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The environmental co-benefit and economic impact of China's low-carbon pathways: Evidence from linking bottom-up and top-down models

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ABSTRACT

Deep decarbonization pathways (DDPs) can be cost-effective for carbon mitigation, but they also have environmental co-benefits and economic impacts that cannot be ignored. Despite many empirical studies on the co-benefits of NDCs at the national or sectoral level, there is lack of integrated assessment on DDPs for their energy, economic, and environmental impact. This is due to the limitations of bottom-up and top-down models when used alone. This paper aims to fill this gap and link the bottom-up MAPLE model with a top-down CGE model to evaluate China's DDPs' comprehensive impacts. First, results show that carbon dioxide emissions can be observed to peak in or before 2030, and non-fossil energy consumption in 2030 is around 27%, which is well above the NDC target of 20%. Second, significant environmental co-benefits can be expected: 7.1 million tons of SO_2, 3.96 million tons of NO_x, and 1.02 million tons of $PM_{2.5}$ will be reduced in the DDP scenario compared to the reference scenario. The health co-benefits demonstrated with the model-linking approach is around 678 billion RMB, and we observe that the linked model results are more in accordance with the conclusions of existing studies. Third, after linking, we find the real GDP loss from deep decarbonization is reduced from 0.92% to 0.54% in 2030. If the environmental co-benefits are considered, the GDP loss is further offset by 0.39%. The primary innovation of this study is to give a full picture of DDPs' impact, considering both environmental co-benefits and economic losses. We aim to provide positive evidence that developing countries can achieve targets higher than stated in the NDCs through DDP efforts, which will have clear environmental co-benefits to offset the economic losses.

1. Introduction

A national deep decarbonization pathway (DDP) represents a hindcasting approach to inform the low-carbon transformation envisaged by the Paris Agreement [1]. DDPs consider a long-term time frame, with an economy-wide perspective and sectoral disaggregation. For developing countries including China, DDPs are not only a carbon mitigation issue, but also highly related to economic development, environmental challenges, and public health [2]. Given these broad linkages, DDPs analysis, especially for developing countries, should be expanded to an integrated assessment that encompasses more than one single issue or single quantitative analysis tools.

Energy system models (ESMs) and integrated assessment models (IAMs) have been widely used for decarbonization pathway analysis. ESMs can answer questions of how to meet current and future energy demand given certain constraints and targets [3]. To understand the comprehensive impact of DDPs, many researchers have evaluated environmental co-benefits by linking IAMs to pollution models, or looked at economic impacts with general equilibrium models linked to technology-rich models [4,5]. However, few studies both assess the economic impact along with environmental health co-benefits. The main reason is the limitation of the analysis tools.

For environmental co-benefit analysis, studies usually link the current energy system to its environmental impacts. Many researchers have analyzed correlations between CO_2 and other local pollutants, such as SO_2, NO_x, and particulate matter (PM) [6,7]. However, for most co-benefit studies, the main method is to link "top-down" energy models like CGE (computable equilibrium model) to local pollutant models, using emission coefficients based on activity levels [8]. Such analysis is

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List of abbreviations

DDP	Deep Decarbonization Pathway
PM	Particulate matter
China-MAPLE	China-Multi-pollutant Abatement Planning and Long-term benefit Evaluation
DDP	Deep decarbonization pathways
CGE	Computable general equilibrium
NOx	Nitrogen oxide
CO2	Carbon dioxide
SO2	Sulfur dioxide
CES	Constant elasticity of substitution
REF	Reference Scenario
GHG	Greenhouse Gas
Mtce	Millon tons of coal equivalent
GDP	Gross Domestic Product
TIMES	The Integrated MARKAL-EFOM System
TWh	Tera Watt hour(s)
kW	kilo Watt

not suitable for DDPs, since the decarbonization is related to technology characteristics, not just activity levels. Some have proposed linking the energy technology-rich model, or the so called "bottom-up" model, to the air pollution model. Scholars have mainly focused on the power sector [9,10] and energy-intensive sectors like the cement industry and the iron and steel industry [11]. However, these studies are mostly focused on one specific sector, like cement or iron and steel. The DDPs are the national blueprint for all sectors. The full picture of inter-sector interactions is ignored in these studies. When assessing the economic impact of DDPs, the partial equilibrium "bottom-up" models have limitations, for example, being unable to consider all markets being cleared [12]. Therefore, in order to analyze the economic impact of DDPs, this paper further linked our own bottom-up model to a top-down model.

Despite many empirical studies on the co-benefit issues, or that use bottom-up or top-down models alone, there are very few integrated studies on DDPs' impact on both economy and environment, based on linking bottom-up models and top-down models. There is no such specific study for China. This study tries to fill this gap and carry out an integrated assessment of environmental impact and economic impact of China's DDPs, and provide a methodological reference for developing countries' DDPs analysis.

In this study, the linkage is between the bottom-up model China-MAPLE (China-Multi-pollutant Abatement Planning and Long-term benefit Evaluation) model and the China-CGE model. We take all economic sectors as our research object, including the energy supply sector, oil refining, the power generation sector, other secondary sectors, the transportation sector, the residential sector, the commercial sector, the industrial sector and its subsectors (chemicals, iron and steel, cement, non-metallic industry, ferrous metals, non-ferrous metals, textiles, and others). In addition, the linking to local pollutant emissions is further improved by being set at the technological level, instead of the fuel consumption level or activity level. This study is trying to answer the following questions: Is China's DDP achievable, affordable, and effective for both optimizing the energy system and improving air quality for health co-benefits?

This study contributes to the literature in two significant ways. First, to the best of our knowledge, it is one of the few studies that links bottom-up and top-down models for all economic sectors when analyzing environmental co-benefits of decarbonization policies. It fills in the shortcomings of each stand-alone model, such as lack of technological details or sector interaction effects when analyzing economic impact. Second, it provides evidence across all economic sectors of positive environmental benefits for China's decarbonization pathways. The environmental co-benefits not only have general equilibrium feedback effects in their overall economic impact, but also have detailed benefits for each sector, which we model with our technology-detailed MAPLE model. This improvement helps to enrich the previous studies on achievable and environmentally-friendly decarbonization pathways in developing countries, and demonstrates a methodological approach that can be valuable to many different countries and stakeholders.

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature on current representative bottom-up model and top-down models, as well as studies on linking two kinds of models. Section 3 focuses on the methodologies used in this study, including the China-MAPLE model, the China-CGE model, and the linking method, as well as the environmental co-benefit evaluation method. Section 4 shows the model results on energy consumption optimization and the decarbonization effects. Section 5 presents the environmental co-benefit evaluation and economic impacts, as well as comparison of the results before and after linking. The final section summarizes the key findings and discussion.

2. Literature review

2.1. Energy models

Modelers have provided strong evidence on the significant mitigation impact for carbon mitigation technologies and policies [13–15]. The IAMs are still dominating the quantitative analysis for decarbonization pathway analysis with constraints [3]. Typically, the most frequently used modeling tools are "top-down" models like CGE (Computable general equilibrium) [16], and "bottom-up" models with partial equilibrium assumption but more energy technological details [17–19]. These model-based studies provide us with rich references for decarbonization pathway in future.

CGE models can take the economy-wide effects from policy instruments or development activities into account [20,21]. Therefore, CGE models are more suitable for assessing the effects of certain policies on economic sectors and agents (households, governments) [22,23]. CGE model can be a good option because it can capture direct and indirect economic effects. CGE models are especially useful when evaluating carbon taxes and carbon trading. Moreover, scholars are increasingly doing analyses at the provincial level in China, focused on topics at the energy-economy-environment nexus. For instance, Liu and Lu investigated carbon tax impact on Chinas economy using a dynamic CGE model [24]. The CGE model can be applied to evaluate carbon tax policy impact on the regional level [25,26]. Dynamic CGE model can be used to explore the impacts of ETS-Carbon tax schemes in China [27]. Some studies have employed recursive dynamic CGE model to analyze appropriate sectoral coverage [28] and the quota allocation [29] at the national level. Many researchers examine price effect and scale effect of carbon tax policy in a specific province or city such as Shanghai [30,31], Liaoning [32], Chongqing [33] by taking advantages of different types of two-region CGE model. However, the database of CGE models are based on Input-output tables, and therefore the analysis is based on sectoral level or activity level, not possible to take technology trade-off impacts into consideration [34,35]. With the deep decarbonization goes deep into the energy technology level, the analysis of impact and potential of mitigation technology with technical-rich model is needed.

With their rich technological description, bottom-up models are widely used to evaluate technology improvement and energy efficiency [17–19]. In the relevant literature, bottom-up models have been widely used to analyze potential improvement in energy efficiency [36], CO_2 emissions [36,37], energy consumption and demand [37], and development pathways [38]. There are versions at the national level [39,40] and global level [41]. Bottom-up models are useful tools when looking into energy-intensive sectors, like the cement sector and the iron and steel sector, as well as for the entire industry sector [38,42,43]. However, there are also limitations for bottom-up models, including that they are usually used for specific sector-level studies [38,42] because it is highly difficult to analyze sector interaction among different sectors from a general equilibrium perspective [44,45].

Overall, top-down and bottom-up approaches have their own strengths and weaknesses. Top-down approaches depict interactions between macro-economic sectors and agents, but when measuring the macroeconomic costs and impacts caused by energy policies, they ignore specific technological details. By contrast, bottom-up approaches have the capacity to assess both the efficiency and costs of distinct technological options [46]. However, they cannot capture the full macro-economic influences of energy policies. Consequently, searching for methods of linking these two approaches to improve the precision of policy simulations is imperative for researchers.

There are two kinds of linking: hard linking and soft linking. Hard linking, sometimes called a hybrid model, directly integrates and optimizes both the top-down and bottom-up models simultaneously instead of using an iterative process [27,47]. However, hard-linking requires for the data restructure and change in the production function of CGE. The limitation of hard linking is that it often requires a simplified model because of limited data. Therefore, hard linking is more applicable for sectoral level analysis. Timilsina and other researchers use hybrid models to study the economic and environmental consequences of transitioning to renewable energy in the electricity sector [35,48,49]. The other type of linking is soft linking, which incorporates top-down and bottom-up models by simulating these two models separately. The simulation results of a bottom-up model are used iteratively as inputs into the top-down model. Typically, soft linking is used to reduce the differences between the results from top-down models and bottom-up models. We have to emphasis that soft linking also needs restructure of the data and sectors. Soft linking method is more applicable for integrated analysis on national level. Krook-Riekkola proposes a soft linking procedure between a CGE model and the TIMES model to improve national energy policy decision-making [34].

When talking about environmental co-benefits, there is limited literature on linking models, and most of the studies are based on stand-alone CGE models linked to an environmental module, or stand-alone bottom-up models linked with a simplified air pollution module. The linking of the two models can help alleviate some of the problems with stand-alone models when evaluating environmental co-benefits.

2.2. Health co-benefit analysis of climate policy

Environmental health co-benefit becomes a hot topic in recent years. The health co-benefit calculation is often combined with energy system model. Some researchers linked the CGE model [5], integrated three models, including GAINS (interaction and synergy of greenhouse gases and air pollution), IMED/HEL (integrated model of energy, environment and economic sustainable development) and IMED/CGE model to identify the health and national economic impacts to health co-benefit [8,50]. The other scholars combined the bottom-up models to the health co-benefit, including LEAP model [12,51,52], ASIF (Activity–-Share–Intensity–Factor) [6] and MARKAL model [7,53]. We make improvement to apply linking bottom-up model and top-down models to get the health co-benefit. Following the famous work of West et al. (2013) [54]. The method of health co-benefit accounting can be divided into 3 types, involving global level, domestic level and regional level. Among those, Matus et al. evaluate the health co-benefit by using their own model, with the VSL selected from EPA [55]. Some researchers use globally VSL estimation from some organizations, such as EPA [55,56], OECD [57,58] adjusted to different world regions and into the future using an income elasticity or per capita consumption as one possible approximation of VSL [59]. In addition, many researchers use domestic VSL to calculate the health economic impact [4,5,50].

Both bottom-up models and top-down models have advantages and disadvantages when evaluating environmental benefits. For top-down models, the costs and benefits are evaluated by default in units of value. However, the emissions coefficient is set at the activity level or the fuel level, and in this case, information from the technological level, including end-of-pipe control for local pollutants, is missing. Given computational formulations of general equilibrium principles, environmental benefits can be represented in CGE functions [51–54]. Bottom-up models have technological detail, and can describe process emissions in addition to fuel combustion-based emissions [10,11,43,55]. However, the environmental co-benefit analysis based on bottom-up model is mainly focused on specific sector, like the cement sector, the iron and steel sector, or the power generation sector. Further studies on full-economy sectors from bottom-up model technological aspect are needed. This study aims to link the bottom-up model with the top-down model for the environmental co-benefit analysis for deep decarbonization pathway. The range of health impact at the national level in China has been given by previous studies as 9.1–25.2 billion USD bib53 [5,53]. In contrast, we adopt direct value of inhale fraction, sensitivity of human health to human pollutants to simplify the accounting method and use domestic VSL [56–60], which accounting results also within this range.

3. Methodology

3.1. Bottom-up China-MAPLE model

The China-MAPLE (China-Multi-pollutant Abatement Planning and Long-term benefit Evaluation)model consists of an energy system optimization module based on the TIMES modeling framework, which provides a technology-rich basis for estimating how energy system operations and will evolve over a long-term, multiple-period time horizon (Fig. 1.). It simulates the investment and operation of major energy technologies under constraints of emissions reductions of GHGs and pollutants in local regions in China and future energy use trends in reference scenarios and other comparative scenarios of varying degrees of mitigation action. The main principle is to minimize the total cost of the energy system to meet the given energy demand and any other major constraints.

In detail, the model performs calculations on five-year steps, from 2010 to 2050. The model includes the full-economy sectors, including energy supply, electricity and heat generation, and final demand sectors. The mitigation measures and technologies reflected by constraints for commodities and processes and reported for each sector, especially for final demand, can be divided into four major sectors, namely the industrial sector, the transportation sector, the building sector (commercial/residential sector), the agricultural sector and others. The policy questions considered in MAPLE mainly orient on emission mitigation, energy policy instruments and multiple kinds of constraints that can be added during the energy system optimization process.

The MAPLE modeling system consists of five modules. The final energy demand module establishes the relationship between energy demand and corresponding drivers. The model is technological rich with details, including over 780 technologies. Among them, there are around 113 resource mining and supply technologies in the energy supply module. For the base-tear technologies, there are around 80 electricity and heat generation technologies, around 70 technologies for transport including different vehicles and emission standards. For industrial sector and subsectors (chemicals, iron and steel, cement, non-metallic industry, ferrous metals, non-ferrous metals, textiles, and others), there are more than 150 technologies for the production processes. Besides, there are totally around 371 new technologies for all sectors, including technologies with higher efficiency and mitigation technologies like CCS (carbon capture and storage) etc. Besides, the end-if-pipe removal technologies are also considered in the MAPLE model. This is also an improvement for the bottom-up method.

Compared with other bottom-up models for China, China-MAPLE integrates local pollutant control and co-benefit modules into the energy system framework based on technical level rather than activity

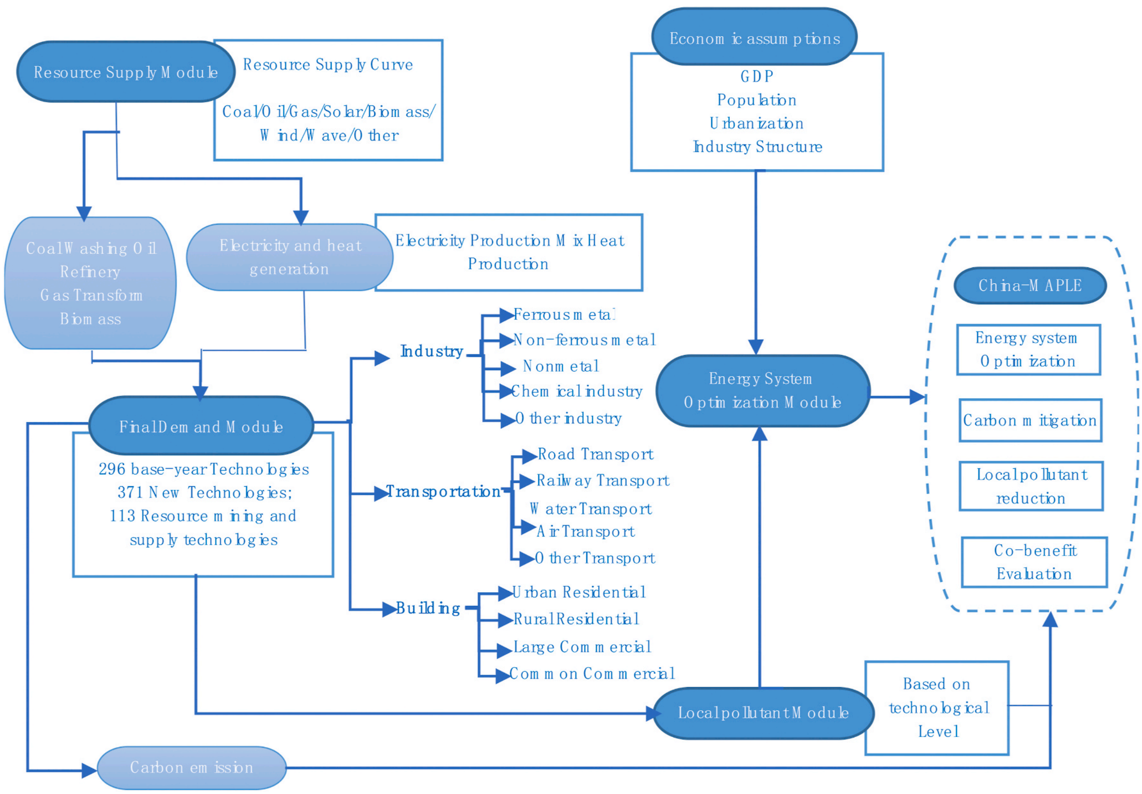


Fig. 1. The structure of the China-MAPLE model.

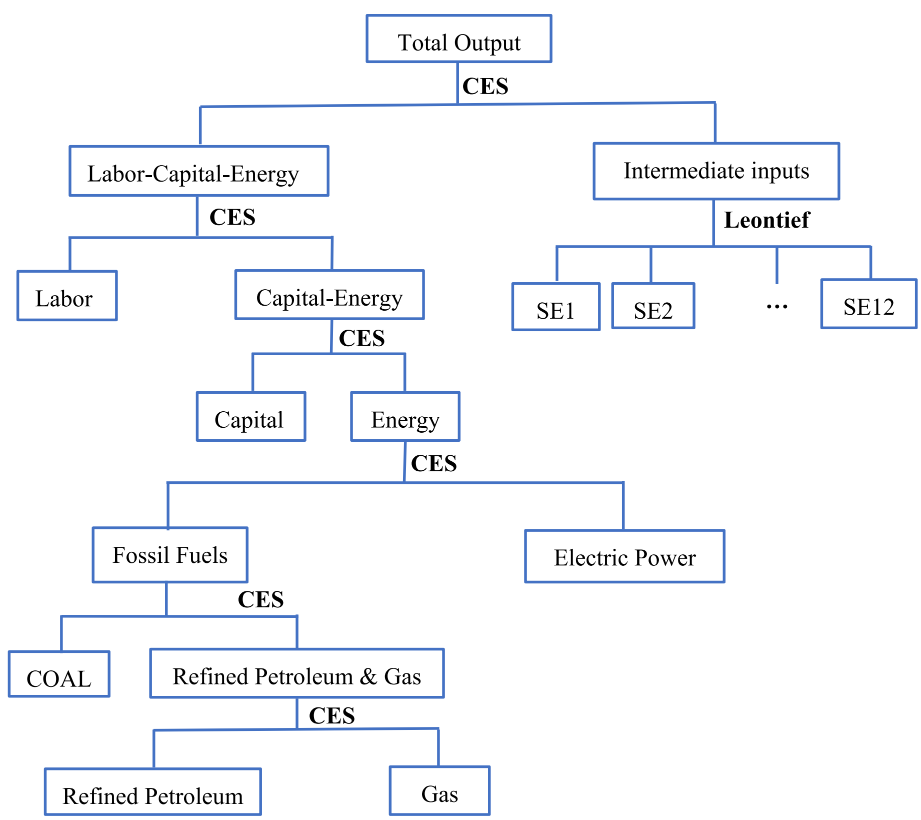


Fig. 2. Structure of production function in the CGE model.

levels to reflect the mitigation effects of technological advances and structural adjustments in key areas. Regarding the benefit evaluation module, it describes the benefits of local pollutants obtained through emissions reduction. China-MAPLE introduces energy supply curves in the energy supply module. The supply of coal, oil and natural gas includes both domestic production and imports, avoiding deviations caused by fixed energy costs. MAPLE model can be considered as a typical bottom-up model to be linked with the typical top-down computable general equilibrium model described in the next session.

3.2. Top-down CGE model

The China-CGE model is a general equilibrium model that aims to assess the economic impact of energy and environmental policies. The CGE model used in the study is a dynamic model, containing 5 main modules: production, trade, income and expenditures, carbon emission and carbon tax, market clearing and macroeconomic balance, and the equations describing dynamic mechanism. The production module is described by a six-layer nested constant elasticity of substitution (CES) function, See Fig. 2.

At the first level, the total output is the aggregate of value-added and intermediate input as shown in the following formula:

$$QA_i = \alpha_i^A \cdot \left[\delta_i^A \cdot VA_i^{\rho_i^A} + \left(1-\delta_i^A\right) \cdot INT_i^{\rho_i^A}\right]^{1/\rho_i^A} \tag{1}$$

where QA_i is the total production of sector i, VA_i and INT_i are the input of value-added and intermediate inputs in sector i respectively, δ_i^A and α_i^A are the share parameter and efficiency parameter; ρ_i^A is the parameter whose value can be calculated from the value of substitution elasticities (σ_i^A) between value-added and intermediate input, and $\sigma_i^A = 1/(1-\rho_i^A)$.

In the trade module, the CET (Constant Elasticity Transformation) function describes the supply distribution between the domestic market and the export market, as shown in equation (5):

$$QA_i = \alpha_i^t \cdot \left[\delta_i^t \cdot QDA_i^{\rho_i^t} + \left(1-\delta_i^t\right) \cdot EX_i^{\rho_i^t}\right]^{1/\rho_i^t},\ \rho_i^t > 1 \tag{2}$$

where QDA_i and EX_i are the supply of the commodity produced by sector i for the domestic market and export respectively, δ_i^t and α_i^t are the share parameter and efficiency parameter; ρ_i^t is the parameter whose value can be calculated from the value of transformation elasticities(σ_i^t) between domestic market supply and exports, and $\sigma_i^t = 1/(\rho_i^t - 1)$.

Another way to model trade is to use the CES function to describe the choice between domestic and imported goods, as shown in equation (6):

$$QQ_i = \alpha_i^q \cdot \left[\delta_i^q \cdot QDC_i^{\rho_i^q} + (1-\delta_i^q) \cdot QM_i^{\rho_i^q}\right]^{1/\rho_i^q} \tag{3}$$

where QQ_i, QDC_i and QM_i are the demand for composite commodity i, domestic commodity i and import commodity i respectively, δ_i^q and α_i^q are the share parameter and efficiency parameter; ρ_i^q is the parameter whose value can be calculated from the value of substitution elasticities (σ_i^q)between domestic and import commodities, and $\sigma_i^q = 1/(1-\rho_i^q)$.

The income and expenditure module mainly cover the income and expenditure of households, enterprises, and governments. The carbon dioxide emission factors of the fossil fuel inputs in various industries in this model can be obtained from the data in the base year, and the calculation of carbon dioxide emissions can be calculated as follows:

$$QEMIS_i = coef_{coal} \cdot QEcoal_i + coef_{oil} \cdot QEoil_i + coef_{gas} \cdot QEgas_i \tag{4}$$

$$QTEMIS = \sum_i QEMIS_i \tag{5}$$

The calculation formula for the carbon tax is as follows:

$$CTR_i = ctax \cdot QEMIS_i \tag{6}$$

$$TOCTR = \sum_i CTR_i \tag{7}$$

where $QEMIS_i$ is the amount of carbon dioxide emissions of industry i, c_{tax} is the carbon tax rate and CTR_i is the carbon tax payable by sector i.

The market clearing and macroeconomic closure module considers two market-clearing conditions in the commodity market and the factor market. In addition, the model also involves three closure principles: government budget balance, investment and savings balance, and foreign income and expenditure balance. In the model, household welfare variation is measured by using the Hicksian equivalent variation (EV). A detailed description of the model is available in Appendix A.

Although CGE models are a common tool for assessing the economic impact of a policy, it needs to be further improved to analyze the DDPs at technological level in this study, like linking to the bottom-up MAPLE model. In the next session, the authors introduce the linking methodology between CGE and MAPLE.

3.3. The linking method between CGE and MAPLE

When linking the top-down and bottom-up models, improvements are expected in both technological details and economic impact. First, the top-down China-CGE model provides the bottom-up MAPLE model with key economic parameters, like GDP, population, and urbanization growth rates, which are otherwise assumptions in the bottom-up model. Second, other key information from the CGE model includes the energy demand quantities and drivers, which are important information for MAPLE's final energy demands. When MAPLE takes the CGE output, the socioeconomic assumptions and demands function can be further improved. Third, based its optimization principle, MAPLE model further generates the optimized energy resource price and energy consumption, to further support the CGE model production function and other system inputs (see Fig. 3.). That's the first linking round, and it will take several rounds for the results to be convergent with lower than 10% difference.

One key issue is that, for most of the time, the database and the definition for "sectors" are different between top-down and bottom-up models. For example, for the power generation sector, the CGE model has the power generation and heating service sectors combined, compared to a stand-alone power sector with each kind of power generation technology at different efficiency levels and different scales. CGE model takes data from the input-output table. For the energy related sectors, the chemical sector, mental sector and non-metallic sector are linked to each industrial sub-sector in MAPLE model. The coal and extraction of natural gas sectors and linked to the energy supply module in TIMES. In this case, we have to restructure the database for each model so that our understanding of the models is consistent. Other harmonizing work has to be done at the same time – for example, for fuel consumption, the CGE model is based on economic value, while the MAPLE model is based on quantity levels. The variable from CGE, the value in CGE is defined as QA_{CGE}; the growth rate is defined as Gr_{CGE}, and the price index is defined as PI_{CGE}. The variable based on MAPLE, Demand quantity with the unit of Mtce (million tons of coal equivalent), is defined as QD_{MAPLE}; with growth rate as $Gr_{MAPLE.}$ The demand of each sub-sector and energy commodity are different. Based on this, we plan to calculate the share of base year and important future years. Based on this share, the single department of CGE is decomposed into sub-sectors and major energy commodities, and the growth rate of each department, $Gr'_{MAPLE\text{-}CGE}$, is updated. Where c stand for commodity, i stands for sector, t stands for year, Gr' denotes the growth rate.

$$SH_{i,c,t} = \frac{QD_{MAPLE,i,c,t}}{\sum_c QD_{MAPLE,i,c,t}} \tag{8}$$

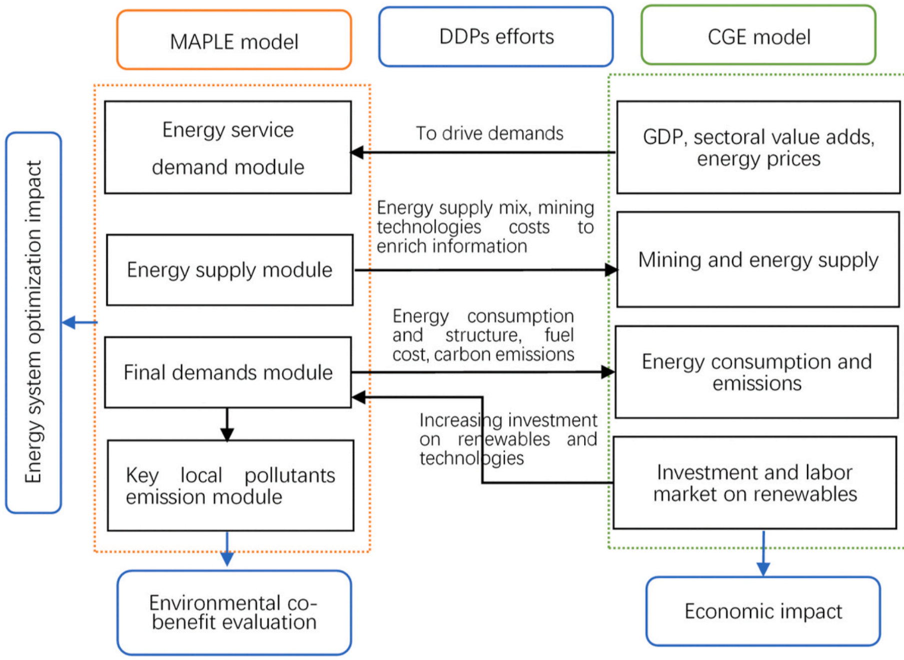


Fig. 3. Framework of linking the CGE and MAPLE models.

$$QA'_{CGE,i,c,t} = QA_{CGE,i,t} * SH_{i,c,t} \tag{9}$$

$$Gr'_{MAPLE-CGE,i,c,t} = \frac{QA'_{CGE,i,c,t}}{QA'_{CGE,i,c,t-1}} \tag{10}$$

$$QD'_{MAPLE-CGE,i,c,t} = Gr'_{MAPLE-CGE,i,c,t} * QD_{MAPLE,i,c,t-1} \tag{11}$$

According to section 2.1, there are two kinds of link: soft linking and hard linking. Although the sector and database are restructured, but authors don't change the main production function in CGE, therefore we take our method as kind of soft-linking method. However, it still takes several rounds to observe the results convergent. Linking models is challenging, and there is still much space for improvement in the future.

3.4. China's decarbonization pathway scenarios

The scenario design is based on China's decarbonization pathways. For the REF (reference) scenario, the decarbonization pathway follows the 13th Five-Year Plan targets at the national level and sectoral level. In the DDP (deep decarbonization pathway) scenario, China deepens fuel substitution and energy efficiency improvements. Specifically, the DDP scenario includes a total coal consumption control plan, with coal consumption capped at 5 billon tce in 2020, while the per GDP energy consumption is reduced by 15% in 2020 compared to 2015 levels. There are also decarbonization pathways by sector, with renewables being further scaled up: wind capacity goes above 0.4 billion kW in 2030, and 1.2 billion kW in 2050. Solar capacity for electricity generation and heating goes above 0.3 and 1.2 billion kW in 2030 and 2050, respectively. The fuel economy in road transportation is further improved with promotion of electric vehicles. Residential heating efficiency is further improved, with fuel substitution enhanced. For end-of-pipe control measures, both the REF scenario and the DDP scenario are kept at the same level of capacity and technological efficiency because we are mainly focused on the co-benefits of local pollutant reduction from deep decarbonization, not the reduction from end-of-pipe control measures.

Table 1
The GDP and GDP growth rate in reference scenario.

	2020	2030	2040	2050
GDP(Trillion yuan)	82.7	145.2	215.6	275.4
GDP growth rate(%)	6.2	4.1	3.2	2.5

In this study, REF scenario is consistent with the IEA outlook for energy use and technology improvement, with other planning targets in China. The baseline macroeconomic trend for reference scenario is shown in Table .1. Comparatively, the DDP scenario is designed to explore the mitigation potential in each sector and the BATs (best available technologies), considering constraints of resources and economy development. Compared to the REF scenario, the DDP scenario design is introduced from the flowing aspects: energy use and technology improvement, coal-fired technology, natural gas power generation, hydropower, nuclear power, solar and wind technologies, passenger and freight transport, residential energy use efficiency and technology improvements (see Table .2).

3.5. Environmental co-benefits evaluation

In the MAPLE model, there is one local pollutant module to evaluate the environmental benefits of deep decarbonization. Before we introduce the mechanism of environmental impact, we must emphasize that this study is not focused on the absolute atmospheric environment for a chemical-level study. Our module uses simplified equations in order to show comparative benefits between scenarios with and without policies at the national level. Future research can further improve the module by linking to a third model: an atmospheric diffusion model that will be of much help if we do further work on the regional level. The main purpose of this study is to assess the potential environmental impact due to the improvement of both technologies and polices before local pollutants are emitted.

The process of energy utilization will inevitably produce air pollutants such as $PM_{2.5}$, sulfur dioxide, and nitrogen oxides. As air pollutants diffuse, the accumulation of pollutants that have spread to residential areas will cause harm to human health. The health cost measurement method includes four steps: emissions, air quality impact, health endpoints, and monetization accounting. We simplify the non-linear exposure-response function based on the results from previous epidemiological literature [61]. Formulas (12)-(14) show the health endpoints and monetization accounting.

Table 2
The REF scenario and DDP scenario.

	Reference scenario (REF)	Deep decarbonization pathways (DDP)
Energy efficiency	The efficiency of new technologies will be updated year by year according to the technical outlook of IEA.	By 2020, steel, cement and high energy consuming sectors eliminate backward production capacity. By 2030, the synthetic ammonia account for more than 60%.
Coal generation	The installation speed of IGCC increased, which account for the main proportion.	To strictly control the development of coal-fired power, add new coal-fired power generation capacity outside cogeneration and CCS after 2020
Natural gas power generation	The new installed capacity of NGCC technology account for the main proportion in 2030.	The planned capacity will reach above 200 million kW in 2030 and 350 million kW in 2050.
Solar energy and wind power generation	In 2030, the wind power planned installed capacity will reach more than 300 million kW by reducing the wind power cost and adding the onshore and offshore wind power construction	The installed capacity of wind power will reach 400 million kW in 2030 and 1.2 billion kW in 2050. The installed capacity of solar power will reach 300 million kW and 1.2 billion kW in 2030 and 2050 respectively.
Passenger transport	The fuel economy of passenger cars will be 7.0 L/100 km by 2030, and the pure electric and plug-in hybrid electric vehicles parc will reach 5 million by 2020.	After 2030, electric vehicles, electric bus and fuel cell bus technology will become the main driving technology. In 2050, the gasoline vehicles will account for less than 30%, mainly concluding hybrid electric vehicles.
Freight transport	The fuel consumption per 100 km in 2050 will be reduced by 18% compared with that in 2010	The fuel consumption per 100 km in 2050 will be reduced by 40% compared to 2010, and the fuel cell trucks will improve rapidly.
Residential sector	The annual growth rate of natural gas heating is 10%. To further increase the proportion of LED and energy-saving appliances and reduce rural non-commercial energy use.	Rural residents will eliminate incandescent lamps and develop LED in 2030; to further improve the efficiency of household energy consumption equipment such as cooking appliances, air conditioners and household appliances. Gas and electricity are the main source of district heating.

$$RR = \exp(ERC * C_1) / \exp(ERC * C_0) = \exp(ERC * (C_1 - C_0)) \tag{12}$$

$$\Delta I = I - I_0 = I - I / RR = I^*(I - I / RR) \tag{13}$$

$$HI = \Delta I^* VSL \tag{14}$$

RR is the relative risk of premature death, *ERC* is the exposure-response coefficient, C_1 is the true concentration, C_0 is the threshold concentration, *I* is the actual mortality, I_0 is Mortality without air pollution exposure, ΔI is premature death due to air pollution, *HI* is the monetary value of health effects, and *VSL* is the value of statistical life. The exposure-response coefficient is 5.37 [62,63]. We introduced the VSL research results from different scholars and research group [56–60]. The provinces which have local VSL surveys can be divided into different areas and each province is set as the benchmark VSL province of that area. For areas that do not have willingness-to-pay survey data, authors use a conversion method with the standard conversion formula shown in equation (15).

$$VSL_a = VSL_b * \left(\frac{Income_a}{Income_b}\right)^e \; B_{p'} = B_s\left(\frac{Yp}{Ys}\right)^\beta \tag{15}$$

where Income refers to the local income level, a is the research area, b is the reference area, and e is the demand income elasticity. The iF path method can be used when the air pollutant discharge and concentration simulation in a large geographical area is used. The iF is a ratio between the amount of air pollutant measured by historical data and the amount of inhalation uptake by the population to calculate the concentration change, shown in (16) and (17).

$$iF = \frac{P^*CON^*BRETH}{EMS} \tag{16}$$

$$CON = \frac{EMS^*iF}{P^*BRETH} \tag{17}$$

where *CON* is the concentration change of air pollutants, *iF* is the inhalation ratio, *P* is the population, and *BRETH* is the respiration rate in cubic meters per day. The respiration rate in cubic meters per day is 14.5 m3/day for China. The intake fraction for SO_2, NOx, and $PM_{2.5}$ are 0.89, 0.18, and 44.10, respectively [64,65].

4. Energy consumption results based on model linking

4.1. Primary energy consumption of REF and DDP when linking with CGE

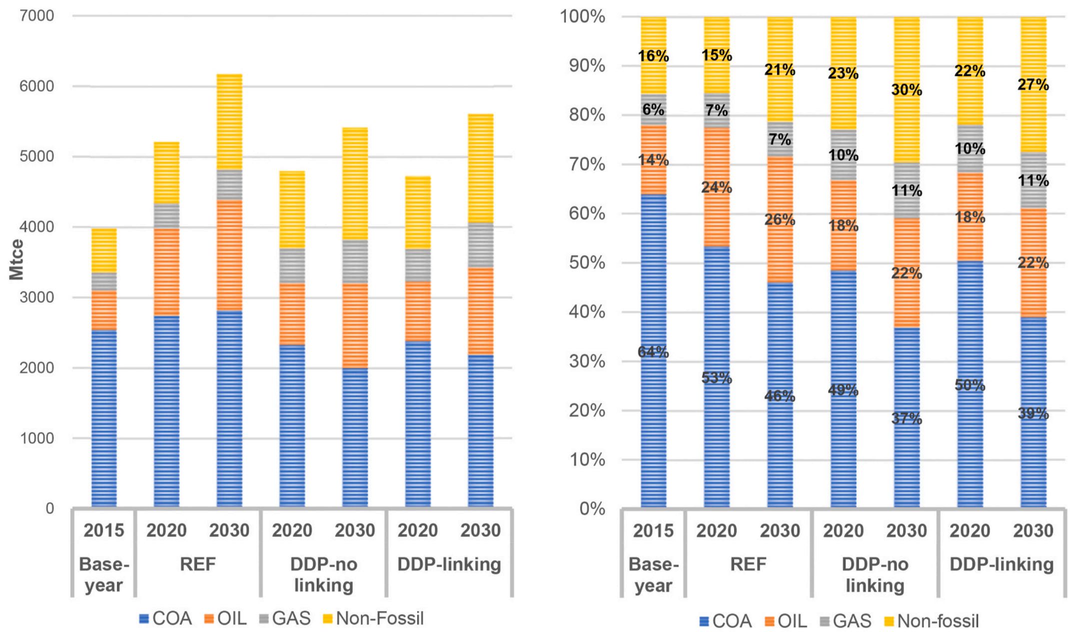
When modeling the deep decarbonization pathway, the mitigation potential of technologies and policies are expected to be fully utilized. One important result is the primary energy consumption, which is highly related to emissions (CO_2, SO_2, NO_X and PM). We show the results of the DDP scenario compared to the REF scenario (Reference Scenario) from MAPLE with and without linking. In Fig. 4, coal consumption in 2030 could be reduced to 2189 Mtce (millon tons of coal equivalents), compared to 2838 Mtce in the REF scenario, a 22.8% reduction. For natural gas, the consumption in the DDP scenario is 640 Mtce, around 1.48 times that of REF 2030 level. When it comes to non-fossil fuels, their primary consumption will increase to 1537 Mtce, compared to 1355 Mtce in the REF scenario, an increase of around 182 Mtce. The total primary energy consumption will be reduced by 8.4% Mtce in 2030 in the DDP scenario. Coal consumption can be successfully reduced if deep decarbonization measures are taken. More than half of coal consumption will be substituted for by natural gas and renewables.

If we take look at the primary energy consumption mix, the evidence for energy substitution is clearer. In the DDP linking scenario, coal will reach 39% in 2030, which is much lower compared to the REF scenario. At the same time, the natural gas will reach a total proportion of 11% in 2030 in the DDP scenarios, which is at the same level as the national planning target of 10% natural gas in 2030. The total non-fossil energy is 27% in 2030 in the DDP linking scenario, which is well above China's target of non-fossil fuels being above 20% [66].

4.2. Electricity generation in the REF and DDP scenarios

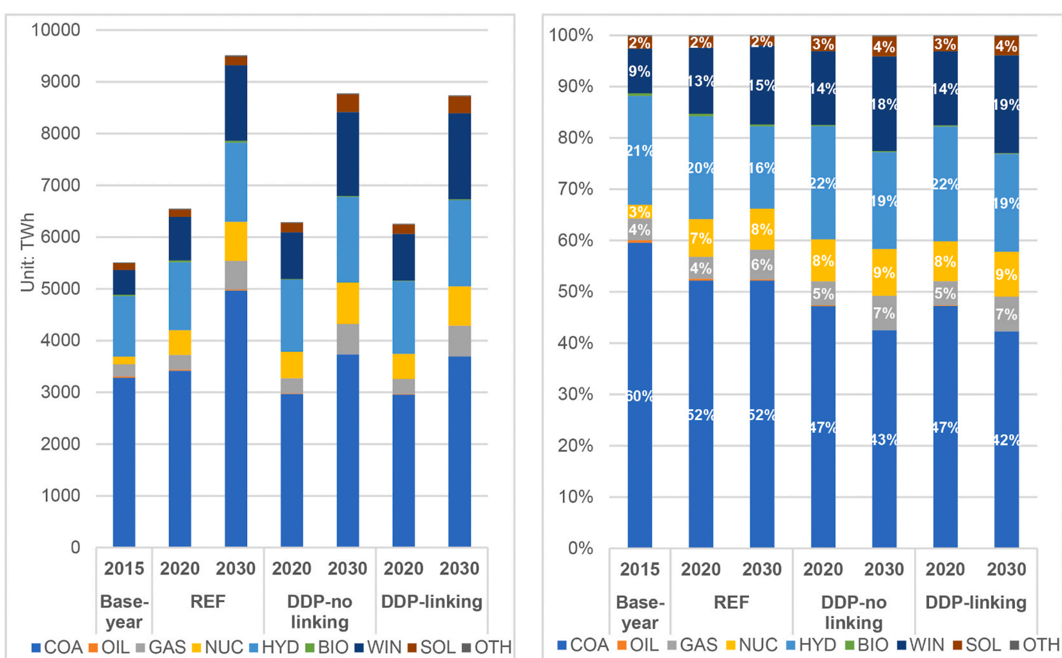
For energy substitution, power generation is one of the key sectors to look into, especially for the integration of renewables in the power sector. First, fossil energy will still dominate energy consumption in electricity generation for the short-term and mid-term. Shown in Fig. 5, coal power generation can be reduced to 3695.73 TWh in 2030 in the DDP scenario, compared to 4966.01 TWh in the REF scenario, a 25.5% reduction. For natural gas, the power generation in the DDP linking scenario is 591.66 TWh, an increase of 6.9% compared to the REF scenario. When it comes to renewable electricity generation, the total renewable electricity generation (including nuclear, wind, solar, and other renewables) will increase from 2408.62 TWh to 2772.1 TWh, a 15.09% increase compared with the REF scenario in 2030.

The proportion of clean energy generation will gradually increase, and the power generation structure can be improved. When comparing the structure of energy power generation, we can observe that, in the DDP-linking scenario, for coal-fired electricity generation, the share is 42%, which is 10% less in 2030 compared with the REF scenario. Gas



(a) (b)

Fig. 4. (a) Primary energy consumption of the REF and DDP scenarios (Unit: Mtce); (b) Primary energy consumption mix (Unit: %).



(a) (b)

Fig. 5. (a) Electricity generation in the REF and DDP scenarios (Unit: TWh); (b) Electricity generation mix in the REF and DDP scenarios (Unit: %).

generation will increase to 7% in 2030 in the DDP-linking scenario, which is 1% higher than the REF scenario. For non-fossil fuels, when comparing to the DDP-linking scenario, hydropower generation is 22% in 2020 and 19% in 2030, 2% more in 2020 and 3% more than in the REF scenario. Wind generation has a 4% increase in 2030, reaching 19% in 2030; and solar generation will reach around 4% in 2030. For total renewable energy, 32% renewables generation in 2030 can be observed in the DDP-linking scenario, which is 6% higher than the REF scenario. A higher proportion of renewables generation will help promote China's progress towards its NDC (NDRC, 2015) [66], or even beyond the NDC targets.

We could observe that after linking, the MAPLE stand-alone has lower coal consumption than before linking, and non-fossil fuel is taking higher share than before. This is highly related to the energy service demands. As we know, the MAPLE has a stand-alone module, to evaluate and predict the final energy service demands, i.e. residential heating demands, cooling demands, cement demands, etc. However, the demands module here has defects, because it is simplified and not consider all the market clear. The CGE model is the best choice to predict the demands here, and one of our important linking is based on demands. With revised demands driven, the energy consumption and structure has been improved. Besides, the dynamic investment changes in future are not considered in MAPLE. With the static investment, there is lack of information like stimulus for investment in renewable energy. Therefore, the linking results on energy structure has better feedback from the general equilibrium market.

4.3. Carbon mitigation effect of the DDP scenario

Firstly, carbon dioxide emissions will peak at or before 2030 under the DDP scenario, and this is followed by a dramatic annual decrease. Compared with the REF scenario, the aggregate carbon dioxide emissions reductions could reach approximately 11.88 billion tons in 2030 (see Table 3). The carbon dioxide emissions in the DDP scenario should decrease to 10.58 billion tons, a 12.4% reduction from the REF scenario. The intensity of emissions per unit of GDP under the DDP scenario will also be significantly reduced, and the intensity of carbon dioxide emissions could decrease by 12.3% and 43.1% respectively in 2030 and 2050 compared to the REF scenario. In the DDP scenario, the carbon intensity will be reduced by 61.7% in 2030 compared to 2010 level. When compared to year 2005, the carbon intensity in 2030 is reduced by 70.7% in DDP scenario. Results show that the DDPs is well above the NDCs target in 2030, which is the carbon intensity should be reduced by 60–65% by 2030 compared to 2005 level.

From the perspective of carbon dioxide emissions of the various sectors, the DDP scenario has a significant effect on carbon dioxide reduction in each sector. Specifically, with energy demand of major energy-intensive sectors peaking around 2020, industrial sector emissions peak around 2020 at approximately 4.63 billion tons of carbon dioxide. The peaking year for the building sector could be between 2030 and 2040. Meanwhile, the transportation sector will achieve peak emissions in 2040 under the DDP scenario. Approaches such as fuel economy improvement, emissions standards upgrading, and more aggressive promotion of electric and hybrid vehicles will hopefully help to reduce carbon dioxide emissions in the transportation sector after 2040.

The emissions reduction effect in the power sector is significant. Under the reference scenario, carbon dioxide emissions from the power sector could increase progressively, while under the DDP scenario, they might reach a peak of about 3.107 billion tons in 2020 and then decrease gradually. This is highly related to the system optimization of China's power sector, especially the sharp increase in renewable energy.

To validate the results of this study, we compare the results from this paper with the main IAMS (integrated assessment models). The typical IAMs include IPAC model developed by ERI (Energy Research Institute), AIM-Enduse model developed by National Institute for Environmental Studies (NIES), MESSAGE model developed by International Institute for Applied Systems Analysis (IIASA), WEM (World Energy Model) developed by International Energy Agency (IEA) and China MARKAL/TIMES model developed by Tsinghua University. We compare the main results of China-MAPLE research with above important studies.

Due to the large difference in the setting of emission reduction scenarios, we compare and validate the main results of MALPE model for the reference scenario, which is basically consistent with the IEA scenario. The comparison of CO_2 emissions of China-MAPLE model and other models is shown in Fig. 6. The results of China-MAPLE model are within the confidence interval and closely consistent with the results of PECE model, China MARKAL Model, MESSAGE model and WEM model.

Table 3
Energy related carbon dioxide emissions in DDP scenario (unit: billion tons).

Scenarios	2020	2025	2030	2035	2040	2045	2050
REF	10.87	11.22	11.88	12.26	12.87	13.35	13.91
DDP	10.87	10.54	10.58	9.97	9.96	8.57	7.71

5. Environmental and economic impact

5.1. Local pollutant emissions

The DDP scenario indeed brings about the reduction of local pollutant emissions. All three types of pollutants will decrease by 4.03–14.98 million tons by 2030, including 2.37–7.10 million tons reduction in SO_2, 1.33–7.30 million tons decrease in NO_X, and 0.33–1.42 million tons abatement in $PM_{2.5}$ (Fig. 7). Before the linking of models, the local pollutant emissions amount of MAPLE and China-CGE are different. Taking 2030 as an example, SO_2, NO_X, $PM_{2.5}$ are the main local pollutants, of which the emissions are 68.67 million tons, 40.84 million tons, 13.96 million tons respectively in MAPLE, and the China-CGE model's predicted emissions are 72.56 million tons, 46.82 million tons, 15.05 million tons respectively, under the DDP scenario without linking. For the same scenario, the local pollutant emission results from CGE and MAPLE have a gap. The main reason for the differences in results between the non-linked and linked models is that the linking of energy activity to local pollutants in the two models is different. For the China-CGE model, the emissions coefficient is based on the fuel level and activity level; however, in the MAPLE model, the emissions coefficient of local pollutants is set on the technological level, for different production technologies.

For the end-of-pipe technologies, the efficiency is set at the same level as the reference scenario. When the linking is done, the main convergence is based on energy consumption, not emissions. We could observe a convergence for the key emissions as more technological level information is added to the CGE model. After linking, under the DDP scenario, the emissions of the three pollutants can be decreased by 7.10 million tons of SO_2, 3.96 million tons of NO_x, 1.02 million tons of $PM_{2.5}$ and total emission could decrease by 12.07 million tons. These significantly lower estimates indicate that the linking of models can fill the gap between the accounting of the two types of models.

5.2. Avoided health damages and environmental co-benefits effects

Our results show that deep decarbonization does lead to the reduction of premature death damages under the DDP scenario. In 2030, the aggregate of both types of deaths decreases by 13,000–38,000, of which the deaths caused by cardiovascular illness and respiratory illness could be reduced by 10,000–38,000 people and 3000–8000 people respectively (Fig. 8).

The results indicate that the DDP scenario has a remarkable effect on health damage reduction. There is prominent effect in 2030. The total health damages could achieve significant reductions by 222–822 billion RMB, with 181–673 billion RMB in reduction and 41–149 billion RMB in reduction of the health damage caused by cardiovascular and respiratory illness respectively.

Before using linking, the results of MAPLE and China-CGE are slightly different for local pollutant health damage. Under the DDP scenario in 2030, for MAPLE, 822 billion RMB reduction in gross health damages could be found, consisting of a decrease of 673 billion RMB and 149 billion RMB in health damages caused by cardiovascular and respiratory illness respectively. For China-CGE, the reduction in health damages could add up to 222 billion RMB, with a decrease of 181 billion RMB in cardiovascular damages and a decrease of 41 billion RMB in respiratory damages. Compared with after linking, the total health damages could be reduced by 678 billion RMB, in which the cardiovascular and respiratory effects could lessen by 552 billion RMB and 125 billion RMB respectively. The convergence results are more conducive to overall accounting. Firstly, in view of the health damages results of MAPLE, they are not immediately compatible with China-CGE's

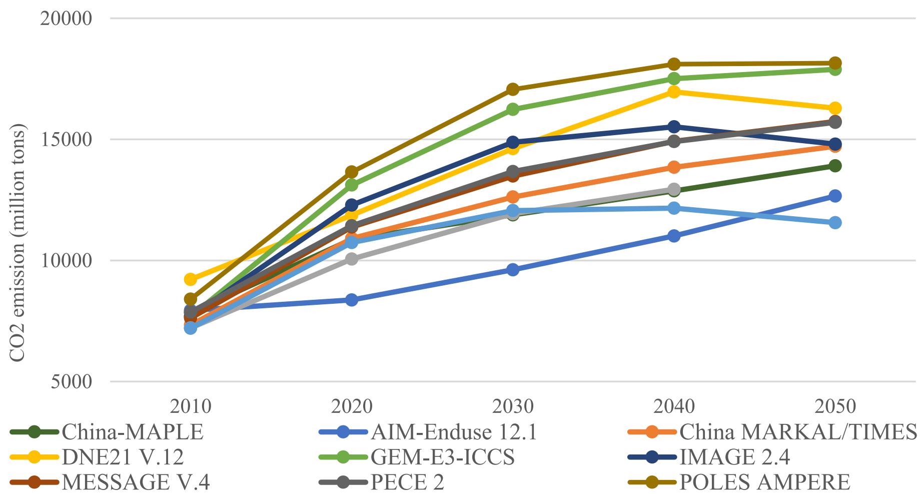


Fig. 6. The results analysis of main models.

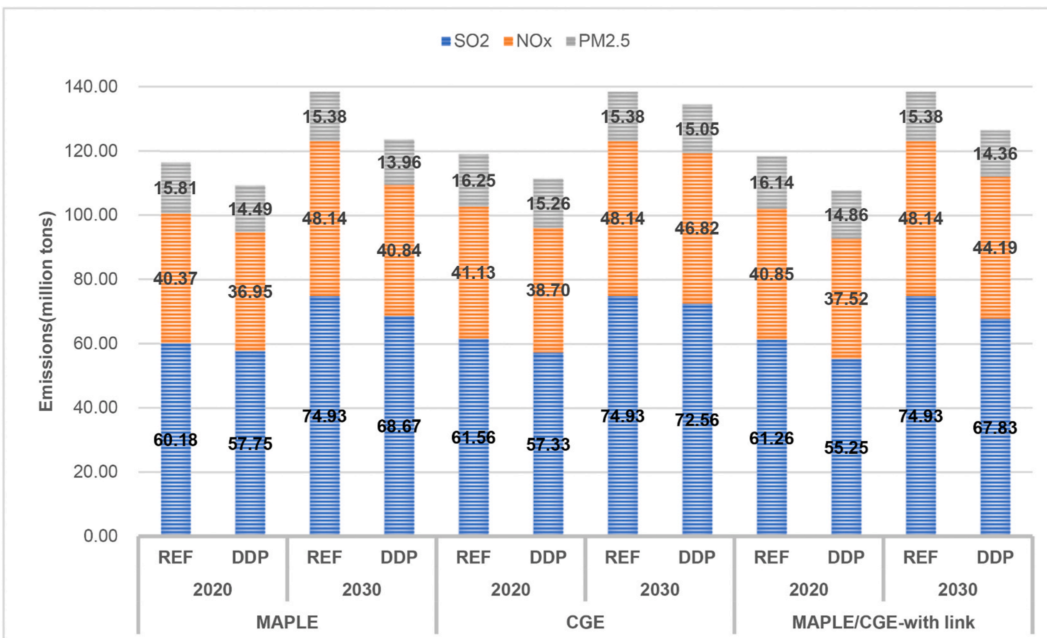


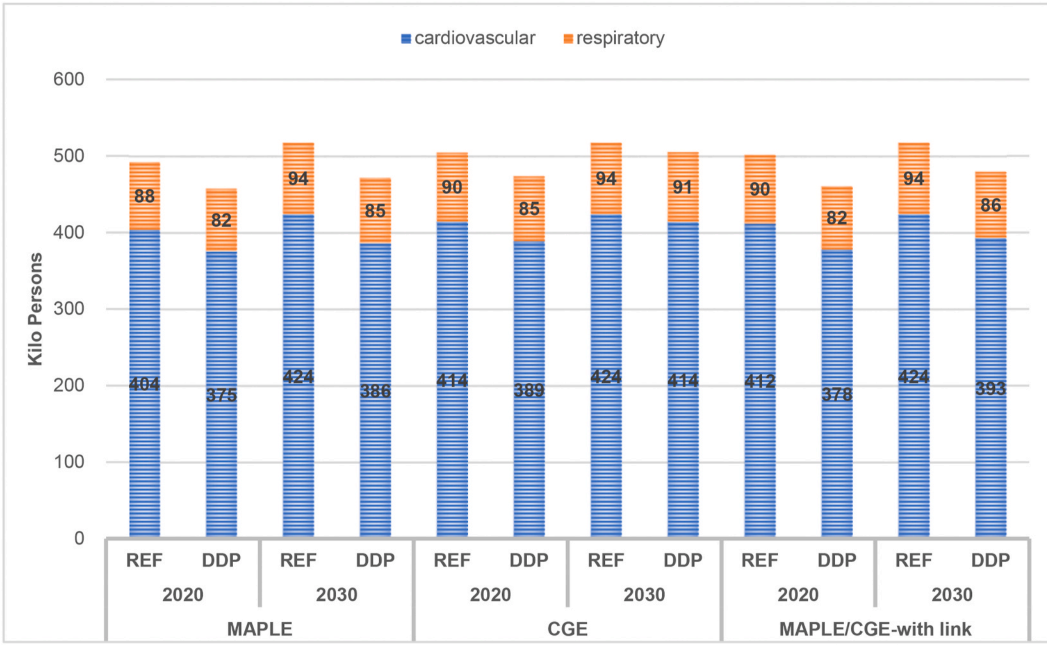
Fig. 7. The main local pollutant emissions in the DDP scenario, for MAPLE, China-CGE, and MAPLE/CGE linking (unit: million tons).

economic equations; furthermore, in the accounting of China-CGE, health damages are only based on sectoral levels, and technological progress is not included in the DDP scenario. Linking makes progress towards solving this problem. Secondly, the avoided health damages are environmental benefits, meaning that the carbon mitigation policy can avoid losses from environmental health problems. More accurately, avoided health damage is a co-benefit of carbon mitigation policy. Based on our calculation, this kind of environmental health co-benefit is worth 730 billion RMB and 678 billion RMB in 2020 and 2030 respectively. Furthermore, according to the prediction of population growth in 2020 and 2030 from the China-CGE model, the per capita environmental health co-benefits in 2020 are 480 RMB/person and in 2030, 359 RMB/person. (Note: Considering the second-child policy, the population is 1.52 billion in 2020, and 1.89 billion in 2030.)

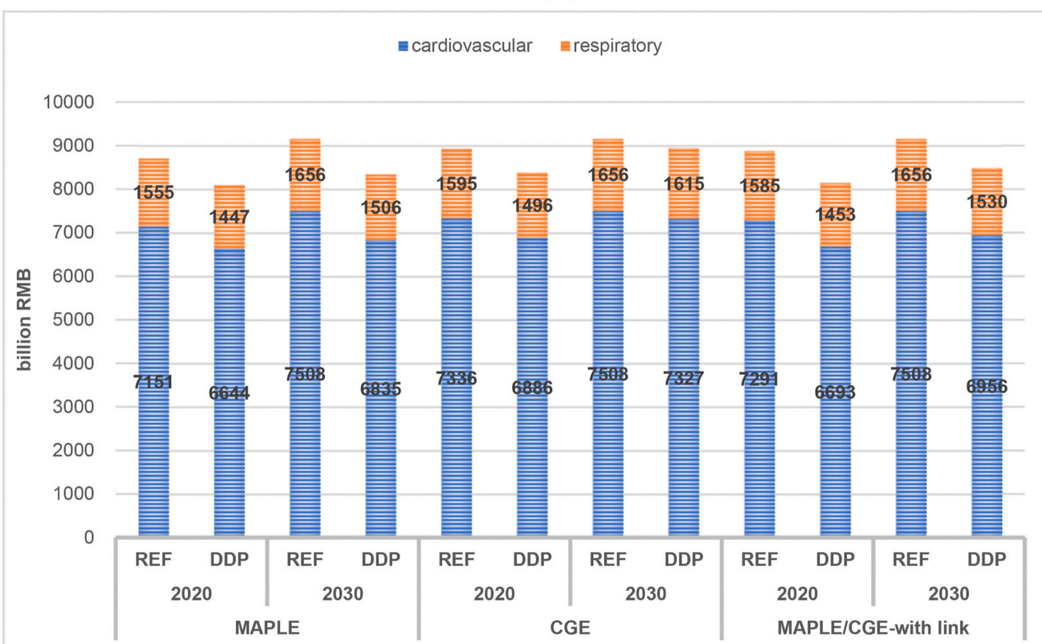
When coming to the validation of this result, authors compared it with the exiting studies. Based on the AIM (Asia-Pacific Integrated Assessment)/CGE model, the health co-benefit is around 6.5–25.2billion USD in 2030 [53]. While with the CMAQ (Community Multiscale Air Quality) model, study show the co-benefit range as 9.1–12.7 billion USD in 2030 [5]. In our study, before linking, our environmental benefits result of MAPLE model and CGE model is 822 billion RMB (11.81billion USD) and 222 billion RMB (3.19 billion USD) respectively in 2030. The health co-benefit after linking is around 678 billion RMB (9.74 billion USD), which is in the confidence range of 9.1–12.7 billion USD and 6.5–25.2 billion USD. We could observe that the linking model help the results more accordance with the conclusion of exiting studies.

5.3. Economic impact

The economic impacts of China's DDP scenario from linking the MAPLE model and the CGE model, as well as the stand-alone results, are shown in Fig. 9. The increase/decrease rates are compared to the REF scenario. Economic impacts are found to be much higher when they are estimated using a stand-alone CGE model as compared to the estimates made by the CGE model after it is linked with the MAPLE model. Impacts on key economic variables are 36.8%–47.5% lower when they are measured linking the CGE model with the MAPLE model than when they are measured using the CGE model without linking. For example, the



(a)



(b)

Fig. 8. (a) Avoided deaths caused by local pollutants in the DDP scenario, for MAPLE, China-CGE and MAPLE/CGE linking (unit: thousand persons); **(b)** Avoided health damages by local pollutants, for MAPLE, China-CGE and MAPLE/CGE linking (unit: billion RMB).

GDP impact estimated through the linked model is now −0.54%, around 58.7% smaller than that measured with the not-linked CGE model. The welfare loss is around 0.92%, compared to 1.49% from the CGE stand-alone model. The GDP loss, welfare loss, and reduction in household income is reduced when we link the two models. Compared to the stand-alone CGE model, the ratio of coal consumption have been reduced significantly when the CGE model is linked with the TIMES model, whereas the consumption of non-fossil energy is increased in the linked model, so the negative impacts on main economic indicators, such as GDP, gross output, welfare, import/export, is reduced when adopting decarbonization measures, which means the simulation results about the negative impacts of decarbonization measures on the economy by stand-alone CGE model might be higher than the actual situation.

Since the initial growth rates of fossil fuels and CO2 emissions under the MAPLE model are much lower than those in the CGE model, it causes reductions in baseline emissions in the hybrid model (after linkage). The main reason for the higher baseline emissions in the top-down model is that it often excludes existing policies specific to sectors, sub-sectors and technologies not explicitly available in databases, the social accounting matrix (SAM), or input-output (I–O) tables. Furthermore, if we take GDP loss as example, when we consider the environmental co-benefits, the total GDP loss will be lower in a linked model. In 2030, the total

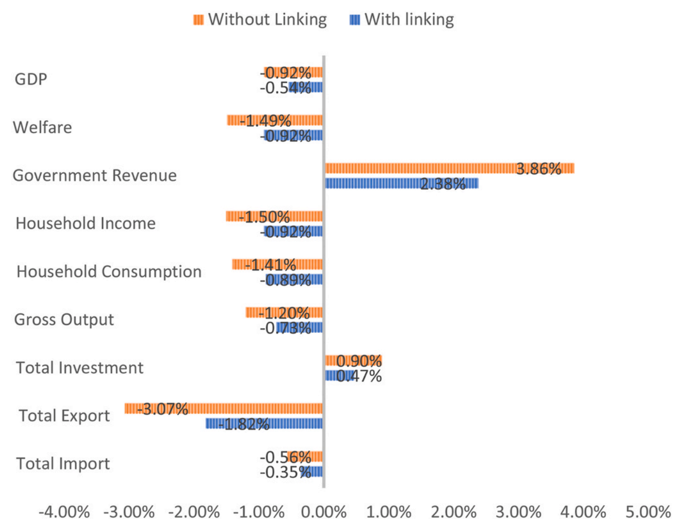


Fig. 9. Economic Impacts of the DDP scenario relative to the REF scenario.

environmental health co-benefits are 678 billion RMB, and the per capita co-benefit will be around 461RMB/person, which will help to avoid 0.39% of China's GDP loss. Therefore, in 2030, not only early carbon dioxide emissions peaking can be expected, but also the environmental co-benefits will offset the costs for government.

The MAPLE model has a variety of energy technologies to achieve DDPs, especially the multiple renewable energy power generation technologies in the MAPLE model has enriched the input options of energy elements in various industries of CGE. After the linking, the CGE model introduces the energy input structure information optimized by the MAPLE model. Based on our calculation, the carbon emissions of the same energy input in each industry will decrease compared with the previous case, so the industry pays for the same emission reduction target with less cost. The cost of carbon emission reduction is relatively low, so the negative impact on major macroeconomic indicators is smaller than before linking.

Compared with the existing studies related to the carbon mitigation target by using CGE model, studies found that the current carbon mitigation policy implemented in China would have negative impacts on the economy with GDP loss by 0.004%–3.8% [67–69]. Xie Y et al. (2020) show that the range of the GDP loss is from 3.8% to 0.004% [67]. The economic loss result of Mu Y et al. (2018) [68] and Dai H et al. [69] is 0.11%–0.43% and 1.2%–2.3% respectively. In our study, the GDP loss of achieving DDP target in without linking model and linking model are 0.92% and 0.54%, respectively, which is within the range of the previous studies.

6. Conclusion and discussion

6.1. Main conclusions

Both top-down models and bottom-models have limitations. There are few studies that link top-down and bottom-up models to analyze environmental health co-benefits, and there is no such linking study for China. This study has filled this gap and carried out an integrated analysis for DDPs in China, to assess both its carbon mitigation potential, environmental impacts, and economic effects. The study aims to provide a methodological framework and useful results for other developing countries for their DDPs analysis. The answer to the question raised in the first section of this paper is clear: China's DDP is achievable, affordable, and effective for both optimizing the energy system and improving air quality, when taking co-benefits into consideration.

First, from the energy system optimization perspective, we found that, in the DDP scenario, 11.88 billion tons of carbon dioxide emissions, with a 1.8 billion tons reduction below baseline, can be expected in 2030, and peaking emissions before 2030 is likely. The peaking year of carbon dioxide emissions for each sector are different, ranging between 2020 and 2040. Furthermore, the primary energy consumption mix could be further improved. The coal-dominant situation can change, and in 2030, coal consumption can be reduced to 39% of the total primary energy mix. Gas consumption increases to around 11% in 2030, which is slightly above the 10% expectation of the government. The non-fossil fuel share will reach 27% in 2030 in the deep decarbonization pathway, which is well above the 20% target in China's NDC. We also validated our results by comparing them with the results of other models, and our calculation is consistent with typical IAMs results.

Second, there are obvious environmental co-benefits that can be observed. First, after linking, in the DDP scenario, the reduced SO_2 is around 7.10 million tons, NO_x reduction is 3.96 million tons, and $PM_{2.5}$ reduction is 1.02 million tons. Total emissions reduction of the three key local pollutants reaches 12.07 million tons, which is approximately 8.7% below the REF scenario levels. Second, the number of deaths can be diminished through the co-benefits of deep decarbonization. In 2030, with deep decarbonization, there are 31,000 avoided deaths caused by cardiovascular problems and 7000 avoided deaths caused by respiratory illness, which also has significant economic value. If we calculate the economic loss of these premature deaths, the total health co-benefits will be around 678 billion RMB in 2030.

Furthermore, when it comes to economic impacts, our CGE model can provide a clearer picture of general equilibrium effects. We can observe that after linking, the key economic variables are 36.8%–47.5% lower than the CGE stand-alone version. Notably for GDP, the GDP loss is reduced from 0.92% to 0.54% when taking model linkages into account. Furthermore, 0.39% of that GDP loss is negated when considering the health co-benefits in the DDP scenario. The health co-benefits of DDPs have an obvious impact on offsetting the total system costs and GDP loss.

We validated the results by comparison to key results from other environmental co-benefit studies. Based on the literature, the environmental health co-benefits estimated by top-down models and bottom-up models vary. We found that the linking helps to narrow the range of estimates and help the results fall in the confidence interval range of key studies. Model linkage could help reduce the uncertainties caused by using top-down or bottom-up models alone, and therefore provide a feasible solution for countries' DDPs environmental co-benefit analysis.

6.2. Limitations of this study

In this study, authors linked the bottom-up MAPLE model with the top-down China-CGE model. The model linking has challenges and still needs further methodological improvement. For example, currently, the linking is based on energy prices, energy consumption, primary energy demand, and economic drivers. However, the databases of China-CGE and the MAPLE model are quite different, for both sector boundary definitions and units. Further improvement on data restructuring should be done for the CGE I–O table. In addition, for the key local pollutants, we mainly focused on the energy-related emissions reductions prior to actual emitting, so a simplified environmental impact evaluation module is developed to calculate the co-benefits. Since we are focusing on the future prediction of co-benefits, the core focus is on energy system optimization. For the next steps, more detailed work will be done based on linking these models to mature atmospheric diffusion models.

6.3. Discussion on DDPs

Besides the national-level analysis on DDPs, this study also has sectoral-level observations related to policy applications. First, based on our previous study [70], end-of-pipe control measures will have a significant effect on reducing key local pollutants – for example, in the power generation sector, 67.2% of reductions came from local pollutant control. However, there is still un-ignorable mitigation potential left for energy conservation measures. Based on the results of this study, we observe that the accumulation of typical pollutants can be significantly reduced in the DDP scenario, which means that the DDP's measures pertaining to energy structure and energy efficiency improvement will have an additional effect on reducing the amount of pollutants, even without considering end-of-pipe controls. For policies at the sectoral level, in the industry sector, coal replacement and biomass application, together with hydrogen and methane syngas, can play important role in decarbonization. In addition, the decarbonization of the industry sector mainly depends on the energy consumption structure of the power sector. In the electricity sector, efforts on promoting hydropower, onshore/offshore wind power, and solar photovoltaic will have obvious impact on decarbonization. In addition, decarbonization measures in the residential sector have positive effects both on reducing carbon dioxide emissions and local pollutant emissions, especially for primary $PM_{2.5}$. Furthermore, the cross-sector mitigation potential could be further increased by using energy conversion measures, renewable energy development policy, and carbon pricing [71].

When it comes to the environmental impact of DDPs, the most significant contribution to the reduction of SO_2 and NO_x is from the power generation sector, and the contribution ratio is around 69% and 67% in 2030. The contribution of the transportation sector to emissions reductions also deserves attention, as it constitutes around 25% of NO_x reduction in 2030. Also, the energy-intensive industry sectors will contribute around 20–26% of SO_2 reduction in 2030. The sectoral contribution of $PM_{2.5}$ emissions reduction is slightly different from the above two pollutants. The building sector (residential and commercial sub-sectors) is the sector that accounts for the largest proportion of total $PM_{2.5}$ emissions, and its contribution to reducing $PM_{2.5}$ emissions keeps increasing over time, from a 15% contribution in 2020 to a 25% contribution in 2030. The improvement of residential energy consumption efficiency will affect the amount of emissions to a large extent.

We want to emphasize that the mitigation of key local pollutants will be highly effective if it is done through original source control, like decarbonization measures. Expensive end-of-pipe control measures are not the only solution for pollutant control. Therefore, in addition to paying attention to the improvement of end-of-pipe controls, original source control of pollutant emissions should not be ignored, and this could also have a positive effect on reducing emissions in the short-to medium-term as the co-benefits of China's decarbonization pathway.

Most developing countries are facing challenges for both carbon mitigation and economic development. Some of these countries also have serious air pollution problems. This study provides evidence that DDPs can help developing countries balance their economic development, carbon mitigation and air quality. For example, DDPs can prompt the government and stakeholders in developing regions to envision and plan policy packages to begin a long-run shift from a fossil fuel-oriented pathway towards a zero emissions future [72]. For some developing countries, advanced mitigation technologies might be very expensive, but the DDP's efforts on efficiency improvement and electrification can be effective for both energy structure adjustment and environmental protection [73,74]. A narrow focus on techno-economic optimization could be detrimental to realizing even modest progress on decarbonization [75]. China, based on its deep decarbonization efforts at the sectoral and technological level, will have carbon mitigation and environmental co-benefits in the mid- and long term [76–78]. This study linking a bottom-up model and a top-down model to assess environmental co-benefits is an attempt to prove the effective, affordable, and environmentally beneficial impacts of DDPs. The economic impact and environmental impact of DDPs are worthy of more attention in developing countries, and their combined consideration in this novel model-linkage approach makes the case for the economic and environmental benefits of decarbonization.

Credit author statement

Xi Yang: Conceptualization, Methodology, Software, Original draft preparation and revisions. Jun Pang: Data curation, software (CGE model); Fei Teng: Visualization, Investigation. Ruixin Gong: Investigation, Data curation; Cecilia Springer: Writing-Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Detailed Description of the CGE Model

The Naming rules for variables:

(1) Endogenous variables are named as uppercase letters, and exogenous variables are named as uppercase letters with a cross line above; (2) Variables are generally named as their recognized prefix, as Q is quantity, P is commodity price, W is factor price, Y is income, E is expenditure; (3) The initial value of all variables in business-as-usual scenario are used as parameters and are named as original names with 0 added behind, while other parameters are named as lowercase letters.

Definition of sets:

I,J = {production sectors or commodities};
F = {factors, including capital and labor};
E($\subset$I,J) = {energy sector or commodity};
NE($\subset$I,J) = {non-energy sector or commodity};

A1.1 Production module

Constant elasticity of substitution (CES) functions with six levels of nesting are used to characterize production behaviors in this model: the first level is the aggregation of production factors and non-energy intermediate inputs; the second level includes the aggregation of labor and capital-energy and that of each non-energy intermediate input; the third level is the aggregation of capital and energy; the fourth level is the aggregation of electric power and fossil fuels; the fifth level is the aggregation of coal and the composite inputs of refined petroleum and gas; the sixth level is the aggregation of refined petroleum and gas.

The definition of CGE sectors are shown in table A1 and the structure of the production function is given in Fig. 2 in the main text of the paper.

Table A1
Definition of sectors/commodities in the CGE model

Sector Name	Definition or coverage
AGRI	Agriculture, Forestry, Animal Husbandry and Fishery
COAL	Mining and washing of coal
OILNG	Extraction of petroleum and natural gas
MINE	Mining and processing of metal and nonmetal
FTPMF	Food, tobacco, textile, leather, fur, feather, timber, furniture, paper, printing
PETRO	Processing of petroleum, coking, processing of nuclear fuel
CHEMI	Manufacture of chemical products
NMETA	Manufacture of non-metallic mineral products
METAL	Smelting and processing of metals
OTHMF	Other manufacture
ELECT	Production and distribution of electric power and heat power
GAS	Production and distribution of gas
WATER	Production and distribution of tap water
CONST	Construction
TRANS	Transport, storage and postal services
SERVI	Other services

A1.1.1 The first level of CES function of total productivity

The aggregation of value-added and intermediate input:

$$QA_i = \alpha_i^A \cdot \left[\delta_i^A \cdot QVA_i^{\rho_i^A} + \left(1-\delta_i^A\right) \cdot QINTA_i^{\rho_i^A}\right]^{1/\rho_i^A} \tag{1.1}$$

where QA_i is the total production of sector i, QVA_i and $QINTA_i$ are the input of value-added and intermediate input in sector i respectively, δ_i^A and α_i^A are the share parameter and efficiency parameter; ρ_i^A is the substitution elasticity parameter between value-added and intermediate input, and $\sigma_i^A = 1/(1-\rho_i^A)$, $\sigma_{i,r}^A$ is the substitution elasticity between value-added and intermediate input.

Optimal factor input under total production:

$$\frac{PVA_i}{PINTA_i} = \frac{\delta_i^A}{1-\delta_i^A} \cdot \left(\frac{QINTA_i}{QVA_i}\right)^{1-\rho_i^A} \tag{1.2}$$

where PVA_i and $PINTA_i$ are the price of value-added and intermediate input in sector i respectively.

Relationship of price of total output:

$$PA_i \cdot QA_i = PVA_i \cdot QVA_i + PINTA_i \cdot QINTA_i \tag{1.3}$$

where PA_i is the producer price of sector i.

A1.1.2 Intermediate input function

The quantity of intermediate input of non-energy commodity:

$$QINT_{j,i} = ica_{j,i} \cdot QINTA_i \quad j \in NE \tag{1.4}$$

The price of intermediate input:

$$PINTA_i = \sum_j ica_{j,i} \cdot PQ_i \quad j \in NE \tag{1.5}$$

where $QINT_{j,i}$ is the quantity of the input of non-energy commodity j as intermediate input of sector i, $ica_{j,i}$ is the intermediate input coefficient, denoting the proportion of the input of non-energy commodity j in the total intermediate input of sector i.

A1.1.3 The second level of CES function of value-added

The aggregation of labor and capital-energy:

$$QVA_i = \alpha_i^{va} \cdot \left[\delta_i^{va} \cdot QLD_i^{\rho_i^{va}} + \left(1-\delta_i^{va}\right) \cdot QKED_i^{\rho_i^{va}}\right]^{1/\rho_i^{va}} \tag{1.6}$$

where QLD_i and $QKED_i$ are the input of labor and capital-energy in sector i respectively, δ_i^{va} and α_i^{va} are the share parameter and efficiency parameter; ρ_i^{va} is the substitution elasticity parameter between labor and capital-energy, and $\sigma_i^{va} = 1/(1-\rho_i^{va})$, σ_i^{va} is the substitution elasticity between labor and capital-energy.

Optimal factor input of value-added:

$$\frac{WL_i}{PKE_i}=\frac{\delta_i^{va}}{1-\delta_i^{va}}\cdot\left(\frac{QKED_i}{QLD_i}\right)^{1-\rho_i^{va}} \tag{1.7}$$

Relationship of price of the input of value-added:

$$PVA_i\cdot QVA_i = WL\cdot QLD_i + PKE_i\cdot QKED_i \tag{1.8}$$

where WL_i and PKE_i are the price of the input of labor and capital-energy in sector i respectively.

A1.1.4 The third level of CES function of capital-energy

The aggregation of capital and energy:

$$QKED_i=\alpha_i^{ke}\cdot\left[\delta_i^{ke}\cdot QKD_i^{\rho_i^{ke}}+\left(1-\delta_i^{ke}\right)\cdot QED_i^{\rho_i^{ke}}\right]^{1/\rho_i^{ke}} \tag{1.9}$$

where QKD_i and QED_i are the input of capital and energy in sector i respectively, δ_i^{ke} and α_i^{ke} are the share parameter and efficiency parameter; ρ_i^{ke} is the substitution elasticity parameter between the input of capital and energy, and $\sigma_i^{ke}=1/(1-\rho_i^{ke})$, σ_i^{ke} is the substitution elasticity between the input of capital and energy.

Optimal factor input:

$$\frac{WK_i}{PEC_i}=\frac{\delta_i^{ke}}{1-\delta_i^{ke}}\cdot\left(\frac{QED_i}{QKD_i}\right)^{1-\rho_i^{ke}} \tag{1.10}$$

where WK_i and PEC_i are the price of the input of capital and energy in sector i respectively.

Relationship of price of the input of capital and energy:

$$PKE_i\cdot QKED_i = WK\cdot QKD_i + PEC_i\cdot QED_i \tag{1.11}$$

A1.1.5 The fourth level of CES function of the aggregation of energy

The aggregation of fossil fuels and electric power:

$$QED_i=\alpha_i^{ec}\cdot\left[\delta_i^{ec}\cdot QEF_i^{\rho_i^{ec}}+\left(1-\delta_i^{ec}\right)\cdot QEE_i^{\rho_i^{ec}}\right]^{1/\rho_i^{ec}} \tag{1.12}$$

where QEF_i and QEE_i are the input of fossil fuels and electric power in sector i respectively, δ_i^{ec} and α_i^{ec} are the share parameter and efficiency parameter; ρ_i^{ec} is the substitution elasticity parameter between the input of fossil fuels and electric power, and $\sigma_i^{ec}=1/(1-\rho_i^{ec})$, σ_i^{ec} is the substitution elasticity between the input of fossil fuels and electric power.

Optimal factor input of the aggregation of energy:

$$\frac{PEF_i}{PEE_i}=\frac{\delta_i^{ec}}{1-\delta_i^{ec}}\cdot\left(\frac{QEE_i}{QEF_i}\right)^{1-\rho_i^{ec}} \tag{1.13}$$

where PEF_i and PEE_i are the price of the input of fossil fuels and electric power in sector i respectively.

Price relationship of the input of the aggregation of energy:

$$PEC_i\cdot QED_i = PEF_i\cdot QEF_i + PEE_i\cdot QEE_i \tag{1.14}$$

A1.1.6 The fifth level of CES function of the aggregation of fossil fuels

The aggregation of coal and refined petroleum-gas:

$$QEF_i=\alpha_i^{ef}\times\left[\delta_i^{ef}\times QEcoal_i^{\rho_i^{ef}}+\left(1-\delta_i^{ef}\right)\times QEoilgas_i^{\rho_i^{ef}}\right]^{1/\rho_i^{ef}} \tag{1.15}$$

where $QEcoal_i$ and $QEoilgas_i$ are the input of coal and refined petroleum-gas in sector i respectively, δ_i^{ef} and α_i^{ef} are the share parameter and efficiency parameter; ρ_i^{ef} is the substitution elasticity parameter between the input of coal and refined petroleum-gas, and $\sigma_i^{ef}=1/(1-\rho_i^{ef})$, σ_i^{ef} is the substitution elasticity between the input of coal and refined petroleum-gas.

First order condition of optimal factor input:

$$\frac{PEcoal_i}{PEoilgas_i}=\frac{\delta_i^{ef}}{\left(1-\delta_i^{ef}\right)}\cdot\left(\frac{QEoilgas_i}{QEcoal_i}\right)^{1-\rho_i^{ef}} \tag{1.16}$$

where $PEcoal_i$ and $PEoilgas_i$ are the price of the input of coal and refined petroleum-gas in sector i respectively.

Price relationship of the input of the aggregation of fossil fuels:

$$PEF_i \cdot QEF_i = PEcoal_i \cdot QEcoal_i + PEoilgas_i \cdot QEoilgas_i \tag{1.17}$$

A1.1.7 The sixth level of CES function of the aggregation of gas and refined petroleum

The aggregation of gas and refined petroleum:

$$QEoilgas_i = \alpha_i^{pg} \cdot \left[\delta_i^{pg} \cdot QEgas_i^{\rho_i^{pg}} + (1-\delta_i^{pg}) \cdot QEoil_i^{\rho_i^{pg}}\right]^{1/\rho_i^{pg}} \tag{1.18}$$

where $QEgas_i$ and $QEoil_i$ are the input of gas and refined petroleum in sector i respectively, δ_i^{pg} and α_i^{pg} are the share parameter and efficiency parameter; ρ_i^{pg} is the substitution elasticity parameter between the input of gas and refined petroleum, and $\sigma_i^{pg} = 1/(1-\rho_i^{pg})$, σ_i^{pg} is the substitution elasticity between the input of gas and refined petroleum.

First order condition of optimal factor input:

$$\frac{PEgas_i}{PEoil_i} = \frac{\delta_i^{pg}}{(1-\delta_i^{pg})} \cdot \left(\frac{QEoil_i}{QEgas_i}\right)^{1-\rho_i^{pg}} \tag{1.19}$$

where $PEgas_i$ and $PEoil_i$ are the price of the input of gas and refined petroleum in sector i respectively.

Price relationship of the input of the aggregation of refined petroleum and gas:

$$PEoilgas_i \cdot QEoilgas_i = PEoil_i \cdot QEoil_i + PEgas_i \cdot QEgas_i \tag{1.20}$$

A1.2 Trade module

A1.2.1 Export

CET function is adopted to describe the allocation of supply between domestic market and export:

$$QA_i = \alpha_i^t \cdot \left[\delta_i^t \cdot QDA_i^{\rho_i^t} + \left(1-\delta_i^t\right) \cdot QE_i^{\rho_i^t}\right] \; p_t^i > 1 \tag{1.21}$$

where QDA_i and QE_i are the supply of commodity produced in sector i to domestic market and export respectively, δ_i^t and α_i^t are the share parameter and efficiency parameter; ρ_i^t is the transformation elasticity parameter between domestic market supply and export, and $\sigma_i^t = 1/(\rho_i^t - 1)$, σ_i^t is the transformation elasticity between domestic market supply and export.

First order condition:

$$\frac{PDA_i}{PE_i} = \left(\frac{\delta_i^t}{1-\delta_i^t}\right) \cdot \left(\frac{QE_i}{QDA_i}\right)^{1-\rho_i^t} \tag{1.22}$$

where PDA_i and PE_i are the domestic price and export price of commodity produced in sector i.

Relationship of price:

$$PA_i \cdot QA_i = PDA_i \cdot QDA_i + PE_i \cdot QE_i \tag{1.23}$$

Exchange rate conversion between the price of export commodity in the global market and SAR:

$$PE_i = \overline{PWE}_i \cdot EXR \tag{1.24}$$

where $\overline{PWE_i}$ is the international market price of exported commodity i, EXR is the exchange rate.

A1.2.2 Import

CES function is adopted to describe the choice between domestic and import commodity:

$$QQ_i = \alpha_i^q \cdot \left[\delta_i^q \cdot QDC_i^{\rho_i^q} + (1-\delta_i^q) \cdot QM_i^{\rho_i^q}\right]^{1/\rho_i^q} \tag{1.25}$$

where QQ_i, QDC_i and QM_i are the demand for composite commodity i, domestic commodity i and import commodity i respectively, δ_i^q and α_i^q are the share parameter and efficiency parameter; ρ_i^q is the substitution elasticity parameter between domestic and import commodity, and $\sigma_i^q = 1/(1-\rho_i^q)$, σ_i^q is the substitution elasticity between domestic and import commodity.

First order condition:

$$\frac{PDC_i}{PM_i} = \left(\frac{\delta_i^q}{1-\delta_i^q}\right) \cdot \left(\frac{QM_i}{QDC_i}\right)^{1-\rho_i^q} \tag{1.26}$$

where $PDC_{i,r}$ is the price of domestic commodity i, $PM_{i,r}$ is the price of import commodity i.

Composite commodity price is the weighted mean of the price of domestic and import commodity:

$$PQ_i \cdot QQ_i = PDC_i \cdot QDC_i + PM_i \cdot QM_i \tag{27}$$

where PQ_i is the price of composite commodity i.

Exchange rate conversion between the price of import commodity in the international market and China:

$$PM_i = \overline{PMW}_i \cdot (1 + tm_i) \cdot EXR \tag{28}$$

where $\overline{PMW}_i$ is the international market price of import commodity i, tm_i is the import tariff rate of import commodity i.

A1.3 Income and expenditure module

A1.3.1 Income and expenditure of households

A1.3.1.1 Income of households

In this model, the households' income is composed of labor payment, capital revenue and transfer payments from government and foreign countries.

$$YH = \sum_i WL \cdot QLD_i + shifhk \sum_i WK \cdot QKD_i + \overline{TSGTOH} + \overline{TSETOH} + EXR \cdot \overline{TSWTOH} \tag{1.29}$$

where YH is the income of households, $shifhk$ is the coefficient of the households' share in capital revenue, $\overline{TSGTOH}$ is transfer payments from government, $\overline{TSETOH}$ is transfer payments from enterprises, $\overline{TSWTOH}$ is transfer payments from foreign countries.

A1.3.1.2 Expenditure of households

The consumption function of households is assumed as a Cobb-Douglas utility function in this model, which can derive the final consumption of households as the following equation:

$$PQ_i \cdot QH_i = shrh_i \cdot mpc \cdot (1 - th) \cdot YH \tag{1.30}$$

where QH_i is the consumption of commodity i of households, mpc is the marginal propensity to consume of the household, $shrh_i$ is the share of the consumption of commodity i in the expenditure of households, th is the rate of household's income tax.

The households' expenditure contains total final consumption:

$$EH = \sum_i PQ_i \cdot QH_i + th \cdot YH \tag{1.31}$$

where EH is the expenditure of households.

Accordingly, household saving is:

$$HSAV = YH - EH \tag{1.32}$$

where $HSAV$ is household saving.

A1.3.2 Income and expenditure of governments

A1.3.2.1 Income of government

The government's income is composed of tariff, capital revenue and carbon tax.

$$YG = \sum_i tcind_i \cdot PA_i \cdot QA_i + \sum_i tm_i \cdot QM_i \cdot \overline{PMW}_i \cdot EXR + th \cdot YH + te \cdot shifek \cdot \sum_i WK_i \cdot QKD_i + EXR \cdot \overline{TSWTOG} + TOCTR \tag{1.33}$$

where YG is the income of government, $tcind_i$ is the rate of indirect tax paid to government of industry i, $shifek$ is coefficient of enterprise' share in total capital revenue, te is the rate of enterprise's income tax, $\overline{TSWTOG}$ is the transfer payments from foreign countries to government, $TOCTR$ is carbon tax revenue.

A1.3.2.2 Expenditure of government

The government's expenditure includes commodity consumption, energy subsidy, transfer payments to the local government.

$$EG = \sum_i PQ_i \cdot QG_i + \overline{TSGTOH} + \overline{TSGTOE} + EXR \cdot \overline{TSGTOW} \tag{1.34}$$

where EG is the government's expenditure, $\overline{TSGTOH}$, $\overline{TSGTOE}$ and $\overline{TSGTOW}$ are government's transfer payments to household, enterprises and foreign counties respectively.

In the equation above, consumption demand of the government is:

$$PQ_i \cdot QG_i = shrg_i \cdot mpcg \cdot YG \tag{1.35}$$

where $shrg_i$ is the spending share of government's consumption of commodity i, $mpcg$ is government's marginal propensity to consume.

Accordingly, government saving is:

$$GSAV = YG - EG \tag{1.36}$$

where $GSAV$ is government saving.

A1.3.3 Income and expenditure of enterprises

A1.3.3.1 Income of enterprises

The enterprises' income includes capital revenue and transfer payments from the government.

$$YENT = shifek \sum_i WK_i \cdot QKD_i + \overline{TSGTOE} \tag{1.37}$$

where $YENT_r$ is the income of enterprises, $shifek$ is the coefficient of the enterprises' share in capital revenue.

A1.3.3.2 Expenditure of enterprises

The enterprises' expenditure consists of the enterprise income taxes paid to the government and the transfer payments to the household.

$$EXENT = te \cdot fhifek \cdot \sum_i WK_i \cdot QKD_i + \overline{TSETOH} \tag{1.38}$$

where $EXENT$ is the expenditure of enterprises.

Accordingly, enterprise saving is:

$$ESAV = YENT - EXENT \tag{1.39}$$

where $ESAV$ is enterprise saving.

A1.4 Carbon emission and carbon tax module

A1.4.1 Carbon emission

Carbon emission coefficient (ton CO_2/10,000 Yuan) of three kinds of fossil fuel inputs (coal, refined petroleum, gas) of each industry in this model can be obtained from the data of base year, which can derive the calculation of carbon emission as the following equations:

$$QEMIS_i = coef_{coal} \cdot QEcoal_i + coef_{oil} \cdot QEoil_i + coef_{gas} \cdot QEgas_i \tag{1.40}$$

$$QTEMIS = \sum_i QEMIS_i \tag{1.41}$$

where $QEMIS_i$ is the amount of carbon emission of industry i, $QTEMIS$ is total amount of national carbon emissions.

A1.4.2 Carbon tax

$$CTR_i = ctax \cdot QEMIS_i \tag{1.42}$$

$$TOCTR = \sum_i CTR_i \tag{1.43}$$

where $ctax$ is the carbon tax rate, CTR_i is the carbon tax payable of sector i.

A1.4.3 Adjustments of production function equation

The first order condition of the fifth level of production function should be adjusted as:

$$\frac{(1 + ctax \cdot coef_{coal}) \cdot PEcoal_i}{PEoilgas_i} = \frac{\delta_i^{ef}}{\left(1 - \delta_i^{ef}\right)} \cdot \left(\frac{QEoilgas_i}{QEcoal_i}\right)^{1-\rho_i^{ef}} \tag{16a}$$

Meanwhile, the price relationship of the input of the aggregation of fossil fuels should be adjusted as:

$$PEF_i \cdot QEF_i = (1 + ctax \cdot coef_{coal}) \cdot PEcoal_i \cdot QEcoal_i + PEoilgas_i \cdot QEoilgas_i \tag{17a}$$

The first order condition of the sixth level of production function should be adjusted as:

$$\frac{(1 + ctax \cdot coef_{gas}) \cdot PEgas_i}{(1 + ctax \cdot coef_{oil}) \cdot PEoil_i} = \frac{\delta_i^{pg}}{(1 - \delta_i^{pg})} \cdot \left(\frac{QEoil_i}{QEgas_i}\right)^{1-\rho_i^{pg}} \tag{19a}$$

Meanwhile, the price relationship of the input of the aggregation of refined petroleum and gas should be adjusted as:

$$PEoilgas_{i,r} \cdot QEoilgas_{i,r} = (1 + ctax \cdot coef_{oil}) PEoil_{i,r} \cdot QEoil_{i,r} + (1 + ctax \cdot coef_{gas}) \cdot PEgas_{i,r} \cdot QEgas_{i,r} \tag{20a}$$

A1.5 Market clearing and macroeconomic closure module

A1.5.1 Commodity market clearing

For the non-energy commodities as intermediate inputs, we have:

$$QQ_i = \sum_j ica_{i,j} \cdot QINTA_j + QH_i + QG_i + QINV_i + \overline{QSTOCK}_i, \quad i \in NE \tag{1.44}$$

where $QINV_i$ is the demands for commodities i used as investment, $\overline{QSTOCK_i}$ is the demands for commodities i used as stock.

For energy commodities, we have:

$$QQ_i = \sum_j QE_{i,j} + QH_i + QG_i + QINV_i + \overline{QSTOCK}_i, \quad i \in E \tag{44a}$$

where $QE_{i,j}$ is the inputs of different energy commodity of every industry, here i refers to four kinds of energy commodities inputs of industry j, i.e., QEE_j, $QEcoal_j$, $QEoil_j$, $QEgas_j$.

A1.5.2 Factor market clearing

The labor supply equal to the labor demand:

$$\overline{QLS} = \sum_i QLD_i \tag{1.45}$$

For capital, the same assumption as follows:

$$QKD_i = TQKA_i \cdot krent_i \tag{1.46}$$

$$\overline{QKS} = \sum_i TQKA_i \tag{1.47}$$

where $TQKA_i$ is the capital stock of industry i, $krent_i$ is the capital rent of industry i, $\overline{QKS}$ is the total capital stock of the whole economy.

A1.5.3 Governmental budget balance

Government savings is the difference value of governmental income and governmental expenditure, see equation(36).

A1.5.4 Investment and saving balance

This model is a savings-driven model in which total investment is decided by total savings.

$$TOTINV + \sum_i PQ_i \cdot \overline{QSTOCK}_i = HSAV + ESAV + GSAV + EXR \cdot FSAV + WALRAS \tag{1.48}$$

$$PQ_i \cdot QINV_i = shareinv_i \cdot TOTINV \tag{1.49}$$

where*TOTINV* is total investment, *FSAV* is foreign savings, *WALRAS* is dummy variable. $shareinv_i$ is the share of commodity i used as investment in the total investment.

A1.5.4 Foreign income and expenditure balance

The difference value of income and expenditure of foreign countries is foreign savings.

$$\sum_i PWM_i \cdot QM_i + \overline{TSGTOW} = \sum_i PWE_i \cdot QE_i + \overline{TSWTOG} + \overline{TSWTOH} + FSAV \tag{1.50}$$

A1.5.6 Macroeconomic closure

The "neoclassic closure" rule is adopted in this model. In this model, all the savings are transformed into investment, and the total investment equals total savings endogenously. Labor supply at the national level is exogenous, and all factors are fully employment in the whole economy.

The nominal GDP can be calculated from the following equation:

$$GDPVA = \sum_i PQ_i \cdot \left(QH_i + QG_i + QINV_i + \overline{QSTOCK}_i \right) + \sum_i PE_i \cdot QE_i - \sum_i PM_i \cdot QM_i + \sum_i tm_i \cdot QM_i \cdot \overline{PMW}_i \cdot EXR \tag{1.51}$$

where *GDPVA* is the nominal GDP.

The real GDP can be calculated as follows:

$$GDP = \sum_i \left(QH_i + QG_i + \mathrm{QINV}_i + \overline{QSTOCK}_i \right) + \sum_i QE_i - \sum_i \left(QM_i - tm_i \cdot QM_i \cdot \overline{PMW}_i \cdot EXR \right) \tag{1.52}$$

where *GDP* is the real GDP.

Therefore, the GDP index can be obtained by the following equation:

$$PGDP = \frac{GDP}{GDPVA} \tag{1.53}$$

where *RGDP* is the GDP index.

Meanwhile, the CPI can be obtained as follows:

$$CPI = \frac{\sum_i PQ_i \times QH0_i}{\sum_i PQ0_i \times QH0_i} \tag{1.54}$$

where *CPI* is the consumer price index.

In the model, household welfare variation is measured by using the Hicksian equivalent variation (EV).

A1.6 Dynamic mechanism

This model is a recursive dynamic CGE model, and the dynamic mechanism includes labor supply growth, increase of total factor productivity (TFP) and capital accumulation.

A1.6.1 Labor supply growth

Labor supply in different period is described as:

$$\overline{TTQL}_{t+1} = (1 + lgow)\overline{TTQL}_t \tag{55}$$

where *lgow* is the annual growth rate of labor supply.

A1.6.2 TFP increase

In the model, TFP Increase is represented by the change of technology parameter in the second level of CES production function.

$$\alpha_i^{va}{}_{t+1} = (1 + tgrow) \cdot \alpha_i^{va}{}_t \tag{1.56}$$

where *tgrow* is the annual growth rate of TFP.

A1.6.3 Capital Accumulation

We adopted the method used by James Thurlow (2004)[1] to describe the capital accumulation in different period. In the model, total capital supply is endogenous in a given period and the total available capital is determined by the previous period's capital stock and new investment.

In this model, the new capital stock resulting from the previous investment is allocated across sectors in proportion to each sector's share in aggregate capital income, and these proportions are adjusted by the ratio of each sector's profit rate to the average profit rate for the whole economy.

$$WKA_t = \sum_i \frac{QKD_{i,t}}{\sum_i QKD_{i,t}} \cdot WK_{i,t} \tag{1.57}$$

[1] Thurlow, J. (2004). A Dynamic Computable General Equilibrium (CGE) Model for South Africa: Extending the Static IFPRI Model. TIPS Working Paper Series (WP1-2004), 53–55.

where WKA_t is the average economy-wide rental rate of capital at time period t.

$$\text{share}enk_{i,t} = \frac{QKD_{i,t}}{\sum_i QKD_{i,t}} \cdot \left[1 + \beta_i \cdot \left(\frac{WK_{i,t}}{WKA_t} - 1\right)\right] \tag{1.58}$$

where share$enk_{i,t}$ is the share of the new capital investment of industry i at period t, β_i is the inter-sectoral mobility coefficient of investment. The value of β_i can be chosen from 0 to 1, β_i is 0 means there is no inter-sectoral mobility of investment, whereas β_i is 1 means there is full inter-sectoral mobility of investment.

$$PK_t = \sum_i PQ_{i,t} \cdot \frac{QINV_{i,t}}{\sum_i QINV_{i,t}} \tag{1.59}$$

where PK_t is the price of capital at period t.

$$QIND_{i,t} = sharenk_{i,t} \cdot \frac{\sum_i PQ_{i,t} \cdot QINV_{i,t}}{PK_t} \tag{1.60}$$

where $QIND_{i,t}$ is the new-added capital of industry i at period t.

$$TQKA_{i,t+1} = TQKA_{i,t} \cdot (1 - depr_i) + QIND_{i,t} \tag{1.61}$$

where $TQKA_{i,t+1}$ is the capital stock of industry i at time period t+1, $depr_i$ is the depreciation rate of industry i.

References

[1] Chris Bataille, Waisman Henri, Colombier Michel, Segafredo Laura, Williams Jim. The deep decarbonization pathways Project (DDPP): insights and emerging issues. Clim Pol 2016;16:S1–6. sup.1.
[2] Wang R. Energy efficiency in China's industry sectors: a non-parametric production frontier approach analysis. J Clean Prod 2018;200:880–9.
[3] Ajay Gambhir. Planning a low-carbon energy transition: what can and can't the models tell us? Joule 2019;3(8):1795–8.
[4] Xie Y, Dai H, Xu X, Fujimori S, Hasgwa T, Yi K, et al. Co-benefits of climate mitigation on air quality and human health in Asian countries. Environ Int 2018;109:309–18.
[5] Xie Y, Dai H, Dong H, Hanaoka T, Masui T. Economic impacts from Pm2.5 pollution-related health effects in China: a provincial-level analysis. Environ Sci Technol 2016;50(9):4836–43.
[6] Panwar M, et al. Analysis of environmental Co-benefits of transportation sub-system of Delhi. Alexandria Engineering Journal 2018;57(4):2649–58.
[7] Li N, Zhang X, Shi M, Hewings G. Does China's air pollution abatement policy matter? An assessment of the Beijing-Tianjin-Hebei region based on a multi-regional CGE model. Energy Pol 2019;127:213–27.
[8] Tian X, et al. Economic impacts from Pm2.5 pollution-related health effects in China's road transport sector: a provincial-level analysis. Environ Int 2018;115:220–9.
[9] Wang Z, Su B, Xie R, Long H. China's aggregate embodied CO2 emission intensity from 2007 to 2012: a multi-region multiplicative structural decomposition analysis. Energy Econ 2020;85:104568.
[10] Cao C, Cui X, Cai W, Wang C, Xing L, Zhang N, et al. Incorporating health co-benefits into regional carbon emission reduction policy making: a case study of China's power sector. Appl Energy 2019;253:113498.
[11] Ma D, Chen W, Yin X, Wang L. Quantifying the co-benefits of decarbonization in China's steel sector: an integrated assessment approach. Appl Energy 2016;162:1225–37.
[12] Liu L, et al. Assessing energy consumption, Co2 and pollutant emissions and health benefits from China's transport sector through 2050. Energy Pol 2018;116:382–96.
[13] Duan H, Wang S. Potential impacts of China's climate policies on energy security. Environ Impact Assess Rev 2018;71:94–101.
[14] Tong D, Geng G, Jiang K, Cheng J, Zheng Y, Hong C, et al. Energy and emission pathways towards PM2.5 air quality attainment in the Beijing-Tianjin-Hebei region by 2030. Sci Total Environ 2019;692:361–70.
[15] He C, Jiang K, Chen S, Jiang W, Liu J. Zero CO2 emissions for an ultra-large city by 2050: case study for Beijing. Current Opinion in Environmental Sustainability 2019;36:141–55.
[16] Chen W, Wu S, Lei Y, Li S. Interprovincial transfer of embodied energy between the Jing-Jin-Ji area and other provinces in China: a quantification using interprovincial input-output model. Sci Total Environ 2017;584–585:990–1003.
[17] Jiang K, He C, Xu X, Jiang W, Xiang P, Li H. Transition scenarios of power generation in China under global 2 °C and 1.5 °C targets. Global Energy Interconnection 2018;1:477–86.
[18] Fan X, Wu S, Li S. Spatial-temporal analysis of carbon emissions embodied in interprovincial trade and optimization strategies: a case study of Hebei, China. Energy 2019;185:1235–49.
[19] Yi B, Xu J, Fan Y. Inter-regional power grid planning up to 2030 in China considering renewable energy development and regional pollutant control: a multi-region bottom-up optimization model. Appl Energy 2016;184:641–58.
[20] Melton Bataille Cand N. Energy efficiency and economic growth: a retrospective CGE analysis for Canada from 2002 to 2012. Energy Econ 2017;64:118–30.
[21] Böhringer C, Rutherford TF. Transition towards a low carbon economy: a computable general equilibrium analysis for Poland. Energy Pol 2013;55:16–26.
[22] He Y, Lin B. The impact of natural gas price control in China: a computable general equilibrium approach. Energy Pol 2017;107:524–31.
[23] Tang L, Shi J, Bao Q. Designing an emissions trading scheme for China with a dynamic computable general equilibrium model. Energy Pol 2016;97:507–20.
[24] Liu Yu, Lu Yingying. The economic impact of different carbon tax revenue recycling schemes in China: a model-based scenario analysis. Appl Energy 2015;141:96–105.
[25] Li N, Shi MJ, Yuan YN. Impacts of carbon tax policy on regional development in China: a dynamic simulation based on a multi-regional cge model. Geographical Science 2010;65(12):1569–80.
[26] Liang Qiao-Mei, Wei Yi-Ming. Distributional impacts of taxing carbon in China: results from the ceepa model. Appl Energy 2012;92:545–51.
[27] Cao Jing, Ho Mun S, Jorgenson Dale W, Nielsen Chris P. China's emissions trading system and an ets-carbon tax hybrid. Energy Econ 2019;253:113498. 2019.
[28] Lin Boqiang, Jia Zhijie. The impact of emission trading scheme (ets) and the choice of coverage industry in ets: a case study in China. Appl Energy 2017;205:1512–27.
[29] Li Wei, Jia Zhijie. The impact of emission trading scheme and the ratio of free quota: a dynamic recursive cge model in China. Appl Energy 2016;174:1–14.
[30] Tian Xu, Dai Hancheng, Geng Yong, Huang Zhen, Masui Toshihiko, Fujita Tsuyoshi. The effects of carbon reduction on sectoral competitiveness in China: a case of Shanghai. Appl Energy 2017;197:270–8.
[31] Wu Rui, Dai Hancheng, Geng Yong, Xie Yang, Masui Toshihiko, Tian Xu. Achieving China's INDC through carbon cap-and-trade: insights from Shanghai. Appl Energy 2016;184:1114–22.
[32] Li Zhaoling, Dai Hancheng, Sun Lu, Xie Yang, Zhu Liu, Wang Peng, Yabar Helmut. Exploring the impacts of regional unbalanced carbon tax on CO2 emissions and industrial competitiveness in liaoning province of China. Energy Pol 2018;113:9–19.
[33] Xie Jiaoyan, Dai Hancheng, Xie Yang, Hong Lixuan. Effect of carbon tax on the industrial competitiveness of chongqing, China. Energy for Sustainable Development 2018;47:114–23.
[34] Krook-Riekkola A, Berg C, Ahlgren E, Söderholm P. Challenges in top-down and bottom-up soft-linking: lessons from linking a Swedish energy system model with a CGE model. Energy 2017;141:803–17.
[35] Timilsina G, Jorgensen E. The economics of greening Romania's energy supply system. Mitig Adapt Strategies Glob Change 2017;23(1):123–44.
[36] Bhadbhade N, Zuberi MJS, Patel MK. A bottom-up analysis of energy efficiency improvement and CO2 emission reduction potentials for the swiss metals sector. Energy 2019;181:173–86.
[37] Chen W, Yin X, Ma D. A bottom-up analysis of China's iron and steel industrial energy consumption and Co2 emissions. Appl Energy 2014;136:1174–83.
[38] Xu J, Yi B-W, Fan Y. A bottom-up optimization model for long-term CO 2 emissions reduction pathway in the cement industry: a case study of China. International Journal of Greenhouse Gas Control 2016;44:199–216.
[39] Comodi G, Cioccolanti L, Gargiulo M. Municipal scale scenario: analysis of an Italian seaside town with MarkAL-TIMES. Energy Pol 2012;41:303–15.

[40] Chen W. The costs of mitigating carbon emissions in China: findings from China MARKAL-MACRO modeling. Energy Pol 2005;33(7):885–96.
[41] Vaillancourt K, Labriet M, Loulou R, Waaub J-P. The role of nuclear energy in long-term climate scenarios: an analysis with the World-TIMES model. Energy Pol 2008;36(7):2296–307.
[42] Fleiter T, Rehfeldt M, Herbst A, Elsland R, Klingler A-L, Manz P, et al. A methodology for bottom-up modelling of energy transitions in the industry sector: the FORECAST model. Energy Strategy Reviews 2018;22:237–54.
[43] Yang X, Teng F, Xi X, Khayrullin E, Zhang Q. Cost–benefit analysis of China's Intended Nationally Determined Contributions based on carbon marginal cost curves. Appl Energy 2018;227:415–25.
[44] Shi J, Chen W, Yin X. Modelling building's decarbonization with application of China TIMES model. Appl Energy 2016;162:1303–12.
[45] Hugues P, Assoumou E, Maizi N. Assessing GHG mitigation and associated cost of French biofuel sector: insights from a TIMES model. Energy 2016;113:288–300.
[46] Dai H, Mischke P, Xie X, Xie Y, Masui T. Closing the gap? Top-down versus bottom-up projections of China's regional energy use and CO2 emissions. Appl Energy 2016;162:1355–73.
[47] Díaz A, Marrero G, Puch L, Rodríguez J. Economic growth, energy intensity and the energy mix. Energy Econ 2019;81:1056–77.
[48] Timilsina GR, Shrestha RM. General equilibrium effects of a supply side GHG mitigation option under the Clean Development Mechanism. J Environ Manag 2006;80(4):327–41.
[49] Rausch S, Zhang D. Capturing natural resource heterogeneity in top-down energy-economic equilibrium models. Energy Econ 2018;74:917–26.
[50] Zhang X, Jin Y, Dai H, Xie Y, Zhang S. Health and economic benefits of cleaner residential heating in the beijing–tianjin–hebei region in China. Energy Pol 2019;127:165–78.
[51] Zhou Y, Ma M, Kong F, Wang K, Bi J. Capturing the co-benefits of energy efficiency in China — a perspective from the water-energy nexus. Resour Conserv Recycl 2019;132:93–101.
[52] Bollen J. The value of air pollution co-benefits of climate policies: analysis with a global sector-trade CGE model called World Scan. Technol Forecast Soc Change 2015;90:178–91.
[53] Xie Y, Dai H, Xu X, Fujimori S, Hasgwa T, Yi K, et al. Co-benefits of climate mitigation on air quality and human health in Asian countries. Environ Int 2018;109:309–18.
[54] Xu Y, Masui T. Local air pollutant emission reduction and ancillary carbon benefits of SO2 control policies: application of AIM/CGE model to China. Eur J Oper Res 2009;198:315–25. 2009.
[55] Lu Z, Huang L, Liu J, Zhou Y, Chen M, Hu J. Carbon dioxide mitigation co-benefit analysis of energy-related measures in the air pollution prevention and control action plan in the jing-jin-ji region of China. Resour Conserv Recycl 2019;1:100006.
[56] Wang H, Mullahy J. Willingness to pay for reducing fatal risk by improving air quality: a contingent valuation study in Chongqing, China. Sci Total Environ 2006;367:50–7.
[57] Zeng X, Jiang Y. Evaluation of value of statistical life in health costs attributable to air pollution. China Environ Sci 2010;2:284–8.
[58] Xu X, Chen RJ, Kan HD, Ying XH. Meta-analysis of contingent valuation studies on air pollution-related value of statistical life in China. Chin Health Resour 2013;1:64–7.
[59] Gao T, Guo-Xing LI, Mei-Mei XU, Wang XY, Liang FC, Zeng Q, Pan XC. Health economic loss evaluation of ambient PM2.5 pollution based on willingness to pay. J Environ Health 2015;8:697–700.
[60] Wang P. Research on the health hazards of atmosphere particulate pollution in Harbin. [master's thesis]. Harbin: Harbin University of Science and Technology; 2015.
[61] Apte JS, Marshall JD, Cohen AJ, Brauer M. Addressing global mortality from ambient PM2. 5. Environ Sci Technol 2015;49:8057–66.
[62] Fang D, Wang Q, Li H, Yu Y, Lu Y, Qian X. Mortality effects assessment of ambient PM2.5 pollution in the 74 leading cities of China. Sci Total Environ 2016;569–570:1545–52.
[63] Die F. Study on the impact of air pollution on population health in major cities in China. Master's Thesis. Nanjing, China: Nanjing University; 2014.
[64] Humbert S, Marshall JD, Shaked S, Spadaro JV, Nishioka Y, Preiss P, McKone TE, Horvath A, Jolliet O. Intake fraction for particulate matter: recommendations for life cycle impact assessment. Environ Sci Technol 2011;45:4808–16.
[65] Apte JS, Bombrun E, Marshall JD, Nazaroff WW. Global intraurban intake fractions for primary air pollutants from vehicles and other distributed sources. Environ Sci Technol 2012;46:3415–23.
[66] NDRC (National Development & Reform Commission of China). Strengthening actions on climate change: China's national independent contribution. 2015. https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/China%20First/China%27s%20First%20NDC%20Submission.pdf.
[67] Xie Y, Liu X, Chen Q, Zhang S. An integrated assessment for achieving the 2°C target pathway in China by 2030. J Clean Prod 2020;268:122238.
[68] Mu Y., Wang C. and Cai W. The economic impact of China's indc: distinguishing the roles of the renewable energy quota and the carbon market. Renew Sustain Energy Rev; 81: 2955-2966.
[69] Dai H, Xie Y, Liu J, Masui T. Aligning renewable energy targets with carbon emissions trading to achieve China's indcs: a general equilibrium assessment. Renew Sustain Energy Rev 2018;82:4121–31.
[70] Yang X, Teng F. Air quality benefit of China's mitigation target to peak its emission by 2030. Clim Pol 2018;18(1):99–110.
[71] Burandt T., Xiong B., Löffler K. and Oei P.-Y. Decarbonizing China's energy system – modeling the transformation of the electricity, transportation, heat, and industrial sectors. Appl Energy; 255: 113820.
[72] Bataille C, Waisman H, Briand Y, Svensson J, Vogt-Schilb A, Jaramillo M. Net-zero deep decarbonization pathways in Latin America: challenges and opportunities. Energy Strategy Reviews 2020;30:100510.
[73] Wang H, Chen W. Modelling deep decarbonization of industrial energy consumption under 2-degree target: comparing China, India and western europe. Appl Energy 2019;238:1563–72.
[74] Burandt T., Xiong B., Löffler K. and Oei P.-Y. Decarbonizing China's energy system – modeling the transformation of the electricity, transportation, heat, and industrial sectors. Appl Energy; 255: 113820.
[75] Barido DPdL, Avila N, Kammen DM. Exploring the enabling environments, inherent characteristics and intrinsic motivations fostering global electricity decarbonization. Energy Research & Social Science 2020;61:101343.
[76] Wu S, Li L, Li S. Natural resource abundance, natural resource-oriented industry dependence, and economic growth: evidence from the provincial level in China. Resour Conserv Recycl 2018;139:163–71.
[77] Guo J, Zhang X, Gu F, Zhang H, Fan Y. Does air pollution stimulate electric vehicle sales? Empirical evidence from twenty major cities in China. J Clean Prod 2019:119372.
[78] Zhou X, Zhou D, Wang Q, Su B. Who shapes China's carbon intensity and how? A demand-side decomposition analysis. Energy Econ 2020;85:104600.