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Multi-model comparison of CO_2 emissions peaking in China: Lessons from CEMF01 study

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Abstract

The paper summarizes results of the China Energy Modeling Forum's (CEMF) first study. Carbon emissions peaking scenarios, consistent with China's Paris commitment, have been simulated with seven national and industry-level energy models and compared. The CO_2 emission trends in the considered scenarios peak from 2015 to 2030 at the level of 9—11 Gt. Sector-level analysis suggests that total emissions pathways before 2030 will be determined mainly by dynamics of emissions in the electric power industry and transportation sector. Both sectors will experience significant increase in demand, but have low-carbon alternative options for development. Based on a side-by-side comparison of modeling input and results, conclusions have been drawn regarding the sources of emissions projections differences, which include data, views on economic perspectives, or models' structure and theoretical framework. Some suggestions have been made regarding energy models' development priorities for further research.

Keywords: Carbon emissions projections; Climate change; CO2 emissions peak; China's Paris commitment; Top-Down energy models; Bottom-Up energy models; Multi model comparative study; China Energy Modeling Forum (CEMF)

1. Introduction

During the annual United Nations Climate Change Conference in Paris (COP21[1], 2015), 196 nations officially agreed on cutting carbon emissions. The parties of the Paris Accord have committed to limit the average global temperature rise below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C. Though the Paris Agreement significantly differs from the Kyoto Protocol, still voluntary and unbinding, it demonstrates a broad acknowledgment of the climate change threat and even set a new, stronger target. As summarized in the IPCC 5th Assessment Report, the 2 °C threshold still leaves the high risk to "unique and threatened systems." The most recent studies argue that the additional 0.5 °C makes a big difference in reducing the overall climate change impact, such as extreme weather events

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[1] http://www.cop21paris.org/about/cop21.

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and reductions in agricultural output (Huang et al., 2017; Sanderson et al., 2017; Wang et al., 2017).[2]

However, the sum of currently committed and intended nationally determined contributions (INDC's) is far from sufficient to achieve the temperature control goal of 2 °C (UNEP, 2016), not to mention 1.5 °C. China, as the largest emitter of greenhouse gases in the world (accounting for around 30% of global emissions), can play a critical role in reducing global greenhouse gas emissions. Also, China is one of world regions with expected significant environmental damages from climate change (TTNCCARWC, 2015; Tong et al., 2016).

The Chinese government recognizes the risk and responsibility and has been persistently strengthening environmental targets during the recent decade. At the United Nations Climate Change Conference in 2009 (COP15), China committed to cut CO_2 emissions per unit of GDP by 40%–45% from its 2005 level by 2020. This target has been reinforced at the COP21 meetings, with the commitment to cut emissions by 60%–65% per unit of GDP, increase the share of non-fossil energy to 20%, and peak CO_2 emissions by 2030. The international commitments have been directed to be implemented in the national targets and plans.

In the 13th Five-Year Plan (13FYP), the Chinese government articulated its ambitions to reduce emissions and foster low-carbon development, including controlling CO_2 emissions in key industries (e.g., power sector, iron and steel, building materials, and chemical and petrochemical industry), promoting low-carbon development in key sectors (e.g., industry, energy, building, and transportation), strengthening adaptation to climate change, and contributing to global climate governance (NDRC, 2016a).

Implementation of the commitment to reduce emissions required plans to specify details of emissions reduction and energy development goals. In particular, the 13th Five-Year Work Plan for Greenhouse Gas Emission Control (SC, 2016), has outlined China's plan for peak carbon emissions in some heavy chemical industries around 2020. The document also noted China's goal of further controlling emissions of greenhouse gases other than CO_2, such as HFC's, methane, nitrous oxide, PFC's, and sulfur hexafluoride. According to the document, China also aims to reduce energy consumption per unit of GDP by 15% over 2015 and cut emissions by continuously reducing coal consumption in heavily polluted regions and cities beginning in 2017. The country hopes to increase the share of non-fossil energy sources in its energy sector; thus, limiting CO_2 emissions per unit of power supplied by large power generation groups below 550 g CO_2 (kW h)$^{-1}$ (SC, 2016).

The 13FYP for Energy Development (NEA, 2016) proposed to control both total energy consumption and energy consumption intensity. The proposal sought to fundamentally reverse the extensive growth pattern of energy consumption and reduce the share of coal in total primary energy supply to 58% or less by 2020 while increasing the combined share of non-fossil energy, natural gas, and other low-carbon energy sources to 25%. On this basis, the Chinese government issued the Energy Production and Consumption Revolution Strategy (2016–2030) (NDRC, 2016b), which advances further energy revolution goals:

- limit total energy consumption below 5 Gtce by 2020, and limit total energy consumption below 6 Gtce by 2030;
- achieve sustainable growth of renewable energy, natural gas, and nuclear power use while drastically reducing high-carbon fossil energy consumption by 2030;
- increase the proportion of non-fossil fuel sources to 20% by 2030;
- increase the natural gas share to 15% or more by 2030;
- satisfy new energy demand mainly with clean and low-carbon energy;
- promote efficient use of fossil energy, peak CO_2 emissions around 2030, and strive for the earliest possible peak;
- reduce energy consumption per unit of GDP to the current world average level;
- establish global leadership in energy science and technology.

The strategy also contains 2050 energy targets, including increasing the share of non-fossil energy to over 50%, while maintaining a stable level of energy consumption.

With the essential steps completed, there are still questions and uncertainties around the targets' feasibility, whether they are strong or nonbinding, regarding the existing potential of emissions reduction with associated costs, and the optimal abatement strategy for reaching maximum emissions reductions without compromising the country's economic development. Reliable answers to the questions are also vital in the international arena, where nations will have to demonstrate good faith efforts in emission reduction.

A number of studies have been undertaken in China and worldwide to address greenhouse gas emission projections, costs of reduction, and carbon emissions peaking pathways (Jiang et al., 2016; Wang et al., 2015; Dong et al., 2015; Huang et al., 2017; Gambhir et al., 2012, ERI, 2016; He et al., 2014). Most of them involve sophisticated modeling techniques to simulate and analyze pathways of long-run development of the economy and the energy sectors. For example, using the Integrated Policy Assessment model for China (IPAC), the Energy Research Institute of National Development and Reform Commission has found that, under certain conditions, emissions from China's energy use could peak by 2025 or even earlier to a level of around 9 Gt (Jiang et al., 2016). Ma and Chen (2016) shows that development of renewable energy coupled with improvements in energy efficiency and emission reduction technology in energy-intensive industries could promote CO_2 emission peaking and energy-intensive industrial sectors at 10.0–10.8 Gt by 2030.

The conditions of scenarios and assumptions vary from study to study and may depend on differences in points of

[2] The special issue of the IPCC report concerning the 1.5 °C rise limit is expected to be in 2018 and will address the difference in details.

view of researchers on the same problems. The consideration and comparison of a higher number of scenarios may potentially provide more information, i.e. it may provide some robustness to the case, if results are similar, or it may evaluate a range of uncertainties in the projections. Hu (2016) collected more than 30 scenarios of several domestic and international modeling groups and found that, in the baseline scenario, China's CO_2 emissions will peak at about 13.5−17.0 Gt in 2040−2050. Around half of the low-carbon scenarios peak at 8.2−13.0 Gt of CO_2 during 2020−2030, and reduce to 5.0−8.0 Gt by 2050, while the other half peak at 8.4−11.0 Gt by 2020, with reduction to 2.5−3.0 Gt by 2050.

Another comparison was provided by *The Third National Climate Change Assessment Report* (TTNCCARWC, 2015), in which scenarios of CO_2 emissions in China, from 2005 to 2050, were collected from studies published after 2010. The researchers found that China's future CO_2 emissions are quite uncertain and that the uncertainty is increasing over time. Projections of emissions in 2020 vary between 7.1 Gt and 13.4 Gt, while the 2030 emission level could be between 6.1 Gt and 14.9 Gt. The range will be particularly large in 2050, namely, 3.5−16.7 Gt. The comparative analysis also showed that China's CO_2 emissions from energy in the high-emission scenario would be, on average, 11.2 Gt, and peak in 2040 at 13.8 Gt. In the medium-emission scenario, the figures would be, on average, 9.6 Gt, and peaking in 2030 at 10.5 Gt. And, in the low-emission scenario, around 8.9 Gt in 2020, and peaking in 2025 at 9.1 Gt.

Green and Stern (2015) discuss China's economic transformation, and anticipate earlier (than 2030) emissions peak. However, it cannot be concluded based on the modeling results in general. The gap between projections even within grouped scenarios is significant enough to conclude that China's CO_2 emissions' perspectives are quite uncertain, depending on a number of factors. The gap becomes larger when more modeling results are considered. Fig. 1 shows a range of emissions projections from 80+ models collected from various studies and emissions projections databases. All scenarios are grouped by emissions peak time: before 2030 representing China's Paris commitment, and after 2030 (or no peak). As shown in Fig. 1, the two groups of scenarios overlay in emissions levels.

Certainly, the scenarios have different underlying conditions, and Fig. 1 demonstrates the range of uncertainty resulting from various assumptions, causing more challenges for direct consumers of the projections, including the policymakers. Grubb at al. (2015) review publicaly available projections of China's CO_2 emissions from different models, and also indicate importance of models' structure and assumptions. A comparative analysis of modeling methods, data sources, key hypotheses, and assumptions can potentially shed light on the differences in projections, improve understanding of models and their applications, and build confidence in modeling results. However, such a side-by-side model comparison requires more information than normally available with published projections, as well as input from the modelers themselves.

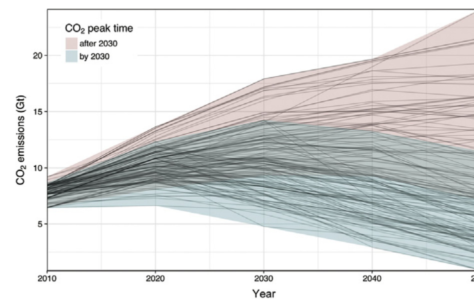

Fig. 1. Combined emissions projections from international sources, grouped by emissions peak time. Source: BP (2016), Calvin et al. (2012), EIA (2016), IEA (2016), Kriegler et al. (2013, 2015), Liu et al. (2017), Reilly et al. (2015), Riahi et al. (2015), Sachs et al. (2014), Tavoni et al. (2013), WB (2013), Zhou et al. (2011).

China Energy Modeling Forum (CEMF) is an initiative which establishes a model comparison and exchange platform guided by the principles of openness, fairness, transparency, and neutrality. The platform promotes communication and gives researchers opportunities to deeply discuss their tools and findings, it allows the participants to investigate the divergences in modeling results, and to improve their models accordingly. The format of open discussion of modeling techniques has proved itself internationally. The Stanford Energy Modeling Forum[3] (EMF) likely has the longest history and reputation of bridging the gap between policymakers and modelers. Several initiatives of multi-model studies and model comparisons have been arranged in Asia, and China.[4] CEMF is a new independent from other forums initiative, hosted by Tsinghua University.

In light of the ongoing discussion on the carbon emissions peaking and its importance for China's low-carbon transformation and sustainable development, in 2015 CEMF initiated the comparative study of China's carbon emissions peak level and timing. The study aims to identify sources of potential divergence between the projections of CO_2 emission levels and peak by making a side-by-side comparison of input and output for models, with classification of the differences. Five modeling teams with seven different models participated in the study. CEMF conducted three semi-annual open meetings, several technical workshops, and ad-hoc meetings. Experts from industries and economic sectors, businesses, public institutions, and academia were invited to discuss and compare

[3] https://emf.stanford.edu/.

[4] The AIM research program, a.k.a. Asia−Pacific Integrated Model, is an international modeling initiative started by the National Institute for Environmental Studies of Japan (http://www-iam.nies.go.jp/aim/about_us/index.html); China Economic and Environmental Modeling Workshop or China-Korea-U.S. Economic and Environmental Modeling Workshop, sponsored by U.S. Environmental Protection Agency, organized by University of Maryland and Pacific Northwest National Laboratory (see Logan et al., 1999, 2001); Sino−U.S.−Korea Economic and Environmental Modeling Workshop (http://en.ccchina.gov.cn/Detail.aspx?newsId=38630&TId=101), and Energy Research Institute modeling forum in collaboration with Integrated Assessment Modeling Community (http://www.globalchange.umd.edu/iamc/events/ninth-annual-meeting-of-the-iamc-2016/) and International Energy Workshop (www.ipac-model.org/iew2014).

data, assumptions, emissions, and energy balance projections. The focus of the study was directed towards emissions peak time and level in the Chinese economy and main energy consuming sectors and industries. The CEMF01 study concluded at the end of 2016. This report describes the structure and the key findings of the study, as well as lays out demand for further research, energy models, and emissions analyses improvements.

2. Methodology

The main idea of a multi-model study is based on beliefs that scientific inference should not depend on an arbitrary model selection. If modelers agree on assumptions, the results should be consistent across models, i.e., considered reliable. Differences in results should have a rational explanation either stemming from data, subjective views on economic perspectives, or from models themselves.

Since every model is just a set of mathematical equations which express relations between variables and parameters, the link between the model's output and input is rational by definition and, in theory, can be traced, though, in practice, it is not easy to achieve. Due to growing complexity and a demand for higher precision and more details, this rational link can be hidden under a number of variables and dependencies. Even if models share the same techniques and structure, every model is unique in the hands of the researcher who calibrates it, reviews data and parameters, and designs policy experiments. All of the steps require input from researchers and include some subjectivity. Harmonization of key inputs should presumably reduce divergence between models' outputs, i.e., provide more comparable and consistent results across models.

The harmonization of models' inputs has several goals. First, it reveals differences in modelers' views and promotes discussion. Second, it helps to identify the level of uncertainty on each particular topic of disagreement. When it is hard to reach consensus on the level of a particular parameter or input, the potential range can be identified instead, expressing the boundaries of the uncertainty. A serious obstacle to harmonization is the models' theory and structure. In cases when the models' input is not harmonized, the comparative differences in results will be likely assigned to both (the models' theory and parametrization), and is thus hard to decompose.

In this section, we describe the two key types of models applied to energy and emissions projection, characterize participating in the CEMF01 study models, and discuss the design of comparative analyses, scenarios, and the CEMF01 process. We start with comparative details of the mainstream modeling techniques, general features and assumptions of their theoretical framework, and underlying assumptions of the models involved in the study.

2.1. Modeling approaches and CEMF01 study models

A broad variety of computational models applied to energy, economy, and climate change-related analyses can be sorted into two groups based on the way the models approach the link between energy, emissions, and economic activity. The first group, the so-called "Top-Down" (TD) models, describe an economy as a system that is linked by equations of economic aggregates, reported by statistical agencies, and expressed in currency units. GDP, output, value added, capital stock, employment, input/output tables (IOT), and social accounting matrices (SAM) are the standard elements of TD models. Computable (or applied) general equilibrium models (CGE or AGE) are mainstream TD models.

The second group is the engineering, technological, and so-called "Bottom Up" (BU) models, which focus on material and energy flows in physical quantities. BU models are also referred to as "reference energy system" (RES) models because they represent a snapshot of an energy balance starting from production through all stages of transformation to the final use and provide perspectives on the energy system development, based on available technological options. The mainstream BU models, such as TIMES/MARKAL,[5] OSeMOSYS,[6] and MESSAGE[7] are systems of linear equations, with an objective to optimize the development of an energy system over time based on the least costs, taking into account resources and policy constraints. Contrary to the general equilibrium models, BU models cover only a part of the economy. Depending on a model scope, it can be national, regional, or industry-level energy system.

Both types of models are actively involved in emissions simulation and assessment of climate and energy policies impact on the economy, energy costs, and feasibility of emissions abatement. However, they are approaching the issues from different perspectives, designed to answer different questions. TD models are more focused on macro-level adjustments of the economy to the being studied "exogenous shocks," such as changes in taxes and tariffs or the introduction of a carbon price or a cap. While mainstream TD models are not designed to provide clear insights about how switching between energy types can be achieved from a technology perspective, BU models do not operate with such key macroeconomic variables as GDP or employment. Their main focus is the technological feasibility of a particular policy with the associated direct costs and required investments.

Though the two modeling approaches have enough differences in the underlying theoretical framework, Table 1 summarizes some of the common characteristics that are relevant to mainstream models of the two classes and that are potentially important for the comparative analysis of emissions projections.

It would be useful to classify all factors affecting the emissions level and peak into four broadly-defined groups:

(a) the level of economic activity,
(b) energy efficiency,

[5] http://iea-etsap.org/index.php/etsap-tools/model-generators/times.
[6] http://www.osemosys.org/.
[7] http://www.iiasa.ac.at/web/home/research/researchPrograms/Energy/MESSAGE.en.html.

Table 1
Technical differences between the TD and BU modeling approaches.

Characteristic	Mainstream top-down	Mainstream bottom-up
Model's "top" level	Social accounting matrix (SAM)	Energy balance
Model's "bottom" level	Production and consumption functions, expressing production possibility frontier and consumer(s) preferences	A set of technologies, describing current and alternative ways of production (transformation) of one commodity into another
Economic agents	Producers and consumers, maximizing their objective functions (profits, utility)	Central planner, optimizing the energy system over the long term
Primary data and exogenous parameters (model input)	SAM, key parameters of production, consumption (utility), and trade functions, taxes and tariff rates	A stock of technologies with potential alternatives described as a set of technical (efficiency) parameters and costs
Endogenous variables (model output)	Aggregated welfare and GDP, output, capital, and employment by sectors	A set of technologies, linked into chains to produce every final product, with associated costs
Drivers of economic activity growth	Exogenous productivity growth, capital, labor, resources supply, and external demand	Exogenous demand for every final commodity
Productivity growth	TFP, capital, labor, materials, and energy productivity growths are exogenous parameters, assigned to every sector.	In the absence of labor in the models, the productivity is attributed to capital, energy, and materials' input. The technology-level productivity is exogenous, but aggregated productivity is endogenous
Energy efficiency	Exogenous part (parameters of production functions) and endogenous part (substitution between capital and energy, also interpreted as non-fossil energy use)	Energy intensity of final products is a result of endogenous technological choice and exogenous changes in technical parameters, as well as exogenous pathways
Energy substitution	Based on elasticity parameters in production functions	Based on available alternative technologies and their costs
Dynamics	Recursive (static model with step-by-step updating)	Inter-temporal optimization
Expectations	Myopic, an expected policy or technological change is not included in the optimization	Perfect foresight, all future changes are included in the optimization
Policy	Expressed as a change in exogenous parameters, or constraints on a particular endogenous variable	Expressed as a set of physical constraints, or costs (taxes/subsidies) on technologies, commodities, and activities
Algebraic representation	A system of nonlinear (or linearized) equations	A system of linear equations
Solution method	Various rebalancing algorithms to fit a new set of exogenous parameters and constraints	Linear programming algorithms

(c) energy substitution (switching to low-carbon fuels), and
(d) direct emissions control.

For the comparative modeling study, it is essential to distinguish between the extent to which the results, i.e. the emissions level and time of the peak, are predetermined by a model's input, and which part is an outcome of the model's endogenous variables interaction. Some high-level judgments can be made, based on a model theory only.[8]

Economic activity requires energy. Higher economic activity (ceteris paribus) requires more energy with a direct consequences for carbon emissions. It is apparent from Table 1 above that the growth of economic activity in both model types are directly linked to exogenous drivers. In the case of TD models, the baseline economic growth is mostly defined by exogenous productivity growth assumptions and capital and labor supply assumptions. In BU models, the production of final commodities is predetermined by exogenously assumed final demand. Depending on a model structure, the final demand can be electricity, steel, or any other products like passengers-kilometers, building area lighting, or (more abstract) use of electronics. Since the aggregated economic activity dynamics in a baseline heavily depends on a set of exogenous parameters in both types of models, a substantial part of this factor of demand for energy can be considered as predetermined by the models input. Certainly, a restrictive policy can potentially affect the level of the output, especially in TD equilibrium models and special cases of BU models with endogenous demand. Structural economic changes we attribute to the following two factors.

Energy efficiency, the second factor, can be defined on different levels of aggregation. In TD models it can be a particular parameter in production functions or, more broadly, an energy intensity of industry output or the economy, i.e. energy intensity of GDP. The exogenous part in TD models is introduced as an energy efficiency improvement in production function parameters. A policy-induced, i.e. endogenous change in energy intensity is normally modeled as a substitution between energy and capital. Higher capital costs are interpreted as investments in renewable, nuclear, and/or energy-efficient technologies. Economy-wide energy efficiency (i.e. intensity) measures also depend on the structural

[8] It should be noted, that all simulations made with such optimization models are targeting a unique solution, i.e. global extremum in a numerical optimization routine. The models also have exogenous, fixed structure. Therefore, one can argue, that every unique set of exogenous input to a model, combined with the model itself, produces a predetermined output, i.e. the output is also exogenous by default. However, the output is not necessarily known to a researcher because of comprehensive structure of dependences. Here we aim to split factors into exogenous inputs which directly affect the model's output bypassing endogenous variables, and those which are result of interaction of the model endogenous variables. Also, one of models in the study (LEAP-TRA) doesn't involve any optimization, i.e. output is a summary of exogenous inputs to the model.

changes in the economy, which could be exogenously preset (calibrated) or induced by a studied policy shocks.

In BU models, the exogenous part of energy efficiency is embodied in technical parameters of technologies, which could have higher efficiency parameters. The switching to alternative technologies is usually endogenous (unless it is exogenously specified) and depends on available options and their costs.

The third factor, **energy substitution**, represents changes in energy balance (fuel mix) structure, and works similarly to the energy efficiency. In TD models switching from one energy source to another on the "bottom" level highly depends on exogenously preset elasticity of substitution parameters in production functions. The elasticity concept is a quite rough approximation of available technological options, which are explicitly described in BU models. The downside of the simplification is a progressing penalty for divergence from a baseline state, making any significant change too costly. BU models, on the contrary, are too swift for change from one technology to another. Linearity leads to a "winner takes all" problem, when even a marginal advantage in costs keeps alternative options aside. The properties of the two modeling approaches are well known; a number of studies reported a pattern that TD models tend to overestimate costs of emissions abatement, whereas BU models tend to underestimate inertia of technological transition (see, for example, EMF25 (EMF, 2011)).

The fourth potential source of emissions reductions is **direct emissions control**. It can be an option for emissions reduction without energy efficiency improvement, and changes in fuel mix structure. There are not so many technological options for direct control of CO_2 emissions other than carbon capturing and sequestration (CCS). The technology has been considered as an option in several of those participating in the study BU models. However, it is not used in the scenarios presented below, and this factor will be dropped from further consideration.

The three remaining sources of emissions reductions are consistent with widely used Kaya decomposition (Kaya and Yokobori, 1997). We don't consider Kaya's population growth component since it is more relevant for international comparisons, therefore the discussed groups of factors can be derived from the identity:

$$F = G \cdot \frac{E}{G} \cdot \frac{F}{E} \tag{1}$$

or in growth terms

$$g_F = g_G + g_{\frac{E}{G}} + g_{\frac{F}{E}} \tag{2}$$

where

F is CO_2 emissions from fuel combustion,

G is GDP (for TD models only) or output (composite output index) of a particular sector,

E is total energy consumption by a sector or total primary energy supply for TD models,

and

g_x denotes the logarithmic growth of x.

Eq. (2) will be used for decomposition of CO_2 emissions growth g_F by sources: economic, output or demand growth (g_G), growth of energy intensity of final product ($g_{\frac{E}{G}}$), and growth of carbon emissions intensity of used energy ($g_{\frac{F}{E}}$).

As discussed above, the first component of the decomposition (g_G) is mainly exogenous in both types of models. The level of economic activity highly depends on exogenous drivers (see Table 1), and can be affected by a policy (mostly in TD models and in special cases of BU models e.g. those with a final elastic demand, though the cases are not considered in the study.) Since this part depends on researchers' view or assumptions regarding economic perspectives, the input to models can be discussed and potentially harmonized, to reduce an influence of the factor of emission divergence between the projections. Disagreement about the input could also be an indication, the measure of uncertainty in the expected economic trends.

The remaining two components depend on available in models opportunities for improving energy efficiency and reducing emissions. These options are supplied exogenously to the models, through their parameters and structure. However, the resulting improvements are supposed to be endogenous in energy and emissions-related analyses (relative to the baseline changes). A comparison of the projected changes of the parameters can provide some insight into the sources of the differences between the models.

The CEMF01 study is based on a comparative analysis of emissions projections from seven different models, which are listed in Table 2. The first three models (SICGE, PIC-Macro, and China−MAPLE) cover 100% of CO_2 emissions from fuel combustion in China. SICGE and PIC-Macro relate to Top-Down class, whereas China−MAPLE is a multi-sector Bottom-Up model. The other four models are one-sector Bottom-Up technological systems, which, together, cover around 70%−80% of emissions from fuel combustion (see Table 3). The electric power sector, as well as the iron and steel and cement industries, are minimal cost optimization models. The LEAP-TRA model of the transportation sector is simulation-based, and costs are not considered.

The simulation results from one-sector models could be merged and compared with national-level projections, keeping the following caveats in mind: the estimates for each sector are created by different teams, and, more essentially, there is no coordination and harmonization between the sectors. The combined estimates from one-sector models are referred to in the comparative figures as "COMBI" model (see Table 2). The part of emissions not covered by the four one-sector models has been estimated as the difference between 9 Gt CO_2 (an approximate level in 2015) and the sum of the sectors' emissions in 2015. The dynamics of the remaining part are assumed to follow the same growth rate as the combined sectoral emissions.

Table 3 describes the emissions structure by sectors, covered by the BU models in the study. The two Top-Down models distinguish notable more sectors and cover 100% of emissions. The definition of sectors in the Bottom-Up and Top-Down models differs significantly, which makes it more difficult for comparative analysis. The last column in the table lists models used for sector-level comparative analysis.

The selections of participating CEMF01 study models represents a sample of energy models of diverse structure and theory widely applied for emissions projections and energy and climate policy analysis and thus provides a good platform for comparative analysis on national, sector, and cross-theory levels. With the goal to identify sources of potential divergence between the projections of CO_2 emission peak level and time we procede with a side-by-side comparison of input and output for models of the same theory, combining the factors into more general (Kaya) groups to compare projections across models.

Table 3
Main economic and industry sectors, considered by BU models in the study.

Name of the sector	Share of CO_2 emissions in 2014 (IEA estimates)	Bottom-up models
Electricity and heat	48%	NCSC-ELC, MAPLE
Iron and steel	14%	SIC-IIS, MAPLE
Cement	~7(+7)%[a]	PRCEE-CEMENT, MAPLE
Transportation	8%	PRCEE-TRA, MAPLE
Residential and buildings	~5%[b]	MAPLE
Others	~15%–20%	MAPLE

Note: [a] Estimate, number in parenthesis is CO_2 emissions from industrial processes; [b] Excluding heating.

2.2. Scenarios structure

The set of scenarios in the study pursues two goals: learning about carbon emissions peak and time, as well as sources of differences and uncertainties in the emissions projections. Discussion and harmonization of the exogenous input should presumably reduce divergence in projections leaving the remaining differences for endogenous factors. In the study, we aimed for harmonization within groups of models of the same theory. Some key parameters of CGE models, such as GDP and population growth assumptions are identical in the two TD models. China's economic growth perspective is one of the major uncertainties. Fig. 2 shows a range of GDP projections for China acquired from several studies. The CEMF scenario represents the optimistic growth case consistent with the “New Normal".

The level of drivers for the Bottom-Up models has been left to the discretion of modeling teams, their vision of sectors development, and feasibility of the emissions' peak scenario. Instead of the harmonization of Bottom-Up drivers, we compare them to identify the sources of uncertainties and provide a floor for discussion between modelers and industry experts.

During the CEMF01 process, modeling teams have been asked to provide two scenarios with the commitment peak year (2030), early peak (before 2025) if possible, and voluntary late peak (after 2030) in case the solution of early peaking is considered unrealistic by the teams. Besides the time of emissions peak, some scenarios from the BU models also have a different level of drivers of economic activity. The combined estimated (COMBI) were merged based on levels of emissions and drivers.

Table 4 describes scenarios' matrix based on time of peak and level of drivers. The two levels of drivers were contingently renamed as “Moderate” growth for the lower demand case, and “Soaring” for the higher demand case. For simplicity, we also make an indication of relative emissions level for cases where there are two scenarios available. “High” and “Low” (or “H” and “L” on some figures below) are suffixes that distinguish scenarios with relatively high and low emissions levels for the same model. “Base” suffix in scenario name of the MAPLE model indicates a non-peaking scenario. The suffixes are not assigned for models/sectors with only one projection.

2.3. The CEMF01 process and timeline

The methodology of the comparative study, as described above, has been integrated into the CEMF01 working process, which includes semi-annual conferences, technical workshops, ad hoc meetings, and academic committee meetings. The study announcement (May 2015) was followed with CEMF conference (Nov 2015), where various modeling teams presented their studies on economy-wide and sector-level CO_2 emissions projections, disclosed and discussed details on their modeling methodologies, and expressed their interest in participating in the CEMF01 study. CEMF conferences have a two-day format and include policy and technical discussion. As a result of the conference, the CEMF01 core modeling group has been formed to carry out the study.

Table 2
A set of the participating study energy models.

Model name (abbreviation)	Organization	Sectors and regions	The model theory
SICGE (SGE)	SIC	National, multi-sector	Applied General Equilibrium (AGE), welfare maximizing
PIC-Macro (PIC)	CAS	National, multi-sector	Econometric general equilibrium (REMI-CGE)
MAPLE (MAP)	Tsinghua E3	National, multi-sector	TIMES – partial equilibrium cost-minimizing
NCSC-ELC (ELC)	NCSC	Electric power sector	TIMES – partial equilibrium cost-minimizing
SIC-IIS (IIS)	SIC	Iron and steel sector	"Bottom-Up" partial equilibrium cost-minimizing
PRCEE-CEMENT (CEM)	MEP/PRCEE	Cement industry	TIMES – partial equilibrium cost-minimizing
LEAP-TRA (TRA)	MEP/PRCEE	National, one sector	LEAP – simulation of technological roadmaps
COMBI (COM)	Combined results from four one-sector models: NCSC-ELC, SIC-IIS, PRCEE-CEMENT, LEAP-TRA		

Note: see Li et al. (2018), Liu at al. (2018), and Feng at al. (2018) for SICGE, NCSC-ELC, and PRCEE-CEMENT models' details respectively.

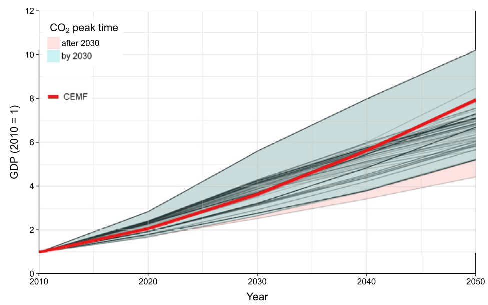

Fig. 2. GDP projections assumption in CEMF and other models, grouped by emissions peak time. Source: BP (2016), Calvin et al. (2012), EIA (2016), IEA (2016), Kriegler et al. (2013, 2015), Liu et al. (2017), Reilly et al. (2015), Riahi et al. (2015), Sachs et al. (2014), Tavoni et al. (2013), WB (2013), Zhou et al. (2011).

During 2016, three technical workshops were conducted, scenarios formulated, and assumptions discussed, with following rerun and reconsideration of modeled pathways when required. Technical workshops are essential stages of the CEMF process, where modelers discuss their results and receive feedback from leading industry experts, stakeholders, and academia, learn industry and policy insights, and share and discuss ideas.

The comparative results were presented and discussed at the CEMF annual meetings in Dec 2016, when the study officially concluded and the CEMF02 study “The low emissions development strategy for China” was launched. The final results of the study were discussed by the CEMF academic committee in June 2017, followed by the publication of the report.

3. Multi-model comparative results

The comparison of national emissions pathways by scenarios and models is presented in Fig. 3a. The base year for the comparative analysis is 2015. However, it differs from model to model. For example, PIC-Macro is calibrated to 2007 input−output data, MAPLE is calibrated to 2010, SICGE to 2015, and the sector-level models were updated to 2013−2014. With the rapid economic growth and structural changes in the Chinese economy in the last decades, energy consumption and emissions are changing accordingly. Models need to be updated consistently to represent actual level of economic variables. Lags in data availability are an obstacle in the process. However, the base year calibration problem becomes less important for one-model studies when scenarios from the same model are compared against each other. Normalization of the base year divergence will prioritize comparison of emissions dynamics over the levels in the start year of the comparison (Fig. 3b).

Table 4
Scenarios matrix based on emissions' peaking time and drivers' level.

Time of the peak	Level of drivers	
	Moderate	Soaring
Before 2025 (early peaking)	NCSC_ELC.Low, COMBI.Low SICGE.Low, PIC_Macro.Low, PRCEE_CEMENT, SIC_IIS	
Before 2030 (commitment)	SICGE.High, PIC_Macro.High, MAPLE.High, LEAP_TRA.Low	COMBI.High
After 2030[a]	MAPLE.Base, LEAP_TRA.High	NCSC_ELC.High

Note: [a] “After 2030” peak is a voluntary scenario that is reserved for cases when “commitment” peaking is difficult to simulate from a particular model's perspective. It is helpful to have such an option from the modeling perspective, especially for some sectors.

Disregarding emissions differences in the starting year, emission levels in “High” emission scenarios are in the range of 9−11 Gt in the year of emissions peak, which is 2030 for all models except SICGE (Fig. 3a). Maximum emissions level in “Low” emission scenarios is around 9 Gt for all models, with the peak around 2020−2025. The level of emissions in SICGE and COMBI models in 2020 is just slightly higher than in 2015, and if ignored, the time of the peak range will be extended to 2015−2025 for “Low” emissions scenarios.

As follows from Fig. 3, all “High” emissions scenarios report emissions growth before 2020. The lowest rate of growth for “High” cases shows COMBI − the combined estimate of sector-level models. The “Low” emission scenarios demonstrate horizontal trends by around 2020−2025 with the following reduction in SICGE and COMBI models. Both PIC-Macro scenarios demonstrate growth by 2025, but since the starting point in the models is lower (see base year discussion above), the level of emissions is reaching 9 Gt by 2025, which is the actual level in 2015 (Fig. 3a). An adjustment to the starting year differences in projections (Fig. 3b) doesn't result in notable changes in the emissions' range. Assuming the total emissions in 2015 were equal 9 Gt, the range of projected emissions in peaking scenarios would be 9.1−10.5 Gt in 2020, and 8.9−11.25 Gt in 2030.

There is no visible difference in the projected national emissions trend between TD and BU models. The upper emissions bound is edged by two models: PIC-Macro (TD) and MAPLE (BU). The lower bound from 2015 to 2030 is outlined by SICGE (TD) and COMBI (BU) with almost coinciding projections in both upper and lower bounds (Fig. 3b).

The variation of the emissions level in the peak is about 2 Gt or around 20%, which is a significant uncertainty, even if it is notably lower when compared with a larger sample of models and scenarios (Fig. 4).

It should be noted that based on the available data in the beginning of 2017, CO_2 emissions in 2016 are lower than 2015.[9] This information is not considered in the projections. If the “plateau” trend continues, the emissions level is not likely to reach the upper bound of the projections, making the realization of “Low” emissions scenarios more likely to happen.

[9] http://www.ccchina.gov.cn/Detail.aspx?newsId=66919&TId=58.

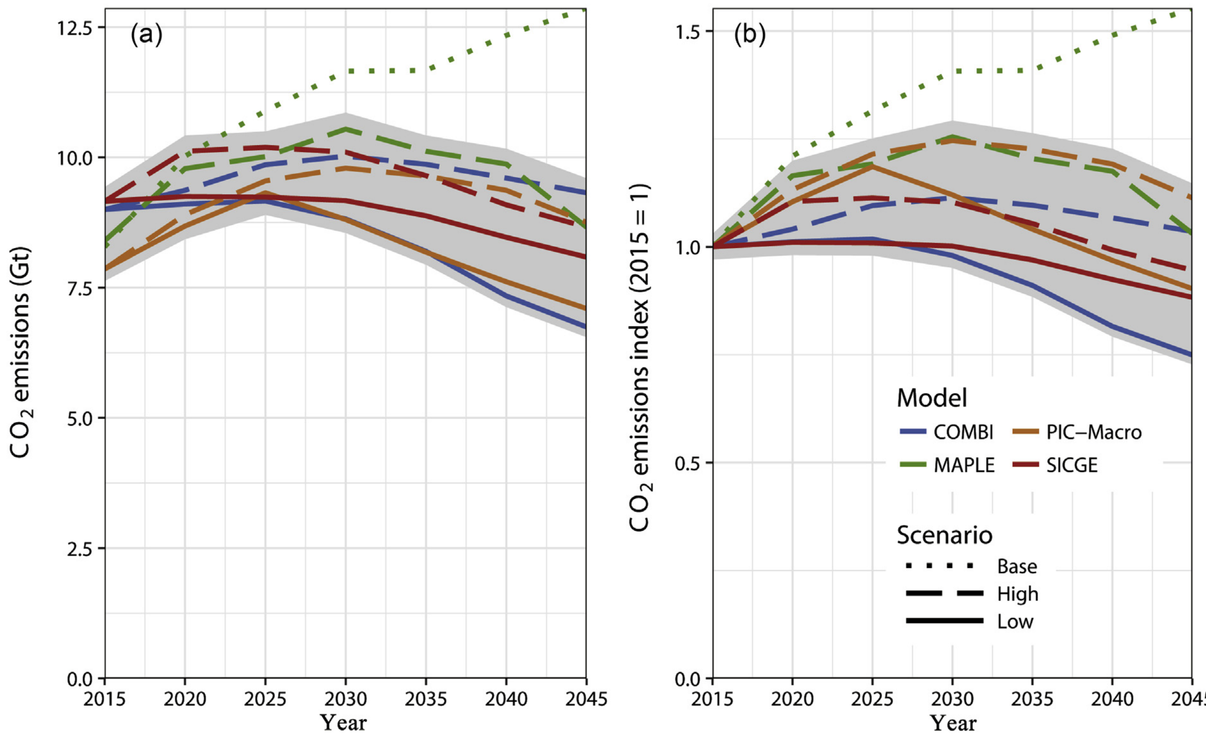

Fig. 3. CO_2 emissions projections by models and scenarios.

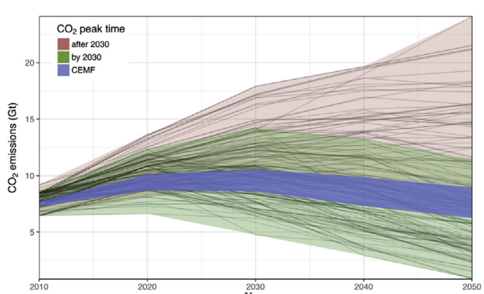

Fig. 4. CEMF peaking scenarios vs. other emissions projections. Source: same as sources for Fig. 1 plus CEMF01 estimates.

It is clear that emission peaking scenarios require phasing out of fossil energy use, especially coal. All models show coal peaking by 2025 in the primary energy mix (Fig. 5). In the “High” emissions cases, coal peaks by 2020 in MAPLE, SICGE, and COMBI models. In “Low” emissions scenarios, coal peaks around 2015 in SICGE and COMBI models, and around 2020 in PIC-Macro (Fig. 5). Consumption of oil and natural gas is growing in all scenarios, though in MAPLE, the peaking scenario of natural gas substitutes the growth of oil whereas other models demonstrate a moderate development of gas consumption.

The dynamic of aggregated non-fossil energy sources is quite similar across models, but the structure[10] to be different. The differences demonstrate uncertainty in non-fossil energy development, as well as in the availability of various options for further development. More studies are required to address the uncertainties and develop optimal and robust technological pathways for particular industries and energy sources.

Fig. 6 provides decomposition o carbon emissions growth by sources according to Eq. (2) for national emissions growth from 2015 to 2030. The application of the decomposition exercise is straightforward for the TD models, where GDP can be used as a final product. Though due to the absence of an output aggregate in BU model, we applied the decomposition for four sectors separately, and aggregated the results using CO_2 emission in 2015 as weights.

As follows from Fig. 6, the growth of output (g_G), which is mostly exogenous in both models, is the most significant factor of emissions changes. Except few cases (COMBI model scenarios), the factor is also only one which pushes emissions up. Energy intensity reduction ($g_{\frac{E}{G}}$) is the main factor to compensate growth of demand in TD models. This type of models considers changes of economic structure towards services, which is consistent with both − growth of the final product (GDP) and reduction of energy intensity. The fuel mix structure ($g_{\frac{F}{E}}$) also shifting towards low-carbon fuels.

Output in BU models is in physical units, and, as shown on Fig. 6, its aggregated growth is relatively lower than growth of GDP. Though its share is also dominating in most scenarios. All scenarios in TD models show energy efficiency improvement during the 15 years. Though fuel mix is almost not changing in MAPLE “Base” scenario (MAP.B), and it is

[10] Excluding PIC-Macro which considers aggregated non-fossil energy.

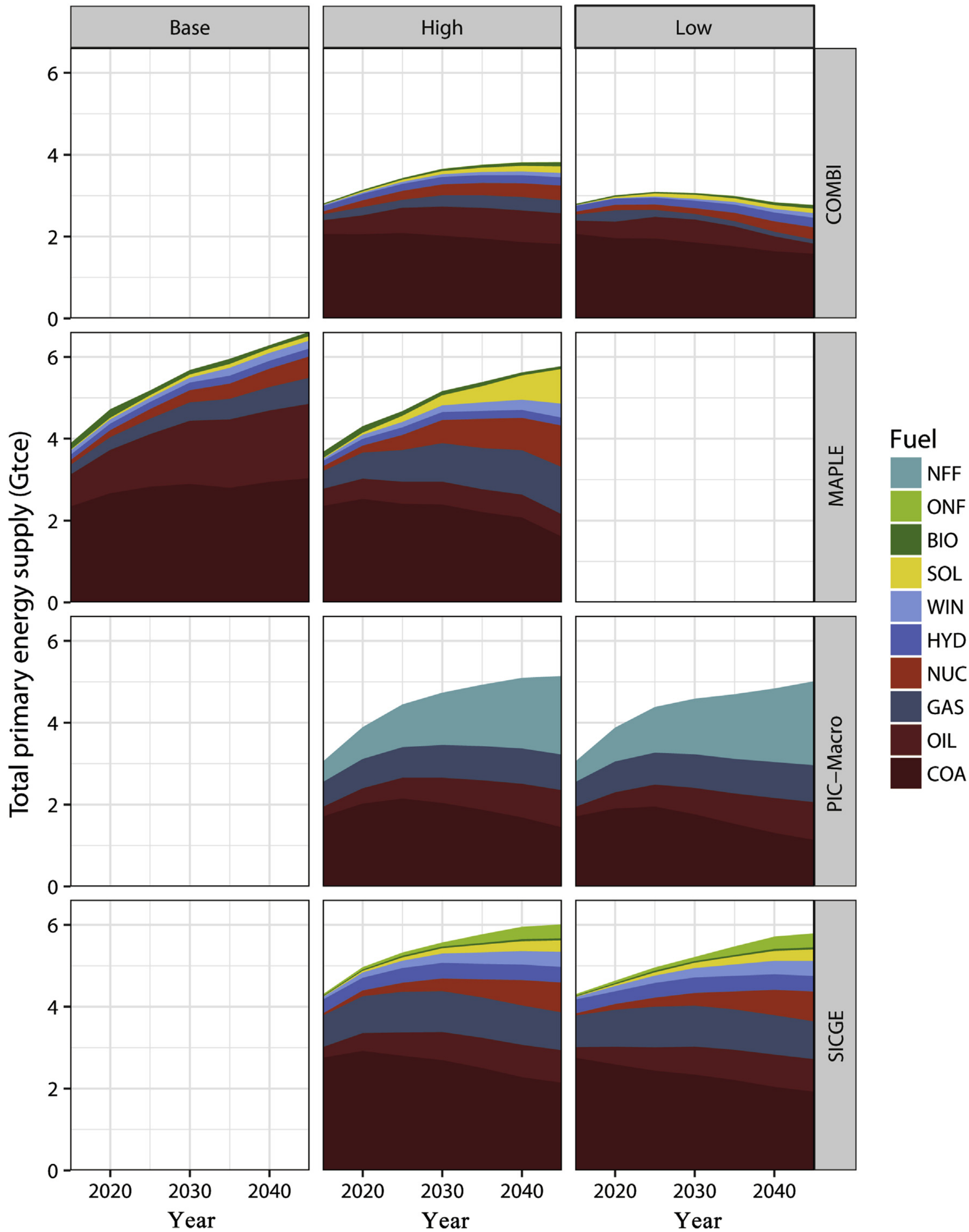

Fig. 5. Total primary energy supply (TPES) by fuel types, models, and scenarios. Note: COA – coal; OIL – oil; GAS – natural, shale, and petroleum gas; NUC – nuclear energy; HYD – all hydro energy; WIN – wind energy; SOL – solar energy; BIO – biomass and biofuels; ONF – other non-fossil; NFF – all non-fossil fuels (for PIC-Macro only).

deteriorating in COMBI scenarios, which is the result of reduction of electricity use in some sectors (discussed with more details below), and also an effect of coordination absence of projections for different sectors.

Unlike the national emissions and energy balance, sector-level projections are completely different in TD and BU models. Below, we discuss only BU projections for sectors, which are more consistent with experts' opinions on the development of the industries and sectors, expressed on CEMF01 meetings. The efforts towards the harmonization of results between TD and BU should be considered in the future to make the results more comparable across models' theory.

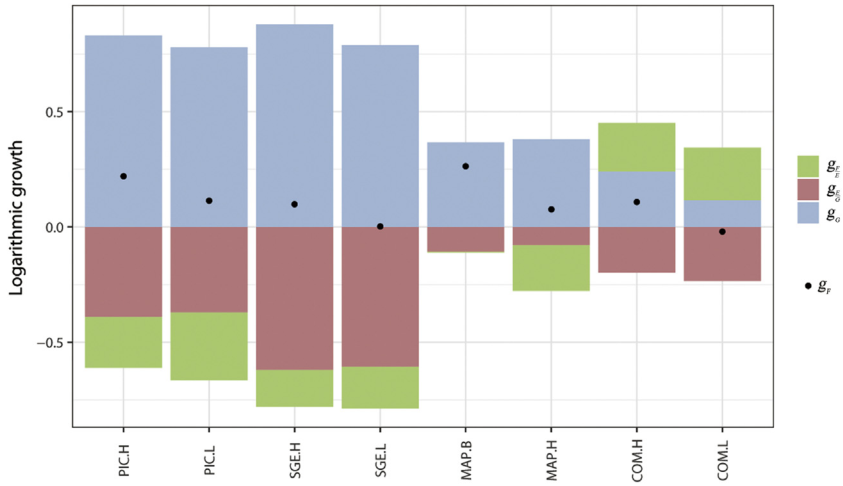

Fig. 6. National carbon emissions decomposition by factors.

The structure of emissions by sectors from bottom-up models is presented in Fig. 7. The main source of carbon emissions is electric power sector, which will continue playing an important role in the coming decades. Emissions from transportation will be growing by 2030, as well as from “Other” sectors in MAPLE model scenarios (the share of “Other” emissions is assumed constant in COMBI). Emissions from iron and steel (IIS) and cement production are declining in all scenarios.

Fig. 8 compares sector-level CO_2 emissions trends and Kaya decomposition of emissions growth by sources (see Eq. (2)) from 2015 to 2030 for BU models and scenarios. The demand-driven emissions growth source (g_G) is solely exogenous in one-sector BU models. The energy and emissions intensity ($g_{\frac{E}{G}}$ and $g_{\frac{F}{E}}$) are endogenous and, as discussed above, depend on the model's available technological options and constraints.

As follows from the Kaya decomposition for the electric power sector (Fig. 8a), the demand for electricity is expected to grow from roughly 25%−50% by scenarios. In the absence of energy efficiency and fuel mix improvement, it would be a significant factor of emissions growth, as represented by the MAPLE “Base” (MAP.B) scenario. The MAPLE “High” (MAP.H) scenario has the highest growth of electric demand across all models and scenarios, though the potential emissions growth is offset by changes in the energy mix, especially the share of non-fossil energy (see also Fig. 5). The changes in fuel mix result in almost zero carbon emissions growth by 2030 in the sector, even in the higher demand vs. “Base” scenario.

NCSC-ELC scenarios have comparable growth of electric demand in the “High” emissions cases, but growth is twice as low in “Low” emissions scenario[11]. From another perspective, NCSC-ELC scenarios demonstrate a higher improvement in energy efficiency in the sector by 2030 vs. MAPLE scenarios ($g_{\frac{E}{G}}$ areas in Fig. 8). The fuel mix changes towards non-fossil energy, with a lower rate than the demand ($g_{\frac{F}{E}}$ in Fig. 8). Therefore, the main source of emissions reduction in the “NCSC.Low” scenario is demand deceleration (g_G in Fig. 8), which indicates the need for demand-side energy efficiency improvements.

The main source of emissions in the transportation sector is the growth of demand. MAPLE scenarios, on average, assume more than double the demand for transportation services.[12] Drivers in the LEAP-TRA scenarios are more moderate and close to GDP growth assumption. The structure of demand for transportation services also differs in the two models. Freight transportation in LEAP-TRA scenarios is growing faster, reducing the aggregated energy efficiency in the sector ($g_{\frac{E}{G}}$ in Fig. 8b.). The carbon intensity of the fuels does not change significantly in the model by 2030. Both MAPLE scenarios show some energy efficiency improvements in the sector. A variation in sources of emissions between the scenarios and models is mainly due to changes in the sector output structure and differences in base-year calibration. Notably, both models don't consider the higher penetration of low-carbon vehicles before 2030. The recent boom in electric and hybrid cars will be considered in further steps of the research.

The cement, iron and steel industries are very different from the electric power and transport sectors dynamic. Both expect a slowdown in demand due to a transformation of China's economy. Scenarios in both models agree with the negative dynamic after 2020, though the speed of reduction and the year of peak differs. MAPLE scenarios expect the

[11] The original names of the NCSC-ELC model scenarios are “Low carbon” and “Enhanced low carbon,” respectively, for “High” and “Low” cases, which are used in the study for comparative reasons across models and don't represent the initial intents of the scenarios.

[12] Transportation services have several components, including several types of road transport, railroads, domestic and international avia- and water-, passenger and freight transportation. All services are aggregated with the weights of consumed primary energy. The equivalent of doubling on a logarithmic growth scale is $\ln(2) \approx 0.7$.

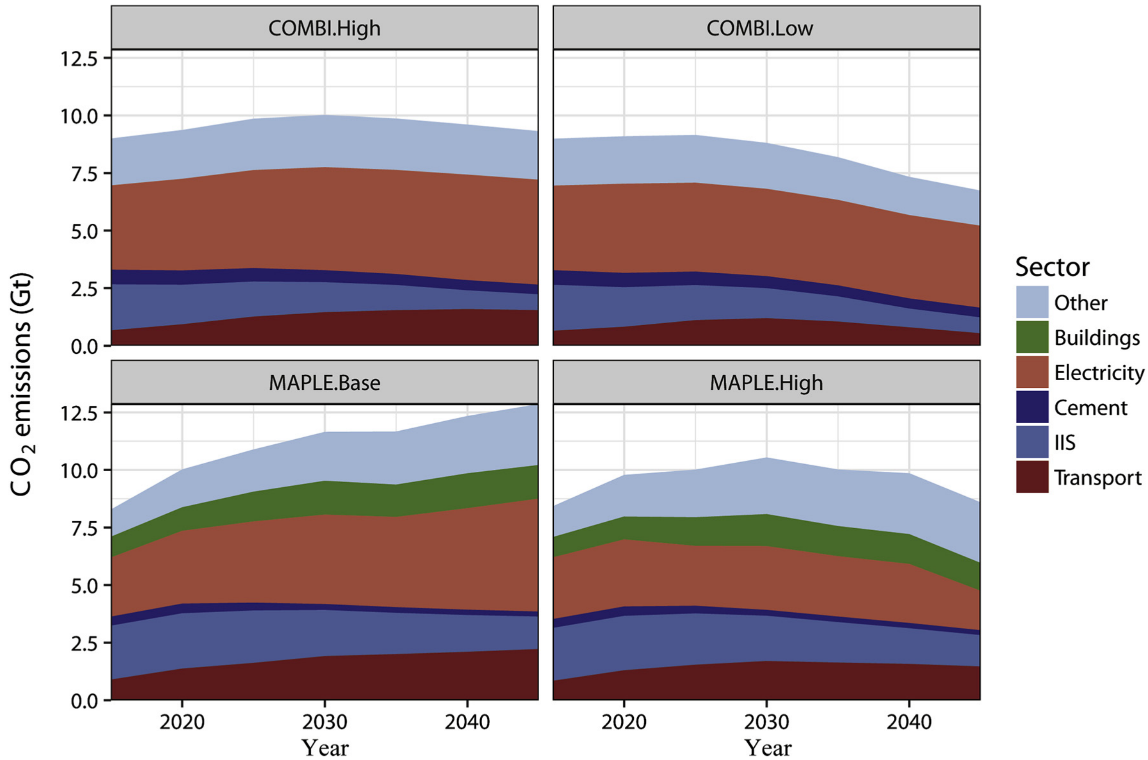

Fig. 7. CO_2 emissions structure by sectors.

peak in demand of both sectors to be around 2020. SIC-IIS and PRCEE-CEMENT models' scenarios assume peaking in IIS and cement industries around 2015. The main driver of emissions reduction in the IIS industry is demand. SIC-IIS scenarios also assume the expansion of heat recovery technologies, which change the overall fuel mix structure and efficiency (installation of heat recovery technologies improves average energy efficiency in the industry and reduces net demand for electricity produced outside the sector − see Kaya decomposition for the sector). The sources of emissions reduction in the cement sector are alike in both models and are driven by demand, energy efficiency improvements, and some growth of carbon intensity of the aggregated fuel mix, which is also a function of the expansion of heat recovery technologies in the industry.

4. Conclusions

The study addresses differences in carbon emission projections across energy models using a side-by-side comparison of the models' input and output. Emissions trends simulated by seven energy models of different theories and scopes have been combined and compared. During the CEMF01 study process, the projections and underlying factors have been openly discussed between modeling teams, industry experts, and academia with an aim to identify sources of the emissions projections' divergence, either originating from data, the models' theory, or the scenarios' assumptions, and also, to reveal uncertainties which affect carbon emission levels and peaks. The results of the study can be summarized into two groups: findings regarding emission levels and peak, along with conclusions regarding modeling practices with suggestions of a roadmap for further improvements of energy models and their applications.

The peaking projections of emissions in the study are conditional to the fulfillment of China's commitment to peak by 2030 or earlier. Though the study did not intend to evaluate any policy measures, the policy efforts are assumed to be efficient enough to reach the peaking and intensity goals. Considering the emissions reduction policy efforts as given, the economic and energy trends were simulated for the national and sector levels to identify potential sources of emissions abatement, as well as the key sectors responsible for the emissions peak and level.

According to the comparative modeling results, the CO_2 emissions from energy use could peak at range from 9 Gt (about the level of 2015) to 11 Gt from 2015 to 2030. The level of emissions peak will be determined mostly by the dynamics before 2020. The timing of the peak depends on the two main factors: the level of economic activity (i.e., economic growth, an output of energy-intensive industries), and the speed of deployment of energy efficient technologies and non-fossil energy, mainly in electricity production and transportation. Taking into account stabilization of emissions in recent years, which is not reflected in the considered scenarios, the earlier peak with lower emissions level could be considered as a very likely scenario (subject to the continuation of the emissions reduction policies).

Two energy-intensive industries − iron and steel, and cement − are expected to meet demand slowdown in the next

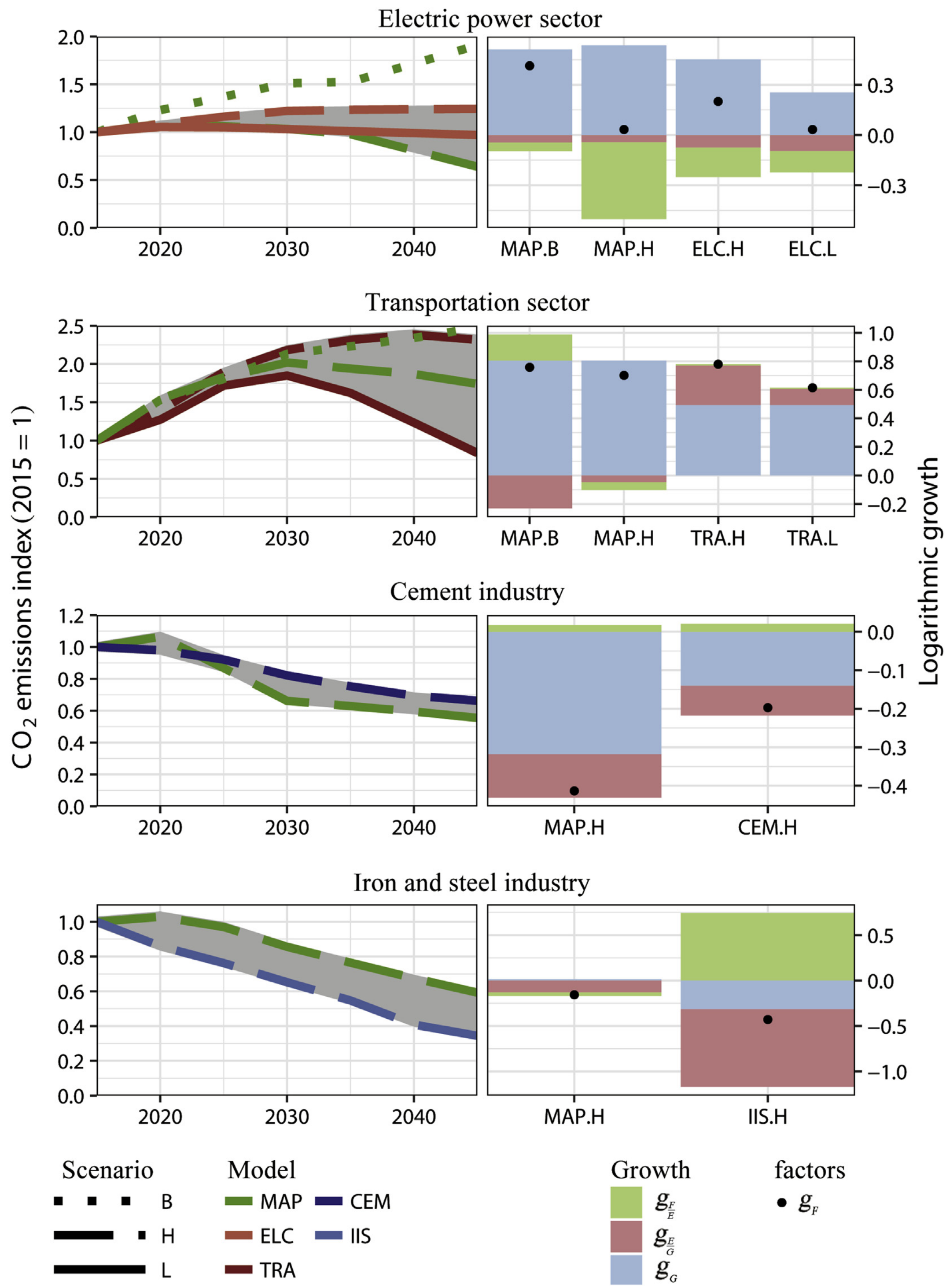

Fig. 8. Carbon emissions dynamics by sectors (left) with decomposition (right). Note: For short model references, see Table 2. "H," "L," and "B" are abbreviations for "High," "Low," and "Bsase" emissions scenarios, respectively.

decade. The CO_2 emissions in the sectors will likely peak by 2020 or have already peaked. Further improvements in energy efficiency could contribute to deeper emissions reduction in the industries. However, due to the reduction in demand, new investments will be relatively harder to accomplish, considering that the study strategies are based on cost-efficient pathways, with the retirement of outdated, inefficient technologies, and the moderate upgrade of the existing stock.

The electric power and transportation sectors are the key in carbon emissions reduction. More research should be carried out, to identify cost-efficient emissions abatement strategies and policy measures. The share of renewables (mostly wind, solar, and bio) and other non-fossil energy sources (nuclear and large hydro) as planned by the 13FYP, will continue to grow by 2020. Further expansion is required to meet the peak commitment and will depend on the competitiveness of technologies (the cost of renewables, grid development, and the implementation of demand-side management programs) and policy (the introduction of ETS, 14FYP targets). The limitations of the integration of renewables to the grid, and the potential share of penetration should be addressed using supply-and-demand balancing models, which are not a part of this study.

The main mitigation technology in transportation is switching to biofuels, natural and petroleum gas, and electrification. Though electric cars are penetrating the market rapidly, aggressive electrification has not been considered in the study scenarios, due to uncertainties with regard to the cost of batteries, the required investments in infrastructure development, and policy support. Higher penetration of electric vehicles should advance the carbon emission peak, lower the level, and will be considered in the further steps.

The Bottom-Up models in the study also don't cover “other sectors” (around 20% of total CO_2 emissions from fuel combustion), which is hard to model and evaluate their technological roadmaps. Although some energy-intensive industries, including non-ferrous metals and refineries, could be considered on the next steps of the research.

Several observations have been made regarding the models' development, application, and modeling approaches.

As learned from the decomposition of the emissions growth factors, at least 50% of simulated emissions dynamics from 2015 to 2030 is predetermined by assumptions of economic development, which is the exogenous input to the both types of energy models. The two remaining factors − energy efficiency and fuel mix structure − have exogenous and endogenous components, which is hard to separate. Thought the fact that more than 50% of emissions growth is determined by models' input, emphasizes the importance of the work which has to be done before application of models to a simulation of an economic activity. Open discussion of the data and assumptions between modeling teams and industry experts is the main method to address the uncertainty, harmonize models' inputs, and reduce the “noise” in projections. Absolute transparency of energy models is another important goal to achieve. CEMF is developing a data and a basic model sharing platform to minimize the uncertainty, improve transparency, and validate the data, models, and estimates.

Base year calibration, though it is less important for comparison of scenarios simulated with the same model, is a significant factor for differences in results in multi-model studies. This factor needs to be minimized in the further steps of research.

The models of the different theoretical frameworks (TD and BU) show similar results on the national level for both energy balances and emission level simulation; however, the two types of modeling approaches project very different structures on the sector and industry levels and, in general, are not comparable. More research is required for the harmonization of the two modeling approaches in order to accommodate their advantages and reduce disadvantages. Hybrid and integrated assessment modeling should be considered as a preferred direction in order to improve emissions projections and policy analysis.

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