oecd.org/eco/outlook/economic-outlook/ ; https://ec.europa.eu/jrc/en/geco; https://www.eia.gov/outlooks/aeo/.

impacts of materials use in the coming decades. The exercise relies on the ENV-LINKAGES model.

The model has been carefully calibrated to reflect plausible developments of macroeconomic drivers, industrial patterns and technological changes up to 2060. The model reproduces several trends and information from different other Directorates at the OECD (including IEA) as well as from other projections. For instance, the GDP projections are based on the official projections of the OECD's Economics Department. Efforts are undertaken also to calibrate the changes that take place over time in the structure of the economy. Electricity power generation is split into different technologies in the model, including three using fossil fuels, four renewable sectors including hydropower, and nuclear power. Anticipated trends in power technologies and demand are reproduced by adapting the CES coefficients of the power-bundle nest. Electricity and other energy demand are calibrated in line with the IEA's *Current policies scenario* in the World Energy Outlook (WEO, 2017) by means of TFP adjustments.

The calibration to the WEO's energy trends, means that the ENV-LINKAGES baseline accounts, inter alia, for expected trends in energy efficiency improvements, investment in electrification infrastructures particularly anticipated in emerging economies, and demand impacts from anticipated deep structural changes in the economies.

The baseline projections are available on a dedicated online data visualization website: http://www.icio.oecd.org:3838/GMRO2018. This website includes projections of economic variables (GDP, consumption, employment), as well as projections of greenhouse gas emissions. It also includes projections of fossil fuels and outputs of key sectors (including agriculture, services, energy, construction and utilities). These results are available at the global and regional level and for each year from 2011 to 2060.

Preference features like substitution and income elasticities are customarily perceived as fundamental and stable. However, sometimes behavioural parameters are also calibrated along the baseline, if they are expected to change over time along with technological options and societal norms. In such cases, estimations based on past observations may be less reliable than subjective estimates given by experts in the field/sector. Since such information is by nature subjective and scarce, this approach calls for caution and should be accompanied with sensitivity testing.

There are some caveats related to targeting external output values and calibrating model parameters that fit exogenous data. First, projections often aim to target many output values, at the macro, sector and specific technology levels. Adjusting several parameters affecting many output variables can be a demanding task. Some technical solutions have been developed to facilitate this process. Jin et al. (2019), for instance, formalize the calibration procedure by using the maximum a posteriori probability estimation from Bayesian statistics. Another approach is described by Weitzel et al. (2019b), building on an iterative procedure with good convergence properties towards the exogenous targeted energy quantities.

An additional, and related, calibration challenge arises from the fact that some of the specified activities have very small shares in the base year. Functional forms like CES will not be able to endogenously produce plausibly large quantity changes by adjusting technological parameters and market trends. The cost shares in the base year, along with the nesting structure and elasticities of factor demand, dictate the main patterns of households' and firms' consumption choices even for future periods. It is even more challenging if the technologies that are expected to appear are absent in the base year. One approach to representing changes in technologies and preferences 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. A second approach would be to include new technologies at higher costs than conventional technologies in the model in a mixed complementarity formulation. This solution is proposed by Böhringer (1998) to integrate a detailed bottom-up representation of energy sectors and applied for instance by Weitzel et al. (2019a) to include bottom-up information on (the marginal costs of) abatement technologies. The advantage is that the technologies are not necessarily operational in the base year, but they can be deployed endogenously when prices change.

There are also techniques for updating input-output tables for future periods, flexibly inserting expected technological changes. Calibrating a CGE model to a projected time series of input-output tables is an approach that is pioneered by Wojtowicz et al. (2019) using the GEM-E3 model. The advantage of the procedure is that internally consistent futures based on transparent assumptions can be obtained. Furthermore, the resulting input-output database can be utilized across models and scrutinized by others. This approach, named PIRAMID, operates as a platform for integrating data and projections. As with all projection approaches, the data can come from various sources.[5]

Linking the CGE model with bottom-up models, i.e., resorting to the approach (c) described above, is a well-proven procedure for strengthening consistency across projected data and parameters. Table 1 shows the procedure exemplified by linking the CGE model TEA with the energy model COFFEE (Cunha et al., 2020). Both models rely on the same exogenous population and GDP projections. After its first run, TEA key outputs on sectoral production and private consumption (blue bold text) serve as key inputs to COFFEE – in terms of generated energy service demands (blue bold text). In the second step, COFFEE runs and sends TEA information about the power generation mix and energy supply, which is translated into exogenous trends on energy efficiency, emissions

[5] PIRAMID = Platform to Integrate, Reconcile and Align Model-based Input-output Data

and technical progress for the TEA model (black bold text) in its next run. For details, see Delzeit et al. (2020).

Table 1. Linking procedure for the TEA and COFFEE models.

	TEA (CGE model)	COFFEE (Energy model)
Focus on	*Monetary flows (values and indices)*	*Physical flows (quantities and prices)*
Common drivers[a]	Population projection GDP projection	
Key inputs[b]	**Energy efficiency** **Emissions trends** **Technical progress**	**Energy service demands** Mobility demands Materials demands Technology costs and efficiencies
Key outputs[b]	**Sectoral production** **Private consumption** Relative prices Indexes: trade, investments	**Energy supply** **Power generation mix** Energy investment profile

Notes: [a] For instance, SSP2 – Middle of the Road or other narratives and macroeconomic projection sources. [b] Information flows from COFFEE to TEA (in black bold text) and from TEA to COFFEE (in blue bold text).

Source: Authors' own elaboration.

The following sections go more into detail on the different practices and approaches at sector level.

3. Fossil fuel extraction

3.1 General trends in the fossil fuel sector's energy and emission characteristics

The fossil fuel sector relies on natural resources, of which there is a fixed supply. The cost of extracting fossil fuels, namely coal oil and gas, rises as they become depleted. The extraction processes in this sector have been undergoing massive technological innovation over the past few decades. For example, the development of hydraulic fracturing (fracking) and horizontal drilling technologies has increased access to tight oil and shale gas resources and led to increased supplies of these fuels, not least in the U.S., in recent years. Similarly, in Canada the development of oil sands has escalated in pace 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 (Empresa de Pesquisa Energética, 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 overall global oil supply, and hence oil pricing, owing to their spare production capacity (Cavallo, 2014). Arezki et al. (2017) find that tight oil production is more responsive to prices than conventional oil. WEO 2018 reveals that while there is a historic shift in energy consumption to Asia, there are mixed signals on the pace and direction of change. Demand for natural gas continues to rise due to a period of renewed uncertainty and volatility in oil markets, halting talk of a glut as China emerges as a giant consumer. Coal demand is projected to decline globally over the next few decades as a result of increased competition from gas and renewables.

The future of this sector will be significantly affected by the climate change policies expected by various nations as well as by technological innovations that will take place within extraction and alternative technologies. The application of artificial intelligence and digital data in this sector is expected to help reduce costs and thus offer good future prospects (Slav, 2018). Although most countries have committed to increasing the share of renewable energy generation, the production of fossil fuels will continue to increase for decades (see WEO 2018 and GECO 2018). 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, and the extraction sector's own innovation and adaptation of abatement technologies, will be decisive for the future outlook of the fossil fuel industry. Negative emission technologies such as direct air capture could bring good prospects for this sector even in a carbon-constrained world.[6] In general, however, it is expected that energy consumption will undergo fundamental changes: consumption of fossil fuel, coal in particular, will be dramatically reduced.

3.2 Modelling technology and behaviour in the fossil fuel sector

In CGE models, the extraction sectors are typically represented as a multi-level nested Leontief or CES function with very low elasticity of substitution (Figure 2). The functional form at different nest levels may vary slightly across models. In contrast to other sectors, a sector-specific resource (RES) is usually represented at the top level; see Figure 2. It 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 used to produce energy to extract natural resources. Emissions are usually linked to the use of coal, oil and gas at this level.

[6] The EC-MSMR model features various negative emission technology such as direct air capture that becomes a viable option under strict carbon constraint scenarios. For a review of literature on negative emission technologies, see Minx et al. (2018).

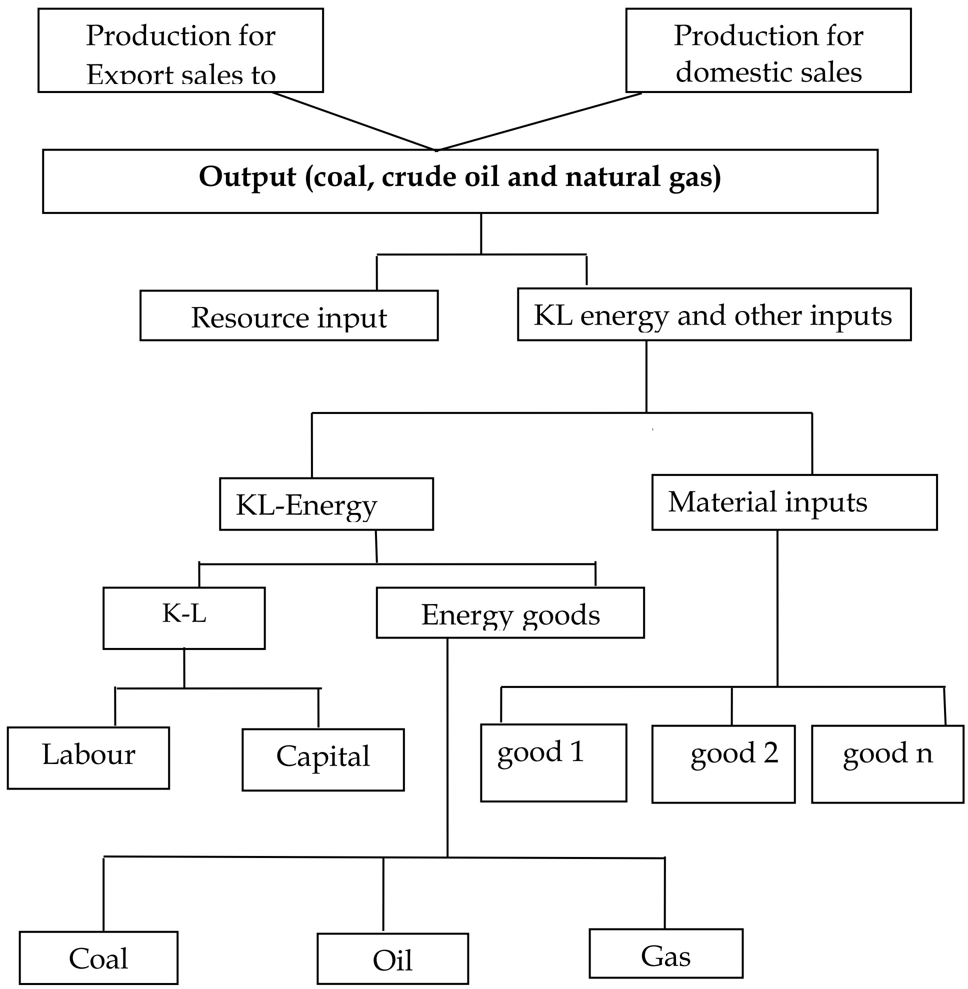

Figure 2. Typical representation of coal, crude oil or natural gas extraction sector

Source: Authors own construction.

This modelling of a fixed proven resource implies resource depletion over time. In a recursive-dynamic structure, resource owners do not have perfect foresight. In the EPPA model, for example, production in any period is subject to a dynamic process that adds reserves from resources and depletes 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. Elasticities of substitution were 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 of the fixed factor in the energy sector production functions. Over time, energy resources *R* in sector *e* are subject to depletion due to physical production of fuel *F* in the previous period. In period *t*:

$$R_{e,t} = R_{e,\,t-1} - F_{e,\,t-1} \tag{1}$$

This specification implies that fluctuations in market prices are accommodated by sector-specific resource rents. In the longer run, the effect is to squeeze out rents and if any production remains it is still priced at long-run marginal cost. The price drop is therefore limited by the resource rents, and with gradual exhaustion of high rent and low-cost fuels, the underlying marginal cost tends to rise. The importance of resource rents can be illustrated by examining the effects of rents on oil and coal prices. Since oil has significant resource rents, and coal has relatively low rents, coal production falls more than oil production in response to a drop in market prices. A description of modelling of these mechanisms in the EPPA model is provided in Babiker et al. (2001), Chan et al. (2012), Paltsev et al. (2011), Paltsev (2012) and Chen et al. (2016).

3.2.1 Multiple technologies

While most models do not distinguish between different production technologies within fossil fuel extraction, a few models incorporate more detailed technology structures. Figure 3 represents crude oil production by technology as in the Environment and Climate Change Canada's (ECCC) provincial CGE model (EC-PRO).[7] The crude oil production is disaggregated into seven technologies. First, crude-oil subsectors produce conventional, synthetic or bitumen crude. Conventional and synthetic crude are treated as imperfect substitutes in the domestic market. Supply response by each technology is controlled by a specific resource (`lmin`, `hmin` and `fmin` for conventional and `sagd`, `csss`, `snds` and `pnds` for non-conventional; see explanation in Figure 3). The value share and substitution elasticity with variable inputs determine the price elasticity of supply. The oil refining sector and the coal and natural gas processing sectors use the same nesting structure as manufacturing sectors, i.e., they do not have resource factors.

[7] ECCC also operates a global CGE model (EC-MSMR) with a similar structure.

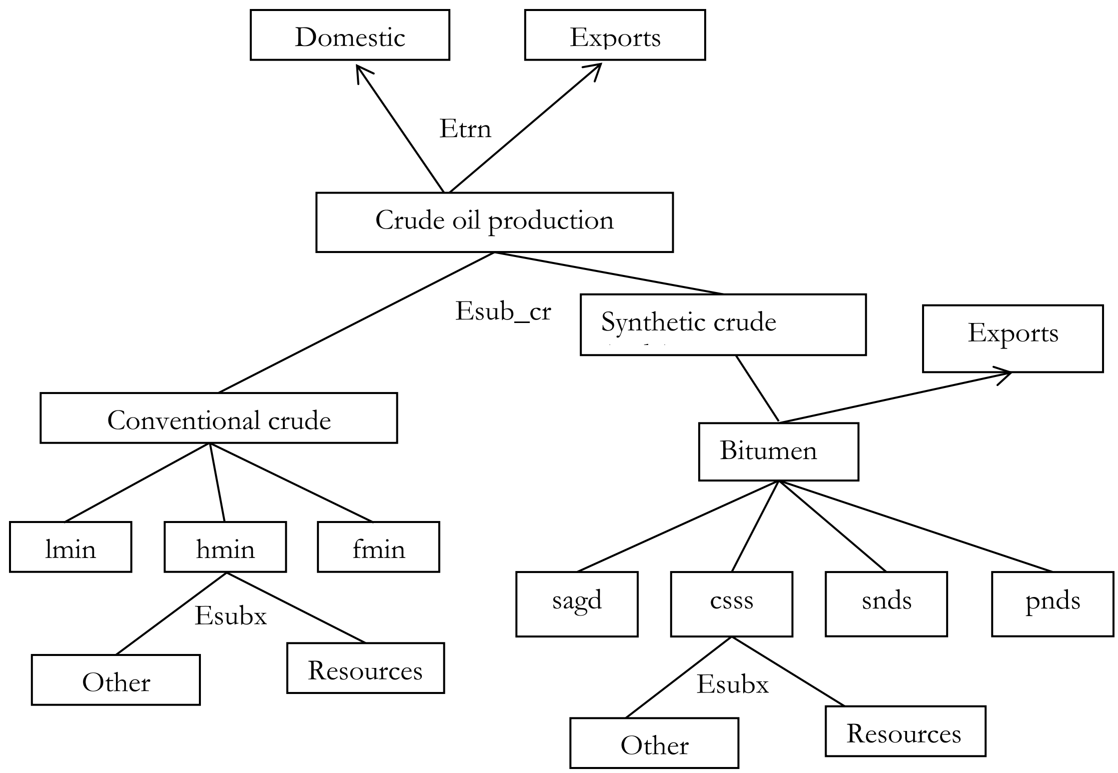

Figure 3. Crude oil production extraction and exports in EC-PRO model

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, etrn= elasticity of transformation, esub_cru = elasticity of substitution across crude oil types, esubx = elasticity of substitution (supply response).

Source: Authors own construction.

The EPPA model represents conventional and backstop fuel production, such as coal gasification and shale (tight) oil, separately. 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 novelty of the IMACLIM-R model is that, along with bottom-up details, it explicitly includes depletion and monopolistic behaviour (in the Middle East). Also unlike the previously 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 allows for short-term constraints.

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

The oil bottom-up modules of IMACLIM-R feature seven categories of conventional and five categories of non-conventional oil resources for each region, and specify threshold selling prices at which investments in production units are made. The maximum rate of increase in production capacity for an oil category reflects prices as well as geological constraints and has a bell-shaped profile, depending on the endogenous amount of oil remaining in the field. The function describing this maximum growth rate is calibrated as in Rehrl and Friedrich (2006).[8]

The production capacity at date *t* is given by the sum over all oil categories and regions. Non-Middle East producers are seen as price takers 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 so as to apply their market power, owing to their low production costs and fluctuation in the rest of the world's conventional discoveries (Gülen, 1996). As long as they have not reached depletion, they strategically determine their level of investment in order to control oil prices through the payload of their production capacities (Kaufmann et al., 2004). This specific representation allows studies of different market power strategies by the Middle East (see, for example, Waisman et al., 2012b and Waisman et al., 2013b).

The gas bottom-up module in IMACLIM-R ensures that the evolution of worldwide natural gas production capacities keeps pace with growing demand until available reserves enter a depletion period. The distribution of regional production capacities in the 'gas supply' dynamic module is represented by 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-JRC energy model (LEPII-EPE and ENERDATA s.a.s., 2009). Gas markets follow oil markets with an elasticity of 0.68 of gas price to oil price. This phenomenon is calibrated on the World Energy Model (see WEO 2007) and holds as long as oil prices remain lower than a threshold $p_{oil/gas}$.

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

3.2.2 Inclusion of renewable fuels

As already mentioned, one component of the backstop fuels in EPPA consists of biomass liquids (together with coal gasification and shale (tight) oil). ADAGE introduces eight types of first-generation biofuels and five types of second-generation biofuels. EC-MSMR features backstop representation of hydrogen, biofuels and renewable natural gas. The ENVISAGE and DART-BIO models endogenously bring in new energy commodities such as biofuels that could penetrate under policy scenarios, but this is not allowed for in the baseline scenario. In most models the bottom-up-informed emulations are left for policy shift analysis, particularly where changes in surrounding conditions are usually more limited. An interesting contribution is found in the MAGNET model, which represents endogenous research and development (R&D) in biofuels (ethanol, biodiesel, 1st and 2nd generation) thereby implying reduced costs along with profit-induced R&D activity (Philippidis et al., 2018).

3.2.3 Emissions and abatement modelling

Extraction of oil and gas and mining activities are major sources of CO_2 emissions as well as significant producers of non-CO_2 emissions. As is the case for other sectors, most models represent the combustion-related emissions in fixed proportions of energy use, and abatement takes place by means of energy efficiency improvements and changes in the energy mix. For process related emissions in the sector, particularly of non-CO_2 GHGs, EC-MSMR adapts a simple procedure whereby estimates of abatement potentials of non-CO_2 emissions at various technological costs are directly integrated into the model by means of an activity analysis approach which is similar to that described in Böhringer and Rutherford (2009). See also Harmsen et al. (2019) for a systematic, empirical review of non-CO_2 MAC curve estimations and Ghosh et al. (2012) for the EC-MSMR procedures. Sector-level MAC curve at county/regional level are available from the United States' Environmental Protection Agency, US EPA (2006, 2013).

A related procedure is used for including abatement costs in the extraction sector in the model version of SNOW calibrated to the Norwegian economy.[9] The lion's share of emissions from Norwegian offshore petroleum extraction is modelled as process emissions from a variety of activities, the most important being flaring and leakage under transportation and combustion. Abatement options include the use of carbon capture and storage (CCS), energy-saving and leakage-reducing investment and electrification. These are inserted into the SNOW model by quantifying a marginal abatement cost function linking the costs of marginal abatement measures to accumulated abatement potentials. The emission intensity is endogenized as a function of the installation and deployment

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

of abatement technologies. To account for the abatement costs, TFP is also endogenized. The higher the abatement costs, the more resources in terms of production factors are needed per output, i.e., the lower TFP is. 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, the inclusion of 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 Calibration of the fossil fuel sector in the base year and the baseline

3.3.1 Base year calibration

The detailed representation of fossil fuel extraction in the models EC-PRO, ADAGE, AIM/CGE, MAGNET, TEA, EPPA and IMACLIM-R require data additional to those typically included in national SAMs. Some make use of more detailed, energy models; e.g. AIM/CGE and TEA (see Section 2). The sources of elasticity values are typically available empirical studies, and some are available in the GTAP Data Base. For EPPA, for example, supply curves for natural gas were updated as reported in Paltsev et al. (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 from simulations of a detailed energy technology model called E3MC. Simulations are undertaken for large number of energy price scenarios (for coal, oil, gas, electricity) scenarios and the results are used to estimate the elasticities. The advantage of this approach is that foreseeable technological progress that is usually captured well in energy models is fed into the CGE model through the values of the elasticity parameters.

While the input-output tables provide data on basic technology, the characteristics of production (and consumption), technology are usually described in terms of the values of marketed transactions (inputs and outputs) in money-metric terms. These often deviate from emission data from countries' emission inventory systems, which may contain emissions from non-marketed energy consumption. Unless these inconsistences in emissions and energy data are addressed, the computed impacts of market interventions such as carbon pricing may be misleading. This inconsistency applies to all energy-consuming and combusting sectors, including the extraction sector. See also Section 2.3.

3.3.2 Baseline projections

The usual procedure for projecting technological change in CGE models is to augment total factor productivity and/or individual factor productivity parameters – cf. Section 2.3 for more details. To illustrate the effect on demand for fossil fuels of adjusting productivity parameters, Figure 4 shows the results of comparing two simulated baselines by means of the ENV-LINKAGES model – one naïve baseline with no adjustments and one ordinary baseline, which is expert-based, i.e., demand for energy is fully calibrated in line with the IEA's *Current policies scenario* in the WEO 2017 report.[10]

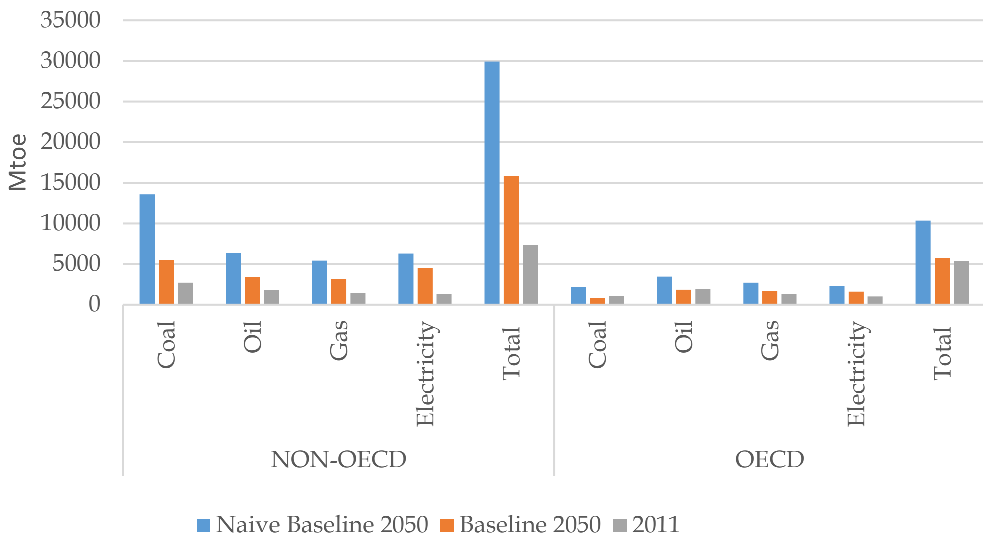

Figure 4. Primary Energy demand (Mtoe)

Source: OECD ENV-LINKAGES model; OECD (2019)

In both OECD and non-OECD countries, by 2050 the naïve baseline reveals much higher demand for energy, in general, and fossil fuels, in particular, than the WEO-based baseline. The latter accounts, inter alia, for expected trends in energy efficiency improvements, investment in infrastructures and structural changes towards higher shares of service sectors.

CGE models are often unable to provide further levels of disaggregation in terms of fuel- and technology-specific energy demand. Only models including hybrid modules, as described in Section 3.2, can project technology developments more explicitly. At this level of detail, expert knowledge is commonly used to track expected trends. One of the used solutions is to link with PE models.

For example, the EC-PRO model for Canada soft-links with the E3MC model for projecting oil and gas supply by technology characteristics. The E3MC

[10] These simulations tie several of the articles of this special issue together: The macroeconomic assumptions are provided in more detail in Fouré et al. (2020). The naïve baseline only accounts for these macroeconomic developments. The expert-based baseline coincides with OECD (2019) and adds a full set of assumptions about structural and energy system changes as described in Chateau et al. (2020)'s "*full structural change*" baseline; see also Section 2.3.

projection incorporates the potential impacts of existing policies and measures already implemented 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 COFFEE energy model 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 changes endogenously until the ratio between total energy consumption (in physical units) and total production (in monetary units) is equal in both models. In this manner, parameters that are normally exogenous now become endogenous, introducing energy efficiency, technical improvement and/or behavioural change into the model. In both models, fossil fuel quantities are also developed in physical units, as are natural fossil fuel endowments, by taking account of efficiency improvements and resource depletion.

4 Power generation

4.1 General trends in the power sector's energy and emission 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. Similarly, global investment in the power system is transitioning from fossil fuels to renewables. While total investment in fossil fuels and renewables was at comparable levels about ten years ago, global investment in renewables has recently reached a level that is more than double the investment in fossil fuel-based electricity generation (WEO, 2018).

Based on recent trends, three important evolutions can be anticipated for the decades ahead. Figure 5 illustrates the evolution of electricity consumption and technology mix over the course of the century, according to the baseline projections in the IPCC's Fifth Assessment Report Database (https://tntcat.iiasa.ac.at/AR5DB). 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) in the course of the period 2020-2050, with levels in 2100 that are twice or three times those in 2020. Second, the share of electricity in the overall energy mix is expected to increase. Third, these baseline projections indicate 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.

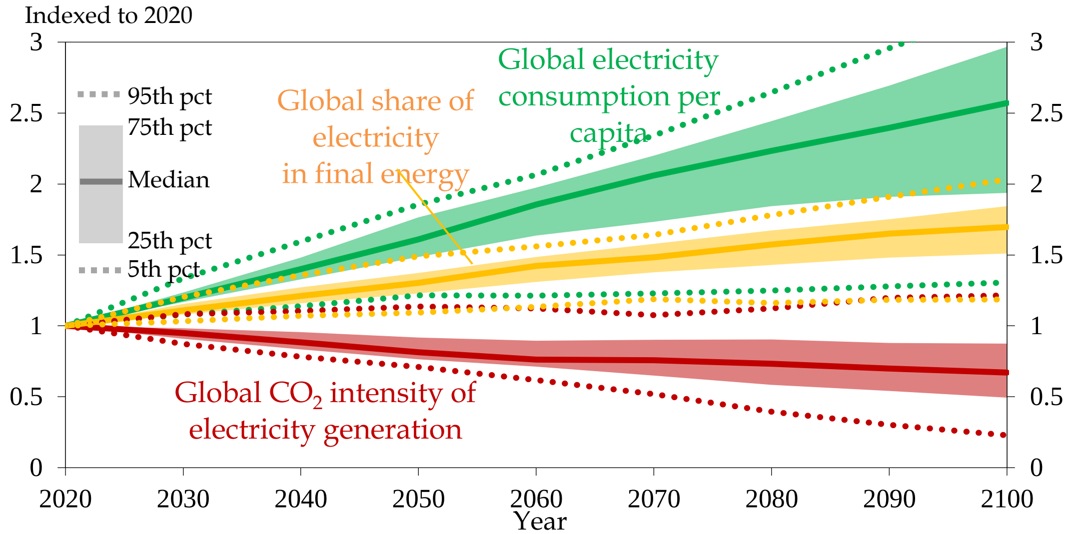

Figure 5. Future electricity consumption and technology mix in BAU baseline

Notes: The figure presents the evolution of electricity consumption per capita (n = 240), the share of electricity in the final energy consumption mix (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.

Source: https://tntcat.iiasa.ac.at/AR5DB

4.2 Modelling technology and behaviour in the power sector

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 of production factors. Emissions from each fossil fuel input (usually split into gas, oil and coal) are linked to demand by means of 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. In order 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, elaborated in the following paragraphs.

4.2 1 Technology disaggregation

Several models have moved toward a hybrid formulation by disaggregating power generation technologies, for instance, the GEM-E3, IMACLIM-R, EPPA, ENV-LINKAGES, TEA, AIM/CGE, ADAGE and WEGDYN models. This approach enables a closer connection between energy or power system models and CGE 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, one can distinguish between models that assume exogenous and endogenous technological progress. The REMIND model provides one example of the latter, including global learning-by-doing curves and internalized spillovers. The DART model provides another example, where cost reductions through learning-by-doing apply only to new capital, tracking vintages over time (see 4.2.3 on vintage modelling).

4.2.2 Intermittency of renewables

Going beyond a disaggregated representation of technologies, some models represent additional features of real-world electricity generation, related in particular 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 it models renewables with fixed back-up requirements as perfect substitutes for 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. (2019a) include the integration costs of intermittent renewables in the form of 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, 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 into the electricity generation mix ($Share_r^{wind}$ and $Share_r^{solar}$):

$$S_r = \alpha_r^{wind}(Share_r^{wind})^{\beta_r^{wind}} + \alpha_r^{solar}(Share_r^{solar})^{\beta_r^{solar}} \qquad (2)$$

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. Nevertheless, cross-border electricity trade is usually represented by standard Armington functions. Although studies point out the potential importance of electricity trade and interconnection capacity (Abrell and Rausch, 2016; Timilsina and Toman, 2016), particularly with high penetration of intermittent renewable energy sources, a detailed treatment has not (yet) become the mainstream modelling approach.

4.2.3 Capacity investments and vintage capital

In the model approaches described above, investment in current and new technologies proceeds smoothly. A realistic assessment of the power system transition could include the time lag for building power plants and their working life. Including these details could be facilitated by modelling a vintage capital structure. In the ENV-LINKAGES model, electricity is produced by different production streams, differentiated by capital vintage (old and new). Each production stream has an identical production structure, but with different technological parameters and substitution elasticities. Production firms can choose to use old or new capital. The distinction between vintages drives the results of emissions in ENV-LINKAGES as the two types of capital rely differently on fossil fuel resources and production inputs. In particular, the elasticities of substitution for new and old capital reflect the difference in the ease with which the two types of capital can substitute away from fossil resources towards cleaner inputs.

4.3 Calibration of the power sector in the base year and the baseline

4.3.1 Base-year calibration

To calibrate parameters in the base year, many models use supplementary accounts with physical energy flows, e.g. as provided by the GTAP-Power Data Base. In the EPPA and ADAGE models the economic values in energy demand and supply are augmented by accounts in physical terms for energy (exajoules) and emissions (tonnes). 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. The GEM-E3 model extends the conventional approach by calibrating the model's parameters not only in the base year, but also in future years according to projections of partial equilibrium models. The procedure, described in Wojtowicz et al. (2019), projects input-output tables in a first step, and calibrates the model correspondingly only in a second, subsequent step. This approach implies that technology parameters evolve over time instead of being fixed at the values of some historic base year.

4.3.2 Baseline projections

The refinements of the power supply modelling described in 4.2. facilitate an emulation of what goes on in more detailed bottom-up models. When exogenous variables like resource constraints, productivity growth and policy interventions are projected, the resulting price and cost impacts, along with the model's endogenous features as discussed in Section 4.2, will drive changes in technological progress and power mix.

There are some concerns associated with relying only on the model's endogenous mechanisms. First, a large variety of assumptions must be consistently implemented, including policies. A variety of policy measures affect the electricity markets in the base year already, and more changes might have been passed in political processes since the data were collected and would need to be included in a 'current policies' baseline. Another challenge is the small-shares problem pointed out in Section 2.3. It implies that profound penetration of known and feasible technologies that are not yet implemented (or to only a very minor extent) 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 that do not yet exist are expected in the future, and trade is based on Armington functions with (nested) CES characteristics. The approach in the AIM/CGE model given in section 4.2 could be considered a case where certain aspects of the detailed dispatch model – storage and curtailment – are emulated in a top-down CGE model.

For these reasons, baseline projections rely mostly on external data and on controlling the model determinants of the power system, including the energy mix in demand and the technology mix in the power sector. To understand the importance of such procedures, two different simulated baselines are compared, using the ENV-LINKAGES model.[11] The naïve baseline relies merely on macro-economic drivers and no energy-specific assumptions. The expert-based baseline is from OECD (2019) and constructed to correspond with the IEA's *Current policies scenario* from WEO 2017.

As seen in Figure 6, the WEO-based baseline shows a moderate increase in energy use by 2050 as well as a change in the mix towards more wind power, and a shift in fossil-fuel power from coal to gas power. Conversely, no such adjustments are imposed in the naïve baseline. As a result, the electricity mix shows a large share of nuclear power and coal in overall power generation. Whereas it makes sense from an economic perspective, since both these two sources of energy are actually cheap, in the long run it does not reflect the European countries' energy road maps and is therefore not a plausible baseline for climate change analysis.

[11] See also Section 2.3 and 3.3 for information about these simulations.

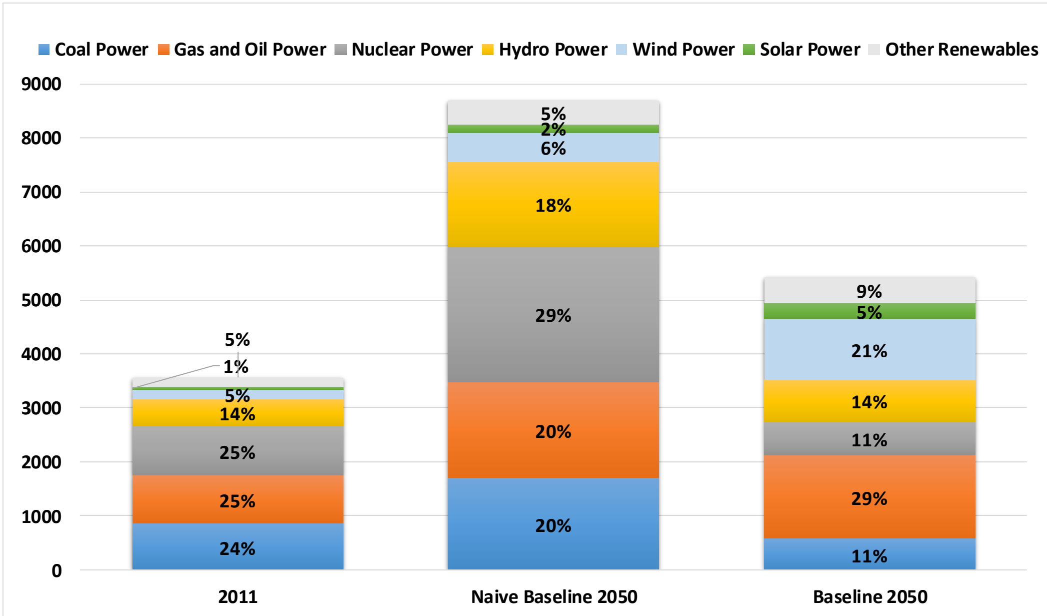

Figure 6. Electricity mix for OECD Europe (TWh)

Source: OECD ENV-LINKAGES model; OECD (2019)

Similar approaches, relying on external data sources, are used in projections made using the ADAGE model, (Ross, 2007). Projections of electricity generation by technology are calibrated to align with the IEA's WEO. In addition, because the model base year of 2010 is extrapolated from a GTAP Data Base characterizing 2004, the base year power sector data are adjusted to capture structural changes taking place between those years. In particular, the energy mix share is recalibrated to capture the rapid switch of power generation from coal to natural gas in the United States in the period 2004-2010 with the development of lower-cost horizontal fracturing (fracking) technology for oil and gas extraction (see also section 3). For future periods in the model projection, a further switch towards natural gas in the U.S. power sector is captured by the CES model structure, as continued positive supply shocks for natural gas reduce its cost relative to other energy sources.

A comparable approach that can extend 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. One can also be more confident that the inputs are consistent. The established links between the POLES-JRC and GEM-E3 models (Vandyck et al., 2016), as well as between the COFFEE and TEA models, are good examples of this approach.

To enable input from the detailed PE models (POLES-JRC and COFFEE) to be fed 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. Thus, 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 taken into account 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 linkage 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 changes endogenously in TEA until the ratio between total energy use (in physical units) and total production (in monetary units) is the same in both models.

Linking procedures can be more ambitious. As discussed by Delzeit et al. (2020) in this Special Issue, 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 the baseline is used as a starting point for a policy study, accuracy can be improved further by simulating the same shift within both models and taking account of the induced output changes in the iterations.

5. Transportation

5.1 General trends in the transportation sector's energy and emission characteristics

The transportation sector covers various economic activities and is usually split into passenger and freight transportation activities. The demand for passenger transportation services is expected to grow with population and GDP and income per capita, but the relation between transport volume and per capita income level varies. Historically, the demand for freight transportation services has been 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 accounted for 24% of the total global CO_2 emissions from fuel combustion in 2017 (IEA, 2018a). The determinants of carbon emissions in the transportation sector are either (i) technological relating to the carbon intensity of the fuels and the energy intensity of operating the vehicles, or (ii) behavioural relating to the modal structure of the mobility and its volume (Chapman, 2007; Schafer, 2012). For full accounting of all life-cycle emissions from transport activities, indirect emissions would also need to be included, like emissions from energy production used for operating vehicles and from vehicle and infrastructure production that arise in relevant manufacturing and constructing sectors.

The 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, the energy efficiency of passenger transport has improved by an annual rate of 0.5% between 2000 and 2016, while the annual efficiency improvement rate of trucks in the same period was less than 0.1%. Past trends in aviation and shipping are much stronger, with annual improvements in efficiency over the same 16 years of about 3.6% and 2.1%, respectively (IEA, 2018b).

In addition to these global efficiency improvements, electrification and biofuels contributed substantially to the slowdown in growth of global transport emissions. Growth in these global sectoral emissions was 0.6% in 2017, whereas they used to grow at an annual rate of 1.7% during the previous decade. However, despite this positive picture, the IEA estimates that far more extensive mitigation efforts are needed to reach the "well below 2°C" target (IEA, 2018c).

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

However, it is worth noting that a shift is expected in road transportation for light duty vehicles, given the increasing market penetration of electrically powered vehicles (EVs). Globally, total EV sales increased from less than 0.5 million units per year in 2013 to over 3 million units per year in 2017 (IEA, 2018d). In the United States, although EV adoption rates are still low, production has been increasing over time and the country represented the largest share of the global EV stock until 2015 (IEA, 2017). In 2016, the production shares of hybrid, plug-in hybrid and electric vehicles in the U.S. were 1.8%, 0.3% and 0.5% respectively. Preliminary data for 2017 suggests that these production shares increased to 3.3% hybrid, 0.9% plug-in and 1.0% electric vehicles (US EPA, 2018). That same year China had become the country with the largest stock of EVs, with more than 30% of the global stock. China still heads the field with respect to the electrification of modes of transportation other than private cars, with more than 200 million twowheeled electric vehicles, almost 4 million low-speed electric vehicles and more than 300000 electric buses (IEA, 2018d). Nevertheless, although the market share of EVs is close to 50% in Norway, the country with the biggest EV market share, this market remains quite small in all other countries. China, which occupies the 4th position, sees its EV market share amounting to 2.2% in 2017 and that of the United-States to 1.2%. Finally, it is noteworthy that EVs are anticipated in many scenarios to represent the bulk of the vehicle fleet by 2050, as a response to environmental challenges. Needless to say, this electrification of the transport sector will only reduce overall emissions if low-emission electricity is available.

In addition to electrification of transport, many countries have expanded their use of biofuels in recent years. Globally, the IEA estimates that biofuel consumption for transportation increased by over 33% between 2010 and 2016, from 59 Mtoe to 79 Mtoe (IEA, 2018e).

5.2 Modelling technology and behaviour in transportation

The default representation of transport activities in CGE models follows the rules of national accounts. 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, household demand for transport is split between services purchased from commercial firms and those supplied by own vehicles in combination with demand for energy (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 as part of aggregate fossil fuel demand and purchased transport services as part of intermediates. The utility functions in CGE models have traditionally been of the LES or CES type, though other functional forms that allow for income elasticities other than unity are becoming more common. Purchased transport services are supplied by firms in production sectors. The supply of passenger and freight transport services is usually merged. A default solution is that commercial transportation sectors are split into the segments water, air and other, the latter covering all land transportation. Production inputs are CES combinations of labour, capital, non-energy intermediates (including commercial transport services) and energy (without specified purposes). This aggregation level is available in the GTAP Data Base. In all specifications, AEEI parameters are used to implement exogenous, factor augmenting energy efficiency improvement for both private transportation in utility functions and suppliers of transport services in productive sectors in their production functions. The following subsections outline refinements to the modelling of both behavioural and technological determinants.

5.2.1 Disaggregating the transportation sector

In the transportation industry, technological improvements, represented by decreased energy consumption per unit of output, varies significantly with transportation mode. Disaggregation of the transportation sector may improve the representation of energy substitution possibilities among and across transportation modes. Many national accounts distinguish between rail and road transportation, as well as domestic and international air and water transport, and these categories can be exploited to capture substitutability and emission impacts at more detailed levels. However, only some models disaggregate road transport into different vehicle and energy modes. Water transportation is not usually disaggregated.

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 tonne-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-miles travelled as well as price of passenger-miles travelled for passenger transportation or ton-miles travelled for freight transportation.

In the WEGDYN_AT 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 of them explicitly modelled by different production functions. The model responds 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_AT model represents three groups: First, *motorized individual transport* 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 the 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, other 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 other land transport infrastructure provision (pipelines), again modelled as nested CES functions. In addition, the model includes a water transport and an air transport sector. All transport sectors are interlinked with the rest of the economy via input-output 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 for their operation - see supplementary materials of Bachner (2017) for details on the nesting structures and elasticities.

The AIM model system adopts a hybrid modelling approach, in which the 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 and technologies endogenously, which allows the AIM/CGE model to reflect detailed behavioural choices.

5.2.2 Modelling alternative fuel vehicles

Because of environmental concerns, high oil prices and prospects of falling oil production, developing 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 some of the models.

The EPPA model represents the penetration of AFVs (electric, hydrogen, compressed natural gas) endogenously (Chen et al., 2016; Paltsev et al., 2018). When initially adopted, an 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 the cost of the technology relative to the internal combustion engine (ICE) vehicle. As ever larger volumes of advanced technology vehicles are introduced, the cost of further upscaling 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, the stringency of fuel economy standards (if applicable), 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 hydrogen fuel cell drivetrains) for all types of road transportation vehicles in the model (light-duty vehicles as well as heavy-duty vehicles such as trucks and buses). The production and consumption of AFVs are defined within the context of the market for transportation services, in terms of passenger-miles travelled for passenger vehicles and ton-miles 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 for ICE vehicles. 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 model, the distinction between the technologies of EVs and ICE vehicles is made in the household utility function, depicted in Figure 7. Both vehicle technologies include the inputs operation and maintenance (O&M), car and energy (electricity and fuel, respectively). The model also allows for substitutability of fossil fuels and biofuels and separates rail from road transport.

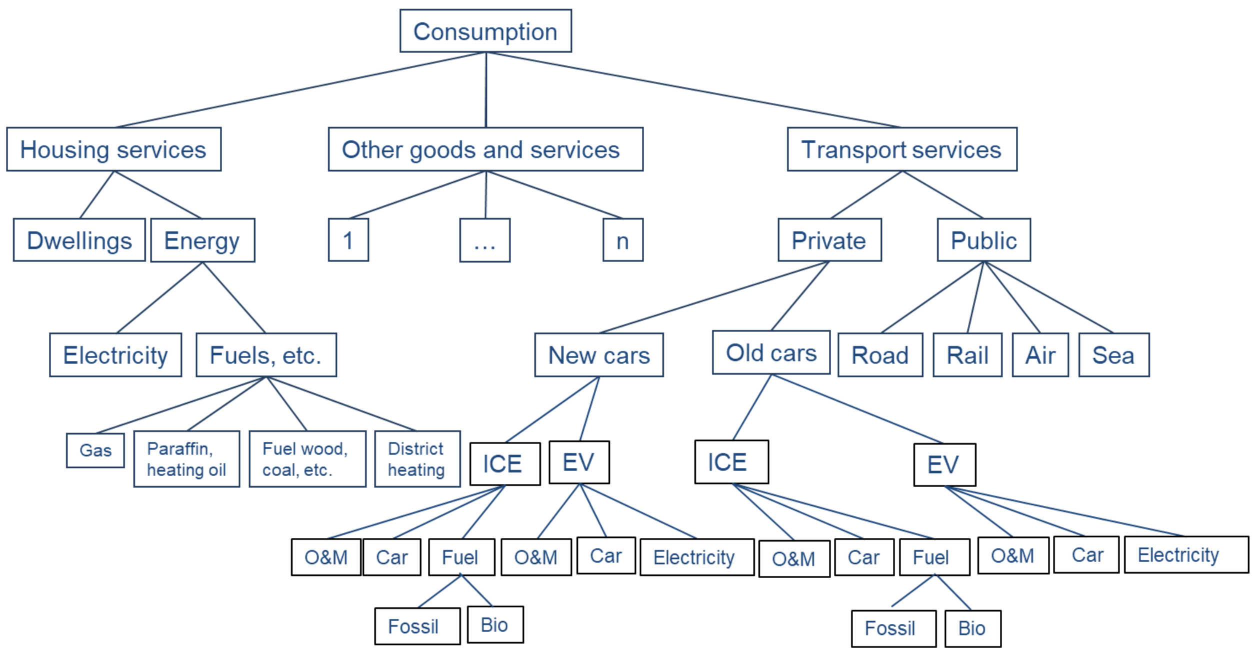

Figure 7: The consumption CES structure in the SNOW model

Source: Authors own construction.

5.2.3 Capital vintage modelling

Vintage modelling has become a common solution in transportation modules for capturing the fact that technological change takes time, since old vintages are assumed to be unable to leave the sector. Figure 7 illustrates how old and new cars are separated in the SNOW model. The use of old cars is given from previous investments in EVs and ICE vehicles and aligned to their expected lifetimes. Similar distinctions are made in the IMACLIM-R and ADAGE models, as well as in the ECCC models (both the global *EC-MSMR* and the country model for Canada *EC-PRO*). Vintage modelling allows different AEEI parameters for energy to be assigned to old and new capital, respectively.

Given that the fuel efficiency and CO_2 standards apply only to new model-year vehicles, differentiating between the new and used vehicle fleets is essential. The

EPPA model includes a parameterization of total miles travelled in both new (0 to 5-year-old) and older (6 years and older) vehicles, tracking changes in travel demand in response to income and cost-per-kilometre changes. The EPPA model also represents the ability to substitute between new and used vehicles as 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 of the representation of fuel and emission standards in the EPPA model are provided in Karplus et al. (2015).

5.2.4 Behavioural aspects: mobility demand and travel time

In the dynamic, recursive and hybrid IMACLIM-R model, the standard representation of transport technologies is supplemented by an explicit representation of the "behavioural" determinants of mobility (Waisman et al., 2013a). Each representative household maximizes its utility through a trade-off between consumption goods and mobility services. The model uses a Stone-Geary utility function in which the consumption of each good must meet or exceed a certain 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) and non-motorized transport (walking and biking) [12].

Households maximize utility under a twofold constraint that affects transportation decisions. On the one hand, the standard budget constraint captures the fact that transport-related expenditures are involved in a trade-off with the consumption of other goods. On the other hand, demand for each modal of transportation service is constrained by a time-budget constraint to represent the stability of the travel-time budget across time and space on a regional or national scale. This constraint allows congestion effects to be taken into account. Travel time, congested traffic, and trip purpose are typical 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 described IMACLIM-R representation, combined with the dialogue between the *top-down* structure and the *bottom-up* modules, makes it possible to represent (i) the rebound effect of energy efficiency improvements on mobility, (ii)

[12] In the personal vehicles market, three types of technology are represented: those with standard internal combustion engines (ICE), those with efficient internal combustion engines, and EVs, which implicitly represent all types of vehicles that use electricity as an energy provider, including fuel cells and hydrogen vehicles)

endogenous mode choices in relation to infrastructure availability, (iii) the impact of investment in infrastructure capacity on the amount of travel, and (iv) the constraints imposed on mobility needs by firm and household location (urban forms).

Still in IMACLIM-R, the production functions of all sectors take the form of Leontief specifications, with fixed equipment stocks and fixed intensity of labour, energy and other intermediary inputs in the short-term[13]. 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 makes it possible to capture changes in *(i)* the energy efficiency of freight vehicles, *(ii)* the logistic organization of the production/distribution processes, and *(iii)* the modal breakdown.

5.2.5 Introducing new transport business models

One crucial element for reducing transport emissions is behavioural change, possibly induced by the availability of new organization forms for transport. In passenger transport, this includes sharing concepts such as car sharing (Prettenthaler and Steininger, 1999). New business models lend themselves particularly well to being analysed by CGE transport models or modules. As a prerequisite, the modeller needs to combine a demand structure similar to that given in Figure 7 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 in 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 in the course of the day by a standard all-day user such as the postal service or mobile health care, can then be analysed with respect to its economic and environmental implications. Based on such BAU modelling and the experience acquired from a field experiment involving a set of commuter and daytime users, a roll out to the entire nation was simulated by means of the WEGDYN_AT model. With the CGE approach taking account of the indirect and aggregate market effects, these simulations allow quantification of the emission reductions due to both (i) the commuters' mode shift to electric trains for the major portion of their trip and (ii) the reduction in the car fleet.

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

5.3 Calibration of the transportation sector in the base year and the baseline

The disaggregate representations of consumption shares, production shares, trade shares, and production cost shares in many of the models (see 5.2.1) exploit different data sources.[14] In the case of the ADAGE model, for instance, input-output data from the GCAM model[15], national input-output accounts data, GTAP Data Base data and the six transportation sectors (road, rail, air, water, pipeline, and other) in the WEO database are used.

The penetration and technological features of future AFVs are likely deviate significantly from the current status. This renders the quantification of the substitutability across vehicle technologies in the decades to come challenging. The SNOW model relies on expert-based projections from the Norwegian Environment Agency, NEA (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 CO_2 emissions levels). [16] In the EPPA and ADAGE models, historical observations form the basis for the elasticity of substitution. In ADAGE an econometrically estimated elasticity is combined with a mark up factor, defined as the relative cost ratio between AFVs and ICE vehicles, which measures the dynamic technological advance.

6. Manufacturing industries

6.1 General trends in the manufacturing sector's energy and emission characteristics

Manufacturing industries are often large consumers of fossil fuels for combustion. In addition, several manufacturing processes generate emissions, so-called process emissions. Indirect emissions from manufacturing industries are also prominent, since they tend to be energy intensive and lead to emissions from energy production, including power generation. In 2010, global GHG emissions related to manufacturing industries accounted for 15.4 $GtCO_2$ eq., representing 30% of total global GHG emissions. There was an increasing trend from 2005 to 2010 of 3.5% p.a. Two thirds (10.2 $GtCO_2$eq.) of these GHG emissions are emitted by the industrial sectors themselves, while the remaining third (5.3 $GtCO_2$eq.) arises indirectly via demand for electricity and heat. Taking a closer look at the within-industry emissions, 75% (7.6 $GtCO_2$eq.) are emitted via the combustion of fossil fuels, whereas 25% (2.6 $GtCO_2$eq.) are attributable to non-energy-related

[14] Owing to space constraints, only some illustrative examples are given here. The reader can refer documentation for the individual model for specific details; see Appendix B.

[15] https://jgcri.github.io/gcam-doc/

[16] The other relevant substitution elasticities are estimated on historical data (Aurland-Bredesen (2017); Aasness and Holtsmark (1993); 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.

industrial processes, such as the chemical processes in cement or steel production (Fischedick et al., 2014).

Across all manufacturing sectors, 50% of total direct GHG emissions result from three sectors: the production of ferrous metals (22%), chemicals (15%) and cement (13%). The rest are emitted by landfills and waste incineration (7%), water treatment (8%) and other industries (36%), including pulp and paper manufacturing, food processing, manufacture of textiles and leather as well as of non-ferrous metals (e.g. aluminium). 85% of the GHG emissions (including indirect emissions) are CO_2, followed by CH_4 (9%), HFCs (3%), N_2O (2%), SF_6 (0,5%) and PFCs (0.5%). In total, non-CO_2 GHG emissions from industry add up to 2.3 $GtCO_2eq$. (Fischedick et al., 2014). As a share of global non-CO_2 GHG emissions, the manufacturing industries account for 13% (in 2005). This share is expected to increase, as industrial emissions tend to rise faster than emissions from other sectors (US EPA, 2012). Key non-CO_2 GHG emission processes are the production of chemicals such as chlorodifluoromethane (which emits HFC-23), adipic and nitric acid (which emits N_2O), aluminium (which emits PFCs) and the manufacture of fertilizers (Harmsen et al., 2019; Fischedick et al., 2014).

GHG emission abatement options in the manufacturing industries are very diverse. The standard approach for economic assessments uses MAC curves, which are often product, region and/or country specific, as there or no "one-size-fits-all"-solutions. In the literature there is a clear focus on CO_2 emissions from the production of basic materials such as cement (e.g. Dai et al., 2017; Kajaste and Hurme, 2016; Talaei et al., 2019; Yang et al., 2013; Zhang et al., 2015) and iron and steel (e.g. Mayer et al., 2019; Milford et al., 2013; Zhang et al., 2014). Some studies cover aluminium production and the associated emissions of PFCs (e.g. Kermeli et al., 2015; Mahadevan, 2001). Abatement options and MAC curves for non-CO_2 industrial GHG emissions are partly covered by Harmsen et al. (2019), who include chemicals and fertilizers, and Ragnauth et al. (2015).

Abatement options for industry can be summarized under six types of efficiency (see Fischedick et al., 2014, p. 746): "*(1) Energy efficiency (e.g. through furnace insulation, process coupling, or increased material recycling); (2) Emissions efficiency (e.g. from switching to non-fossil fuel electricity supply, or applying CCS to cement kilns); (3a) Material efficiency in manufacturing (e.g. through reducing yield losses in blanking and stamping sheet metal or re-using old structural steel without melting); (3b) Material efficiency in product design (e.g. through extended product life, light-weight design, or de-materialization); (4) Product-Service efficiency (e.g. through car sharing, or higher building occupancy) and (5) Service demand reduction (e.g. switching from private to public transport).*"

In many cases, abatement options in the manufacturing industries can also be summarized under the term "electrification". As electricity is very versatile, such electrification can cover the demand for energy, but also for heat and feedstock (mainly via renewable hydrogen). Other specific abatement options for the iron and steel industry are electrowinning, the replacement of coke by gas, hydrogen or bio-char and higher material efficiency. For cement production, replacing current clinker with other materials would reduce GHG emissions, and heat could be supplied via plasma technologies. Fuel switching can also reduce GHG emissions in cement production. Emissions from aluminium production can be reduced via energy efficiency measures and renewable electricity (more than 80% of emissions are indirect emissions), increased recycling rates as well as reduced anode consumption (Fischedick et al., 2014; Lechtenböhmer et al., 2016).

Industrial process emissions present a major challenge to the deep decarbonization of the basic material industries. These emissions are not produced by the combustion of fossil fuels, but stem from other chemical processes. In the EU-28, the most important manufacturing sectors with process-generated emissions, in absolute terms, are the production sectors for metals (including iron and steel), minerals (including cement) and basic chemicals (Lechtenböhmer et al., 2016). Reducing industrial process emissions is particularly challenging, because emission reduction is limited by stoichiometry. This means, for example, that for each tonne of steel that is produced there is a fixed amount of CO_2 released, which is a product of the chemical reaction of oxygen and carbon when the iron ore is de-oxygenated. Efficiency measures can help to some extent, but for deep decarbonization, only three basic means of abatement are available: first, reducing sectoral output and replacing emission-intensive materials (e.g. substituting bio-based polymers for steel in car production); second, changing the whole production process to maintain output (e.g. by switching to electrowinning in steel production, thereby replacing carbon-based processes with renewable electricity) and third, using end-of-pipe technologies (CCS or carbon capture and utilisation (CCU); see Lechtenböhmer et al., 2016).[17] 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 carbon leakage prone (Bednar-Friedl et al., 2012; Schinko et al., 2014).

When looking at recent developments in the steel and cement sectors, the importance of tackling process emissions from these sectors becomes even more evident. Between 1980 and 2010, emissions from these two sectors increased sharply, with annual growth rates of 2-4%. Driven by a strong increase in demand, global steel production 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 to 3.3 Gt and 3.0 Gt, respectively (van Ruijven et al., 2016), with at least half of that attributable to process emissions. Turning to the basic chemical industries, a similar picture is seen, with growth in physical output (measured in tonnes) exceeding that of steel since 1989. Global CO_2 emissions from chemical industries amounted to 1.7 Gt in 2010 (Broeren et al., 2014).

[17] In Fischedick et al. (2014)'s six efficiency types this is covered by "emission efficiency."

Other topics related to reducing process emission reductions are recycling, or more generally, the "circular economy", as well as new materials research, aimed at replacing process-emission-intensive products. These subjects will be addressed further in Section 9.

6. 2 Modelling technology and behaviour in manufacturing

The combustion-induced emissions from industries, including manufacturing, are adequately taken into account in most models. The default in abatement modelling in energy-intensive industries is to include the usual endogenous substitutability of other factors for energy and across energy forms, with AEEIs, substitution elasticities and emission coefficients being exogenous. The modelling of industrial process emissions in CGE models is less well developed. If process emissions are taken into account, they are typically modelled in fixed proportion to sectoral output at the top level of the nested production functions. Examples of this default inclusion are the ENV-Linkages, EPPA and SNOW models. Among models that take account of process emissions, the default is thus exogenous emission factors that can be adjusted in projections to account for anticipated abatement options.

6.2.1 Specifying technologies to reduce emissions

A few models specify endogenous process emission reduction. In SNOW and GEM-E3, 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 technology options based on (renewable) electrification for iron and steel (Mayer et al., 2019; Bachner et al., 2019b; Schinko et al., 2014). A similar approach is used in the MAP-CGE model for cement (Jun et al., 2014).

Inserting MACs implies that changing emission costs can endogenously alter process emissions through the deployment of abatement technologies. Potential technology options are exogenously specified, but endogenously chosen by 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. Price-induced abatement changes the parameters of existing technologies via i) changes in emission intensity and ii) changes in total factor productivity, to account for the additional costs of abatement. Note that since abatement technologies are not modelled explicitly, the cost structures of abatement measures have the same cost structure as the sectors that implement these abatement measures. Thus, unit cost structures do not change due to abatement.

GEM-E3 also models non-combustion CO_2 and 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), thereby capturing the general equilibrium mechanisms of changed unit cost structures (as opposed to the approach in SNOW).

In the WEGDYN model, the approach of modelling abatement of process emissions is different Abatement is not based on a MAC curve, which alters existing technologies, but is modelled by the introduction of a new production technology (activity). This approach is closer to actual technological developments in process emission abatement than the MAC curve approach, as it explicitly models a completely new technology. In WEGDYN, firms in the iron and steel sector, for example, 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 steel industry stakeholders (Bachner et al., 2019b; Mayer et al., 2019). This switch is introduced exogenously and represents a more fundamental change in production technology, rather than merely marginal improvements, as is the case with MAC-curve-based approaches. Note that the approach used in the WEGDYN model deals with the issue that in process industries the emissions reduction of existing technologies is limited by chemistry and stoichiometric principles. This implies that when following a MAC curve approach, a modeller should take care when moving to very high abatement levels in these industries, as the MAC curve must show a discreet change at the point where chemistry limits further marginal improvements, requiring a sudden switch in production processes.

6.3 Calibration of the manufacturing sector in the base year and the baseline

By default, process emissions, if represented, are calibrated on the basis of national accounts and emission inventory data (e.g. UNFCCC, 2017) in the base year, and the emission coefficients are exogenously projected into the future. To represent changes over time, the GEM-E3 model uses baseline emission coefficients calculated in the bottom-up model GAINS of the International Institute for Applied Systems Analysis (IIASA), where process emissions are abatable by end-of-pipe options. That is, although GEM-E3 has modelled MAC curves that endogenize abatement of manufacturing process emissions, only the policy scenarios, not the baseline projections, rely on these mechanisms. The emissions are available for different GAINS scenarios 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 new process-emission-free alternatives only taking place in the policy scenarios. Whether the alternative technology is active already in the baseline is up to the modeller, however, and depends on the scenario framework.

In SNOW, two options are available for baseline construction: either exogenous emission coefficients, as in GEM-E3, or using the endogenous MAC curve to endogenize the coefficient and the related costs. The bottom-up information used to estimate the MACs involves various bio substitutions in processes (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.

7. Buildings

7.1 General trends in the building sector's energy and emission characteristics

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

Globally, the sum of direct and indirect GHG emissions from the building sectors was 9.18 $GtCO_2eq$ in 2010, accounting for around 19% of world's GHG emissions (Lucon et al., 2014). The sectors' emissions have doubled since 1970, even if direct emissions have stayed fairly constant. Indirect emissions accounts for around two thirds, and the rise is first of all explained by increased emissions from the electricity sector.

Consistent with the historical trend, energy consumption in the building sector of developing countries is often projected to increase dramatically, particularly in South Asia; see, e.g., Lucon et al. (2014). A main driver is income growth, which will enable many people currently with limited access to energy to access modern energy options.

7.2 Modelling technology and behaviour in the building sector

Residential energy consumption is included in household energy consumption activities in the CGE models. Energy for cooling, heating, water, lighting and use of other electric appliances usually corresponds to the residential energy consumption in energy system accounting, such as energy balance tables. The energy consumption associated with private car use is not included in this category (see Section 5). The commercial sector includes various kinds of so-called tertiary industrial activities (retail, education, hospital, private and public services and so on) which have similar energy service and consumption patterns. The representations in the current CGEs or even energy system models rarely distinguish between these individual commercial sector energy uses.

Almost all models use the CES production function for the commercial sector with a slight variation in the nesting structure, substitution elasticity parameters and assumptions for future technological parameters.[18] A typical CES structure would resemble the one depicted for the oil and gas sector in Figure 2, except for the reliance on resource input (RES). Typically, energy use in buildings is not explicitly separated from other energy use by firms, and buildings are part of capital input. As regards future technological assumptions, most models assume non-price-induced technological progress in energy consumption represented as exogenous AEEIs.

Various functional forms are used for the household sector, see Section 2.2. Each has its advantages and disadvantages. LES and CES functions are relatively simple structures with a limited number of parameters. They have the advantage of ease of implementation, but they do not always match historical observations well. Other functional forms have more flexibility to specify income, own-price or cross-price elasticities, but more data is required to calibrate the parameters.

7.2.1 More detailed representation of energy use in buildings

Many models use multi-nesting CES structures that are more complex than those mentioned above. A version of the AIM/CGE model explicitly represents individual energy services (e.g. space cooling, lighting and so on) with alternative technological options (e.g., high efficiency air conditioner, traditional biomass cooking device and so on). The demand for energy services are, inter alia, determined by the output level of the sector (or income level for households). 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 into studies both of emission 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).

7.2.2 Linking energy efficiency to physical characteristics of buildings

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

[18] One exception is the IGEM model which uses translog cost function for the commercial sector:https://scholar.harvard.edu/files/jorgenson/files/igem_documentation-1.pdf.

7.3 Calibration of the building sector in the base year and the 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 a TIMES energy system model (Institute for Energy Technology, 2013). The motivation for using this approach rather than ex-post estimations is that energy efficiency improvements are subject to increasing political and societal attention, arguably rendering historical evidence less relevant. See Bye et al. (2018) for the calibration procedure.

8. Agriculture and forestry

8.1 General trends in the agriculture and forestry sectors' emissions and sequestration characteristics

Agriculture, forestry, and other land use are a major source of net GHG emissions. Emissions net of carbon sequestration accounted for about 17% in 2019 (see Figure 1). From 1990-2010, total net emissions from these sectors increased by about 8% (Tubiello et al., 2014). Global GHG emissions from agriculture have generally trended slightly upward over time, with these increases heavily concentrated in less developed countries. Net emissions from forestry and other land use also rose over this time period but underwent a shift between the 1990s and 2000s. While there was a reduction in emissions from net forest conversion over this time period, reflecting lower rates of deforestation, there was an even larger reduction in the average annual net increase in carbon sequestration provided by forests (Tubiello, et al., 2014).

Key sources of agricultural emissions include enteric fermentation (CH_4), manure management (CH_4 and N_2O), rice cultivation (primarily CH_4, but also N_2O and changes in soil carbon), and management of agricultural soils (primarily N_2O but also changes in soil carbon and small effects on CH_4 for crops other than rice). CO_2 and non-CO_2 emissions associated with agricultural energy use account for a relatively small share. An important difference from emission in many other sectors is that relationships between levels of economic activity and non-CO_2 emissions in the agricultural sector typically are non-linear with complex relationships between the quantity and quality of inputs and emissions associated with production of outputs.

US EPA (2019) estimates that agriculture accounted for 48% of global non-CO_2 emissions in 2015 (in terms of CO_2eq) and projects continuing increases in agricultural emissions in coming decades as rising global populations and higher incomes raise global demand for agricultural commodities. Demand for livestock products has been rising faster than overall demand for agricultural products, especially in less developed countries. The use of nitrogen fertilizer (an important contributor to N_2O emissions from agricultural soils) has also been trending upwards in many regions that have historically used relatively little synthetic fertilizer. Overall, agricultural emissions are projected to be relatively constant in more developed countries, while rising in less developed countries. Projections of forestry and other land use emissions are more uncertain given the complex dynamics of forest growth and lack of detailed data on the characteristics of global forest stands that will influence the rates at which their sequestration of carbon will change over time. Baker et al. (2019) provide an overview of alternative methods for projecting forest carbon stocks and implications.

In addition to its contribution to global GHG emissions, Klimont et al. (2017) estimate that agriculture accounted for 10.5% of global anthropogenic emissions of particulate matter (PM) less than or equal to 10 micrometers in diameter (PM_{10}), 8.0% of $PM_{2.5}$, 4.6% of black carbon, and 9.7% of organic carbon in 2010. While not included in global anthropogenic emissions, burning of forest and savannah generate very large quantities of these emissions, accounting for 43.5%, 40.8%, 23.8%, and 59.0% of total global emissions from all sources of PM_{10}, $PM_{2.5}$, black carbon and organic carbon, respectively, in 2010. Thus, it is important to account for non-GHG air pollutants from the agriculture and forestry sectors in studies focused on impacts of such emissions on air quality, water quality, ecosystems, human health, or other systems potentially impacted by particulate emissions.

Agricultural and bioenergy policies as well as climate change impacts are expected to have an important influence on both baseline and policy scenarios. A major expansion in global bioenergy production in recent decades has tightened the linkages between the energy sector and the agriculture and forestry sectors supplying bioenergy feedstocks. Bioenergy policy is an important driver of demand for agricultural commodities and land resources globally and will continue to play an important role in the future development of the agriculture and forestry sectors. Key factors to reflect within models capturing the impacts of bioenergy expansion include conversion rates of alternative feedstocks to bioenergy outputs and production of coproducts (e.g., dried distillers' grains, oil meals). The agriculture and forestry sectors are also expected to be among the most impacted by projected climate change, though productivity impacts are likely to vary substantially between commodities and across space and time. The importance of these interactions with energy and environmental policies as well as susceptibility to environmental change have led to many CGE models enhancing their characterization of these sectors in recent years.

8.2 Modelling technology and behaviour in agriculture and forestry

In general, these sectors are quite heterogeneous spatially and temporally as well as between subsectors.[19] However, many CGE models that are not focused specifically on agriculture and forestry include these sectors at a highly aggregated level. Such characterization may miss important drivers of land use and emissions. CGE models focused on the agricultural sector often supplement characterization of the sector in value terms as available from a SAM with data on areas, yields, number of head of livestock, and other measures provided in biophysical terms, using sources such as FAOSTAT and a variety of other global and national data sources.[20] Studies focusing on the agriculture and forest sectors may also be good potential candidates for linking of CGE models with partial equilibrium or biophysical models to better reflect sectoral characteristics and generate key outputs in physical units; see Delzeit et al. (2020). Some of the important innovations being captured in advanced CGE models being applied to analyses of the agriculture and forestry sectors are summarized below.

8.2.1 Sectoral disaggregation

As noted above, not only are the agriculture and forestry sectors quite heterogenous across time and space, but the subsectors that comprise these sectors also vary significantly in terms of expected productivity improvements, input use, and emissions per unit of output. Thus, disaggregation of this sector is important to meet the needs of analyses where agriculture and forestry responses play a key role. For instance, ADAGE and DART-BIO maintain disaggregation of individual crops most important for biofuels production (e.g., maize, wheat, sugarcane, sugar beets, and soybeans) along with categories for rest of cereal grains, rest of oilseeds, and rest of crops in order to track agricultural market and land use responses to alternative biofuels scenarios. Coproducts such as distillers grains with solubles from ethanol production are also incorporated in multiple models focused on bioenergy. Many coproducts of biofuels production can be used as livestock feed, which will at least partially offset the reduction in feed availability associated with feed crops being used to produce ethanol. Thus, it is important to capture the effects of these coproducts on feed markets and associated land use change.

8.2.2 Additional technologies

Under policy scenarios reflecting incentives for reducing emissions or other activities, one would expect adjustments among inputs in response, but there may also be switching between production technologies. Examples of technologies that

[19] For instance, flooded rice paddies have substantially different emission characteristics than dryland crops and there are large variations in livestock emissions between ruminants and non-ruminants (as well as across species within those broader categories).
[20] The FAOSTAT Database is available at http://www.fao.org/faostat/en/#home.

could be included for certain crops or livestock include alternative practices for manure management, tillage, or irrigation (e.g., Teheripour et al., 2013). Haqiqi et al. (2016) divide crop sectors from the GTAP Data Base Version 9 into irrigated and rainfed categories and explicitly include water for irrigation into the production function of irrigated crops. Ledvina et al. (2018) further advance the development of the irrigated land framework in the GTAP Data Base and provide irrigable land supply curves for 126 global water regions. Winchester et al. (2018) incorporate these irrigable land supply curves into the EPPA model to explore the implications of explicitly incorporating a disaggregated characterization of irrigation technology when modelling carbon policy. The study finds relatively small differences at the global level, but important regional differences when explicitly reflecting irrigated land and water scarcity within a CGE model.

As in other sectors, there are technologies that may not have been present in the base year in a given region (or in any region), but that are expected to enter the market in the future. For instance, while second-generation biofuels are often identified as an important future technology for energy security and GHG mitigation, there is little to no historical use of these fuels in most regions. In models that incorporate second generation biofuels, there may be no production or consumption in the base year database, but production technologies are specified within the model such that they can enter the market in future years as they become competitive. ADAGE includes crop production technologies characterizing switchgrass and miscanthus as well as technologies for converting cellulosic feedstocks into ethanol. As noted elsewhere, bioenergy with CCS is an important backstop technology in many models and application of this technology has important impacts on agriculture, forestry, and land use.

8.2.3 Incorporation of endogenous land use

Land use change in the CGE models that track land use endogenously is typically modelled using one of three general approaches: a nested CET function, represented by the GTAP family of models (e.g., Corong et al., 2017; Ahmed et al., 2008; Golub et al., 2008; Hertel, 1997); a nested CES function, evident in the EPPA models (e.g., Gurgel et al., 2016; Gurgel et al., 2007); or a nested logit specification (e.g., Fujimori et al., 2014). In the CET approach, land is distributed to different land types (e.g., cropland, pastureland, and forestland) on the top nest. At the next nest, land type is allocated to different production uses (e.g., cropland for corn, wheat, soybean production). The CET approach is useful for short-term analysis but has been criticized when used for long-term analysis because of its share-preserving feature (Gurgel et al., 2016).

The substitution parameters define the ease of shifting between land types, but the CET approach does not explicitly account for conversion costs. In contrast, under the CES approach, each land type has its own endowment, land rent, and usage. In equilibrium, the conversion cost between two land types is equal to the difference in land rent between them. Thus, land is not converted from a land type with a lower land rent to one with a higher land rent unless there is sufficient additional benefit to make up for this conversion cost. The returns to a given land use are a combination of market and non-market good for which they receive compensation (e.g., U.S. Conversation Reserve Program provides payments to farmers that voluntarily remove environmentally sensitive land from agricultural production).

While CET and CES approaches are generally easier to implement within modelling tools, the typical model structure does not necessarily constrain physical area used for agriculture, whereas the logit approach has the advantage of maintaining constant total land area. Fujimori et al. (2014) compared CET and logit specifications and found that agricultural land use and production were similar, but CET produced large and heterogeneous violations of area balances across regions. They concluded that a logit approach was preferred in cases where there were large changes from base year assumptions or when the focus was on regional rather than global outcomes. However, they did not consider CET specifications that incorporate an additional constraint to maintain constant area. Both the EPPA and ADAGE models maintain constant total land area. This is implemented by including inputs of another land type in a top-level Leontief nest, e.g. such that land is a given category that can only be increased if there is an equivalent decrease in the area allocated to other land types.

8.2.4 Characterization of forestry dynamics

Accurately depicting dynamics of the forestry sector is challenging within CGE models and the use of CGE models for analysing forestry issues in still in the early stages although relevant global databases have become more available in recent years. One of the key pieces of information that has been difficult to access is information to inform the potential conversion of unmanaged land into land that is managed for economic outputs. In addition, decisions regarding forestry are inherently forward-looking because there are often decades between the time when costs are incurred and revenues are received, which complicates characterization. Golub et al. (2009) modelled forestry within a recursive-dynamic framework, incorporating an iterative linkage to the PE Global Timber Model to improve characterization of the forestry sector. There have been subsequent applications introducing alternative specifications of competition between certain types of land, cost functions to access new lands, characterization of dynamic forest carbon pools, and other innovations but most models continue to characterize forestry in a simplistic manner.

8.2.5 Emissions and abatement modelling

Modelling emissions and abatement from the agriculture and forestry sectors is complex because emissions depend on non-linear relationships with activities or specific production practices. For instance, higher levels of nitrogen fertilizer will tend to improve yields, increase soil carbon sequestration, and increase N_2O emissions, but the magnitude of these impacts all depend on crop, region, and quantity of fertilizer being applied. As the level of fertilizer gets higher, the same increase in quantity of fertilizer provides smaller incremental yield and soil carbon benefits, but larger N_2O emissions. Nonetheless, many CGE models used for energy and environmental applications now incorporate non-CO_2 emissions as a function of sectoral activity. Some models incorporate non-CO_2 emissions into the production nest with substitution between emissions and use of additional inputs, representing the potential for using more labour, capital, or other inputs to reduce emissions analogous to an end-of-pipe option for emissions control. Models such as GEM-E3 incorporate bottom-up marginal abatement cost curves from US EPA (2013) or other sources to characterize relationship between mitigation costs and mitigation achieved by sector. Emissions associated with changes in carbon sequestration due to land use change are captured in ADAGE, AIM/CGE and EPPA models (Cai et al., 2018; Fujimori et al., 2014; Gurgel et al., 2016).

8.3 Calibration of agriculture and forestry in the base year and the baseline

8.3.1 Base year calibration

As for the energy sector, there is a great deal of interest in tracking not only monetary flows, but also biophysical flows for agriculture, forestry, and land use. Many end users of the information generated require outputs in physical units (e.g., land use areas, yields, number of livestock, carbon sequestration). Similar to the calibration procedures often conducted for the energy sectors, CGE models focusing on these sectors typically rely on external information sources to supplement the data on market values available from sources such as the GTAP Data Base. Values are recalibrated to align with physical data. Common sources of information for agricultural activity include FAOSTAT, the Terrestrial Ecosystem Model, and other national and regional estimates of agricultural activity and land use/land cover.

Calibration of GHG emissions and carbon sequestration often rely on data from the EDGAR model, US EPA (2013, 2019), or regional and national data on GHG emissions by sector. Vegetation and soil carbon data are available from GCAM with estimates provided for 18 agro-ecological zones (AEZs) for 14 regions of the world. Timilsina and Mevel (2013) provide land use emissions factors for aboveground and belowground biomass and soil carbon by AEZ. These data can be incorporated to calibrate base year emissions from agriculture, forestry, and land use to exogenous sources.

8.3.2 Baseline projections

GHG emissions per unit of agricultural output tends to decrease over time through improvement of emissions reduction technologies. The implementation of these emissions reduction technologies over time plays an important role in GHG emissions mitigation. Rather than staying constant, the emissions factors for agriculture decline over time with development as more farmers adopt improved practices and as more emissions reduction technology becomes available. It is a challenging task to estimate the dynamic growth path of GHG emissions factors because sector-specific output projections by country are rarely available. The rate at which baseline emissions are projected to change over time can be informed by exogenous projections such as US EPA (2013, 2019).

9. Remaining challenges and research questions

Recent modelling improvements have given us extensive insight into mechanisms of technological change, abatement options, and linking economic activities to emissions of GHGs. 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) a richer context for policy analysis.

9.1 Emission data and modelling

As shown in the previous sections, most major emission sources for CO_2 and non-CO_2 GHG 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 in the case of forest fires, it is challenging to robustly project how emissions will develop in the future, as they vary substantially year by year (though they are generally expected to follow an upward trend as temperatures rise due to climate change). In addition, while it has become more common to include non-combustion GHG emissions, characterization of the complex and non-linear relationships between economic activity and these emissions varies widely. Moving forward, additional attention to these sources of emissions remains an important area of exploration.

The modelling of emission sources and abatement options in transportation also need further improvement, especially as transport is one of the main sources of GHGs, in addition to air pollution. 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 EVs, are represented in some models. Nonetheless, in key areas of technological and behavioural abatement the potential options are still insufficiently explored. Aviation emissions should be better modelled, because they are projected to increase in the absence of further policy action and because they are often regulated only for certain types of airplanes and certain distances, 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, despite being relevant for climate change as well as having 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 to approaching this may be to split the household sector in the urban-rural dimension as in Beck et al. (2016). A more ambitious approach 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[21] 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 the 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 urbanization on emissions and energy use. The ADAGE, AIM/CGE and EPPA models take into consideration land-use change emissions. Nonetheless, most models do not endogenize land use changes but rely on separate partial analysis or link up with other external land use models (e.g. AIM/Spatial land use model; Hasegawa et al. 2016). Better matching between spatial and CGE models would also make it possible to study the development of urban infrastructures and emission reductions in cities, which are central in policy discussions, given the large contribution of cities to overall emission reductions.

9.2 Scenario assumptions

CGE model projections of energy use and emissions are heavily dependent on baseline assumptions. Policy assumptions and developments in a baseline setting

[21] https://www.atmos-chem-phys.net/18/16173/2018/

are important, as they could potentially have large impacts on GHG emissions and other environmental and economic variables. Most teams will include in their baselines existing climate policies, such as the EU carbon pricing system and CO_2 taxes. However, policies in other relevant domains can also affect GHG emissions. Air pollution is one of the main examples, as emission sources of GHGs and key air pollutants overlap. Another example is the emerging interest by governments in improving resource efficiency and facilitating the transition to a circular economy, which may lead to more policies being enacted. A circular economy transition will mean a higher share of secondary materials instead of primary ones, the re-use, extended lifetime and repair of products, which will lower production in some sectors as well as 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 servitization 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 reduce car use by 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, digitization will imply a reduction of some emission sources (e.g. production of paper, commuting and travelling for work, which can be replaced by telework). But it would also mean an increase of other emission sources (e.g. digital storage needs, use of electric appliances). Self-driving cars are also emerging, which may affect mobility and emissions in indefinite ways.

Changes in mind-sets and preferences may also affect energy use and emissions in both households and firms. Even in the absence of new price or policy incentives, a higher awareness of external environmental consequences may lead to a lower use of energy by households. Another key area is the greening of food consumption and the impacts of agriculture and transportation on GHG emissions. On the production side, there is increasing interest in using greener inputs, for instance using substitutes for plastic, and choosing products with low carbon footprints. This can be seen as self-regulation and a shift in attitudes towards greater 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 crucial 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 regulation 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 the economy on GHG emissions but exclude the impact 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 climate modelling in order to form a full loop between economic development, the climate change impacts, and their costs on the economy. IAMs are generally very aggregated and consider a much more stylized representation of the economy than CGEs. However, some CGE models have been expanded into IAMs and to include the full climate loop. There is an increasing empirical literature on the consequences of climate change for energy use, which may be useful for 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 hydropower plants are vulnerable to weather conditions (e.g., Lucena et al., 2018 explore the implications for hydropower in Brazil). 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 the global level is still not sufficient to allow CGE models to include energy supply as one of the climate damage categories.

As highlighted throughout this article, technology assumptions are fundamental to the setting up of a baseline scenario. Current CGE models often fail to provide 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 through large-scale projects, could also change GHG projections. However, it is difficult 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 SSPs scenarios (O'Neill et al., 2014, Dellink et al., 2016). The SSPs work could be further enhanced by developing Monte-Carlo analysis on scenario explorations. Further improvements in highlighting the role of uncertainty can also be made by mapping the 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 for understanding the role of modelling assumptions in creating emission projections.[22] Finally, hindcasting could be used more frequently to investigate the robustness of modelling projections (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 very different from history, as may be expected.

9.3 A richer context for policy analysis

CGE models have been the workhorse for assessing 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. Lee et al., 1994; Burniaux and Troung, 2002). The effects of carbon taxes and emission caps are well understood thanks to a large literature using CGE models. However, with the shift of the policy discussion from climate policy towards green growth and a circular economy, there is a strong need to model other types of policy instruments. For instance, in the recent POLFREE project in the EU's 7th Framework Programme, different modelling teams used various instruments to develop a policy package designed to achieve a circular economy, including recycling, re-use, and energy efficiency. (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 the consequences of policies on various indicators, clarifying the interplay between climate, air pollution, resource use, sustainability and equity, with reference to the UN Sustainable Development Goals. The OECD (2016) contributed to the discussion on interconnections among 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 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 as aiming at well below 2 °C or 1.5°C, global CO_2 emissions likely need to be zero or negative by the middle of this century (Rogelj et al., 2018). Some negative emissions will inevitably be necessary to attain these conditions, since some emission sources are difficult to completely decarbonize. Afforestation and bioenergy combined with CCS (BECCS) are considered possible efforts for large-scale negative emissions. These technologies

[22] See https://emf.stanford.edu/.

are obviously related to land-use, in general, and agriculture, in particular. Bioenergy crops also interact with forestry activity, including reforestation and afforestation. As mentioned above, modelling advances are needed for good representations of such scenarios.

The development of new technologies, especially linked to policy supports such as R&D subsidies, would also help to improve deep de-carbonization pathways aimed 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 recently 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), regionalized 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 issues that would need further modelling in order to be addressed adequately concern the design of climate policies introduced in the presence of alternative behavioural models or market imperfections. The evolution 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.

Types of market imperfections that can hamper transition to low-carbon options are *network externalities* that require a certain market penetration level for demand to take off, lack of infrastructural *public goods*, *commitment problems* that impede responses to announced policies, *credit market imperfections* that hamper optimal investment behaviour, and *market power*. While the market power of the Organization of the Petroleum Exporting Countries (OPEC) in the oil market is described in some models, CGE-based analyses that include barriers to free entry of firms into 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 the fields of modelling various kinds of policy instruments and their efficiency impacts would greatly contribute to a better understanding of baseline emission projections and of the interplay across policy instruments in different environmental fields, as for example between GHG and air pollution mitigation policies.

10. Concluding remarks

CGE modelling provides an important contribution to emissions and energy scenario analysis and policy development. Structural relationships among 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 sectors and different scenarios, as well as their implications for the resulting GHG and air pollution emissions. For given external surroundings, CGE models provide economy-wide, consistent projections of induced investment in different sectors and technologies, the speed of technology adoption and the 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.

This article provides an assessment of the best practices in CGE modelling of baselines and alternative scenarios. While CGE models provide many advanced features for decision-making, creating and maintaining large-scale numerical models is costly, and the need for elaborations and detailed data should be carefully considered. Sharing knowledge about the state-of-the-art options helps provide the modelling community with better and less costly choices. The present assessment offers low-hanging fruit for better practices in research and analysis. Enhanced 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, should help academic researchers and decision-makers to interpret modelling results adequately and to conduct better research and make more informed policies.

Research activities in the fields of CGE modelling and projections in the field of energy and climate have advanced rapidly. Modern approaches to modelling and quantifying power generation, fossil fuel production, transportation, manufacturing industries, buildings, agriculture and land use offer valuable tools for projection and analysis. This assessment concludes that to be reliable, CGE modelling needs to reflect major technological and behavioural mechanisms, well-estimated empirical relationships and plausible future scenarios.

In order to understand the pathways for low-carbon energy development, it has become increasingly important to represent the energy-producing sectors in more detail, because fossil fuels are subject to progressively stronger competition from low-carbon and carbon-free options. Both fossil fuel and the supply of low-carbon energy are subject to technological improvements that are represented in the modelling. Recent modelling advances include 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.

Passenger and freight transportation are significant energy-consuming sectors. State-of-the-art CGE models offer descriptions of current and future vehicle technology, such as improved efficiency of internal combustion engine-based vehicles, adoption of plug-in hybrids, battery electric and 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. An increasing number of CGE models incorporate consumer preference changes towards different modes of transportation. These choices are particularly important with respect to the future evolution of car and ride sharing and the impact of such sharing on demand for transportation services.

Other major energy-intensive sectors are the manufacturing industries. In addition to considerable GHG emissions from combustion, many manufacturing industries emit CO_2 and other GHG gases from other processes. These emissions require different approaches to modelling in a CGE setting because they are tied to sectoral outputs rather than fuel use. Modelling process-related abatement opportunities involves representing abatement costs and/or creating emission-free technologies that are perfect substitutes for the existing production processes. Advanced CGE models offer explicit options for several sectors including cement, metals, chemicals, fertilizers, 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: instead, they are allocated to the corresponding economic sectors (retail, education, services, industrial, etc.). Energy use in residential buildings is taken into account in household consumption as part of the input data. Advanced CGE models represent energy use for heating and cooling needs, and their evolution under different income growth scenarios and energy efficiency improvement patterns.

Agriculture and forestry are important contributors to global GHG emissions as well as playing an important part in many other environmental and natural resource issues. These sectors are uniquely dependent on land resources, are extremely heterogeneous across time and space, and have become increasingly linked to the energy sector in recent years in connection with the major global expansion in bioenergy production. Unlike other economic sectors, most emissions from the agriculture and forestry sectors are not due to combustion, but are non-CO_2 GHGs associated with agricultural production and changes in the carbon sequestration provided by forestry and other land use. To adequately capture the dynamics, changes in land use, and non-linear changes in sectoral emissions, CGE models have been further disaggregating these sectors: refining demand for agricultural and forest commodities; adding bioenergy modules; calibrating their baselines against biophysical data on yields, area, number of livestock, and other information; building in more detailed characterization of land use and land use change; adding new technologies to mitigate environmental impacts; incorporating external data on marginal abatement cost curves for GHG mitigation; and otherwise adding detail to better characterize this sector.

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

Three different approaches to baseline quantification can be distinguished. The first 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 greater is its potential for emulating bottom-up expert opinion or model results. However, these details require a substantial amount of exogenous information. This additional information may be of questionable quality for a number of world regions, or information from different sources may be inconsistent. Moreover, incorrect parameterization may produce non-intuitive impacts on model results.

Another approach is often combined with the first, namely to track key outputs by calibrating the values of parameters and exogenous variables to match some aspects of the baselines to specific projections from reputable sources. For example, projections of energy and electricity mixes from IEA, macroeconomic projections from the World Bank and International Monetary Fund and population projections from the United Nations Population Division can be used for these purposes.

The third approach is to use bottom-up sectoral 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 such as those mentioned above. For example, significant progress has been demonstrated in attempts to link CGE models with more detailed electricity sector models that can provide finer temporal and technological resolution, including a better representation of intermittency constraints that are especially important for an analysis of low-carbon options. For consistency across data sources, linking monetary flows with physical flows of energy makes it possible to assess of production, consumption and international energy trade flows in both monetary and physical units.

Though the three approaches can be combined for certain studies, the risk of double-counting should be borne in mind, for example by including forward-looking trends as both parameter values (e.g., productivity parameter) and endogenous emulating mechanisms (e.g., learning-by-doing).

The last part of this assessment is devoted to several challenges related to the need for better, 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. The present article has concentrated on BAU scenarios that usually take into consideration only policies that are already in place. Although, these scenarios have less policy uncertainties by construction, assumptions about long-term characteristics, such as technological progress, population growth, market structure etc. lead to large variations in potential outcomes. Disruptive technologies may emerge, and products or businesses not known today may appear. The discussion touches upon many alternative assumptions and points to the need for addressing such uncertainties by means of sensitivity analysis, scenario approaches such as those facilitated by the SSP initiative, or hindcasting.

This assessment also sets the stage for additional areas of research and policy analysis that are relevant to and likely to influence the energy and climate nexus, including study of the circular economy, sustainability, induced environmental R&D, behavioural economics and spatial modelling. The CGE modelling community is making steady progress in addressing these and other novel challenges. This survey provides an opportunity for a better understanding of the current successes of CGE and the efforts needed to make CGE modelling even more relevant for robust decision making.

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Appendix A: Acronyms and model names

Table A1. Acronyms

AEEI	Autonomous energy efficiency improvement
AEZs	Agro-ecological zones
AFVs	Alternative fuel vehicle technologies
BAU	Business-as-usual
BECCS	Bioenergy with carbon capture and storage
BF-BOF	Blast furnace-basic oxygen furnace
CCS	Carbon capture and storage
CCU	Carbon capture and utilisation
CDE	Constant-differences-in-elasticities
CES	Constant elasticity of substitution
CET	Constant elasticity of transformation
CGE	Computable general equilibrium
CH_4	Methane
CO_2	Carbon dioxide
CO_2eq	Carbon diocide equivalents
CSR	Corporate social responsibility
EDGAR	Emission Database for Global Atmospheric Research
EIA	Energy Information Administration
ELES	Extended linear expenditure system
EMF	Energy Modelling Forum
EVs	Electric-powered vehicles
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
GDP	Gross domestic product
GECO	Global Energy and Climate Outlook
GHG	Greenhouse gas
Gt	Gigatonnes
GTAP	Global Trade Analysis Project
HFCs	Hydrofluorocarbons
IAMs	Integrated assessment models
ICE	Internal combustion engine
IEA	International Energy Agency
IIASA	International Institute for Applied Systems Analysis
IPCC	International Panel on Climate Change
JRC	Joint Research Centre

Table A1. Acronyms (cont.)

LES	Linear expenditure system
LULUCF	Land use, land-use change and forestry
MAC	Marginal abatement cost
Mtoe	Million tonnes of oil equivalents
N_2O	Nitrous oxide
NEA	Norwegian Environment Agency
NF_3	Nitriousflouride
O&M	Operation and maintenance
OECD	Organisation for Economic Co-operation and Development
OPEC	Organization of the Petroleum Exporting Countries
PE	Partial equilibrium
PFCs	Perfluorinated compound
PIRAMID	Platform to Integrate, Reconcile and Align Model-based Input-output Data
PM	Particulate matter
R&D	Research and development
SAM	Social accounts matrices
SF_6	Sulfur hexafluoride
SSPs	Shared Socioeconomic Pathways
TFP	Total factor productivity
UNFCCC	United Nations Framework Convention on Climate Change
US EPA	United States' Environmental Protection Agency
WEO	World Energy Outlook

Table A.2. Model names

ADAGE	**Applied Dynamic Analysis of the Global Economy**
AIM/CGE	**Asia-Pacific Integrated Model/Computable General Equilibrium**
AIM/Spatial land use model	Asia-Pacific Integrated Model/Spatial
AIM/Transport	Asia-Pacific Integrated Model/Transport
CMAQ	The Community Multiscale Air Quality Model
COFFEE	COmputable Framework For Energy and the Environment
DART	**Dynamic Applied Regional CGE model**
DART-BIO	**Dynamic Applied Regional CGE model -Bio**
E3MC	Energy, Emissions and Economy Model for Canada
EC-MSMR	**Environment Canada Environment Canada Multi-sector, Multiregional CGE model**
EC-PRO	**Environment Canada PROvincial CGE model**
ENVISAGE	**ENVironmental Impact and Sustainability Applied General Equilibrium Model**
ENV-LINKAGES	**ENVironment – LINKAGES**
EPPA	**Emissions Prediction and Policy Analysis**
GAINS	Greenhouse Gas - Air Pollution Interactions and Synergies
GCAM	Global Change Assessment Model
GEM-E3	**General Equilibrium Model for Economy-Energy-Environment**
GTAP	Global Trade Analysis Project
GREEN	The GeneRal Equilibrium ENvironmental model
ICES	Intertemporal Computable Equilibrium System
IGEM	Intertemporal General Equilibrium Model
IMACLIM-R	**Integrated Modeling Approach Climate**
MAGNET	**Modular Applied GeNeral Equilibrium Tool**
MSG-TECH	Multi-Sector Growth – Technologies
POLES-JRC	Prospective Outlook on Long-term Energy Systems - Joint Research Centre
REMIND	**Regional Model of Investments and Development**
SNOW	**Statistics Norway's World model**
TEA	**Total Economy Assessment**
TIMES	The Integrated MARKAL-EFOM System
TM5-FASST	TM5-FAst Scenario Screening Tool
USREP	U.S. Regional Energy Policy
WEGDYN	**Wegener Center Dynamic Recursive CGE Model**
WEGDYN_AT	**Wegener Center Dynamic Recursive CGE Model – Austria**

Notes: Models in bold represent those included in the present survey article.

Appendix B. Represented CGE models

Appendix B. Represented CGE models
Table B.1. Energy and emissions characteristics and baseline sources of represented CGE models.

				Default:					
Model	**General scope and features**	**Fuel supply**	**Power supply**	**Energy demand**	**Agriculture and Land use**	**Emissions**	**Markets**	**Central data sources**	
Default	Global - recursive dynamic - 1-year-steps Monetary input-output structures	CES factor demand Aggregate production function also including Transmission/ distributio n Resource input energy: coal, oil, gas exogenous factor-augmenting productivity growth option to exogenize fossil fuel prices	CES factor demand Aggregate production function energy: coal, oil, gas exogenous factor-augmenting productivity growth	*In households:* Energy use split between transport and housing in CES demand systems usually in composites with vehicles and buildings, resepctively *In firms:* Standard CES factor demand where energy use for transport, buildings and processes usually are merged, as is capital. Transport sector split into air, water and other, but freight and passenger transport merged. Exogenous factor-augmenting technical change	Agriculture represented by 1-12 GTAP-based insdustries, while Forestry is a separate industry Exogenous changes in productivity	CO_2 and often also non-CO_2 Kyoto gases Physical units (t CO_2-equivalent) Linked to demand/ combustion of coal, oil, gas in all sectors Fixed emission coefficients	Competitive	GTAP incl. GTAP-Power, I EA/WEO, Enerdata, OECD/EO, GECO, econometric studies National SAMs, emission inventories	
				Supplements and advancements of represented models:					
Represented model (Organisation)	**General scope and features**	**Fuel supply**	**Power supply**	**Energy demand**	**Agriculture and Land use**	**Emissions**	**Markets**	**Central data sources**	**Documentation**
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	Multiple technologies Physical accounting of energy	*Transport in households:* Multiple types of vehicle and associated fuel demand. Vintage transport capital *Commercial transportation:* Disaggregated. Vintage transport capital	Endogenous land use change between cropland, pasture, managed forest, natural forest, and natural grass Physical accounting of land types	Endogenous abatement, including from land use change		US DOE Energy Information Administration GCAM model FAOSTAT	Ross (2009) Cai et al. (2018)
AIM/CGE (National Institute for Environmental Studies)	In a linked system with AIM/Enduse (Energy System model), AIM/Transport and AIM/PLUM (Spatial land use model)	Multiple technologies Dynamic resource depletion Renewable fuels	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	Land allocation is determined by multinominal logit function.	Non-Kyoto emissions to air have emissions factors according to GAINS emissions scenarios in SSPs. (CO, NH3, NMVOC, NOX, SO2, BC, OC, CFCs) Physical units Non-energy- related GHG emissions abatement are detremined by exponential abatement function.		EDGAR, RCP, IMAGE, own database reconciling international statistics, FAOSTAT/GAEZ AIM/Enduse, AIM/Transport models, AIM/PLUM	Fujimori et al (2017)
DART and DART-BIO (Kiel institute of the world economy)		Learning by doing Renewable fuels	Vintage capital Learning by doing Renewable Energies		Optional hard-link with PROMET dynamic crop growth model used for studies focused on yield impacts				Springer (1998) Calzadilla et al. (2014)
EC-PRO and EC-MSMR (Environment and Climate Change Canada)	SOE Canada disaggregated with provinces and global, respectively Soft-link to energy model (E3MC)	Multiple technologies Renewable fuels	Multiple technologies Physical accounting of energy	Buildings in household, transportation and household automobiles use separated	Backstop treatment of land use change	Endogenous emission abatement from land use change Negative emissions technologies such as direct air capture in EC-MSMR		GTAP, Statistics Canada, E3MC model, IEO	Böhringer et al. (2016) Ghosh et al. (2012), Zhu et al. (2018)

Table B.1. Energy and emissions characteristics and baseline sources of represented CGE models, cont.

Represented model (Organisation)	General scope and features	Fuel supply	Power supply	Energy demand	Agriculture and Land use	Emissions	Markets	Central data sources	Documentation
ENVISAGE (GTAP)		Renewable fuels			Total agricultural land governed by logistic curve Nested A/CET-specification for land supply across agriculture activities				van d Mensbrugghe (2010)
ENV-LINKAGES (OECD)	Soft-link to IEA's WEM (energy model) Physical accounting of energy, land use and crops. Capital vintages		Multiple technologies	*Energy in households and firms:* Specific nest for energy demand *Food in households:* Specific nest for agriculturual food products demand	Fertlizer in crops and feed in livestocks are more substitutable with land inputs than other goods CET-specification for land supply across agriculture activities Productivity over time based information from PE agriculture sector models	Edogenous process emissions in Manufacturing and Agriculture as specific CES-bundle in production function Air pollutant emissions		Macroeconomics: OECD, IMF, World bank Energy: IEA-WEM / Agriculuture: IFPRI-IMPACT, OECD, IIASA-GLOBIOM Emissions: IIASA-GAINS, IEA, EDGAR	Chateau et al. (2014)
EPPA (MIT)	Physical accounting of energy	Multiple technologies Dynamic resource depletion Renewable fuels	Multiple technologies Intermittent renewables	*Transport in households:* Multiple types of vehicle and associated fuel demand *Commercial transportation:* Disaggregate, physical accounting, vintage transport capital	Endogenous land use change between cropland, pasture, managed forest, natural forest, and natural grass Physical accounting of land types	Endogenous Abatement	Market power in oil market		Paltsev et al. (2005) Chen et al. (2016)
GEM-E3 (Joint Research Centre)	Linked with energy model (e.g., POLES-JRC) Physical accounting of energy 5-year steps (currently to 2050)	Multiple technologies	Multiple technologies	*In households:* Consumption of 2 types of durables (residential and transport) that goes with the consumption of linked non-durables (fuels)	Agriculture is split into 3 subsectors: Crops, livestock and forestry Bottom-up MAC curves for crops and livestock separately	Endogenous abatement (sector-wise MAC curves) Process emissions in Manufacturing		GAINS model Energy models (e.g. POLES-JRC, PRIMES)	Capros et al. (2013) Weitzel et al. (2019a)
IMACLIM-R (CIRED)		Multiple technologies Dynamic resource depletion	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			Market power in oil market	World Energy Model	Waisman et al. (2012a)
MAGNET (Thünen Institute of Market Analysis)		Multiple technologies R&D in biofuels			CET-specification for land supply across agriculture activities		Blending targets	FAOSTAT & IMAGE	Woltjer and Kuiper (2014)
REMIND (PIK)			Learning by doing						Luderer et al. (2015)
SNOW (Statistics Norway)	SOE Norway Also intertemporal version and global version	MAC curves		*Transport in households:* Multiple types of vehicle and associated fuel demand	Land represented as an exogenous natural resource input in *Agriculture and Forestry*	Process emissions in Manufacturing, Fossil fuel extraction and Agriculture Endogenous abatement (sector-wise MAC curves) Air pollution compounds linked to energy and processes		Norwegian Env. Agency	Bye et al. (2018) Rosnes et al. (2019)
TEA (COPPE,Universidade Federal do Rio de Janeiro)	Softlink to energy model (COFFEE) Physical accounting of energy	Multiple technologies	Multiple technologies	*Transport in households:* 2 types of vehicle and associated fuel demand	*Agriculture and Forestry; Cattle; Other Animals Production; Fishery* . Represented by GTAP-based industries.	Industrial process emissions in Manufacturing		Macroeconomic: GTAP, SSP, World Bank Energy and emissions: COFFEE model	Cunha et al. (2020)
WEGDYN and WEGDYN_AT(Wegener Center for Climate and Global Change, University of Graz)	SOE Austria (WEGDYN_AT) Global (WEGDYN) 5-year steps until 2050		Exogenous portfolios of technologies Coupled with vintage-based electricity sector investment module	*Transport in households:* exogenous technology switch (in WEGDYN_AT) *Commercial transportation:* Disaggregate land transport, incl. infrastructure services (in WEGDYN_AT) *Manufacturing:* Exogenous technology switch		Industrial process emissions in Manufacturing (Iron&Steel, Cement)		EnergyDatasheets: EU-28 Countries (EC, DG ENER) UNFCCC emission inventory for industrial process emissions	WEGDYN_AT: Bachner (2017) WEGDYN : Mayer et al. (2019); Schinko et al (2014); Bednar-Friedl et al. (2012);