China's unconventional carbon emissions trading market: the impact of a rate-based cap in the power generation sector

Zhongjue Yu [a], Yong Geng [b,c,a,d*], Alvaro Calzadilla [e], Raimund Bleischwitz [e]

[a] School of Environmental Science and Engineering, Shanghai Jiao Tong University, Shanghai, China

[b] School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai, China

[c] China Institute for Urban Governance, Shanghai Jiao Tong University, Shanghai, China

[d] School of Management, China University of Mining and Technology, Xuzhou, China

[e] Institute for Sustainable Resources, University College London, London, UK

Correspondence to:

Professor Yong Geng

School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai, China

E-mail: ygeng@sjtu.edu.cn

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Abstract: China has launched a national level carbon emissions trading market with a rate-based cap and benchmarks in the power generation sector. This emissions trading system (ETS) differs from a mass-based one, which lacks an absolute carbon cap. This study assesses the impact of such an unconventional ETS on economic development, carbon emission mitigation, and power system transition by applying a multi-regional dynamic computable general equilibrium model. The results show that ETS can facilitate the decarbonisation of the power sector and reduce carbon intensities of coal and gas power, the two technologies covered at the first stage of China's ETS. Furthermore, power generation of these technologies will be decreased significantly, and a noticeable fallback of electrification will occur. National GDP loss under a rate-based cap is slightly higher than the one under a mass-based cap, while provincial GDP losses have close relations with coal phaseout and permit scarcity.

Abbreviations

CES	Constant Elasticity of Substitution
CGE	Computable General Equilibrium
ETS	Emissions Trading System
GAMS	General Algebraic Modelling System
GHG	Greenhouse Gas
IEA	International Energy Agency
MCP	Mixed Complementarity Problem
MPSGE	Mathematical Programming System for General Equilibrium
NDC	Nationally Determined Contribution
NLP	Non-Linear Programming
TPS	Tradable Performance Standard

Symbols

i	Set of commodities
r	Set of provinces
$elet$	Set of power technologies
ω	Price of labour
ν	Price of capital
P_i	Price of commodity i
P_w	Price of utility commodity W
L	Labour
K	Capital
Q_i	Supply of commodity i
W	Utility
I	Income
$f_i^c(\omega, \nu)$	Unit cost function of commodity i

$f^w(P_i)$	Unit cost function of utility commodity W
σ_i^c, σ^W	Elasticities of the production of commodity i and utility W
α_i, β_i	Share parameters for commodity i
ϕ_i^c, ϕ^W	Productivity parameters for commodity i and utility W
$GEN_{r,elet}^E, GEN_{r,elet}^H$	Electricity and heat generation in region r from technology $elet$
$\overline{BMK_{elet}^E}, \overline{BMK_{elet}^H}$	Benchmarks of electricity and heat generation from technology $elet$
$\overline{Fl_{r,elet}}$	Cooling correction factor
$\overline{Ff_{r,elet}}$	Load correction factor
$\overline{Q_{r,elet}^H}$	Share of energy input that is used to produce heat in power technology $elet$
$\overline{CAP_t}$	Mass-based cap in year t
$CE_{r,elet,t}$	Carbon emission of region r from technology $elet$ in year t.

1 Introduction

China, as the largest emitter of greenhouse gas (GHG) [1], has pledged to peak its total GHG emission by 2030 and achieve carbon neutrality by 2060. To support such ambitious climate targets, China has been implementing Emissions Trading Systems (ETSs) since 2013, including eight regional pilot systems in Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Hubei, Guangdong, and Fujian. These pilot systems were experimental systems where various market designs and rules, allocation methods, and sector coverages were tested. Based on the experiences of these eight pilot systems, China planned to establish a nationwide ETS in 2017 and formally launched online transactions in 2021. Conventional mass-based ETSs, also known as cap-and-trade schemes, have been widely implemented across the world [2]. Most regional pilot ETSs in China have also implemented a mass-based system since they were initiated. However, China's nationwide ETS implements a rate-based design for political, competitiveness, and equity concerns [3]. This unconventional design would lead to various impacts and challenges in China's climate mitigation efforts.

A conventional mass-based ETS relies on an absolute carbon cap. Such a carbon cap is usually set by those policy makers based on their carbon mitigation plans. Permits are allocated to all the participants based upon their historical emissions and equity principles. These participants can trade their permits freely, thus forming a carbon price. The carbon market will redistribute such permits, driving those participants with higher carbon abatement potential to take mitigation actions to respond such financial costs. Such redistribution can reduce the overall cost of carbon mitigation and improve the overall economic efficiency [4]. This mass-based system is also known as a cap-and-trade scheme as the overall carbon cap is explicit.

In contrast, a rate-based ETS does not have an absolute carbon cap. The total cap is determined by the actual level of production multiplied by a certain rate, known as a benchmark, which is usually the carbon emission per unit of production. A key feature of a rate-based cap is that the actual amount of carbon cap (and permit) adjusts according to the output of the industry, while the benchmark rate remains constant[1]. The impact of this feature is twofold. On one hand, a rate-based cap is more flexible. It would avoid exceptionally high permit prices when the economy is booming, while it would avoid a severe price drop during an economic slump [5]. On the other hand, reducing production under a

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[1] Note the concept difference between ETS with a rate-based cap and ETS with an output-based allocation (OBA). The permit allocation rules of these two schemes are similar, but the key difference is that the latter has an absolute carbon cap while the former does not.

rate-based cap is ineffective for compliance because the permit received by industry reduces along with its output. Concerns have been raised. For instance, the ineffectiveness of reducing production would damage the cost-effectiveness of a rate-based ETS [6]. There are also concerns that a rate-based cap would incentivise industries below the benchmark to increase their production scale [7], while they may be also carbon intensive industries which are just relatively cleaner compared with others.

Currently, most emissions trading systems in the world are mass-based [2]. In this context, several model-based simulation studies on China's ETS have been conducted assuming there will be a mass-based cap [8], both at the national level [4,9,10] and at the provincial levels [11–14] . Their research topics focus on the design and mechanisms of ETS, such as cap settings [15], initial allocation rules [4,16], and the corresponding economic efficiency [17]. A general conclusion of these studies on a mass-based ETS is that it will effectively reduce carbon emissions and shift production to less carbon intensive industries while economically being more cost-effective than command-and-control policies.

In contrast, only a few studies have evaluated the impacts of a rate-based cap. In this regard, IEA [18] developed a capacity expansion and dispatch model to evaluate the decarbonisation in China's power system under a rate-based ETS. They found that a rate-based ETS can cost-effectively peak the carbon emissions in China's power sector and improve the efficiency of coal power, while multiple benchmarks and free allocation would limit the incentive to switch to gas and non-fossil fuel power technologies. Goulder et al. [6] employed matching analytically and numerically solved models to assess the impact of a rate-based ETS in China's power generation sector. They concluded that a rate-based ETS would have a larger economic loss than a mass-based one, and further loss would occur when implementing multiple benchmarks. Apart from the studies in China, other studies on the tradable performance standard (TPS), which is in essence a similar scheme as a rate-based ETS, have drawn similar conclusions. For example, Holland et al. [19] argued that a TPS is less efficient than a cap-and-trade scheme because a TPS will subsidise those technologies below the standard (benchmark) while the efficient principle requires all industries with fuels use to be taxed but not to be subsidised. Palmer et al. [20] reviewed the proposed schemes under the Clean Power Plan in the United States, including cap-and-trade, TPS, and Clean Energy Standard. They concluded that cap-and-trade with particular allocation arrangements would be a more economically efficient option compared with TPS. The reason is that it imposes an explicit price on carbon emissions, does not incentivise the emission related productions, and makes productive use of allowance (permit) value. Given the narrow focus on the economic efficiency of rate-based ETS in the previous studies, studies on rate-based cap settings are lacking, namely benchmark settings. This issue includes what levels of benchmarks, as well as what trajectories of benchmarks should be designed. The “rate”, namely carbon emission per unit of power generation in China’s current case, will decrease with the application of improved technologies. If the benchmark is fixed over time, there will soon be an oversupply of permits in the market, which will lead to a sharp drop of carbon price and consequently make ETS ineffective. Therefore, further assessment on the design of a progressively decreasing (more stringent) benchmark is necessary for China’s medium- and long-term ETS.

Among all the industries, power generation sector has a special role in carbon mitigation. China’s national ETS only covers power generation sector at the first stage; however, only a few studies have evaluated the impacts of such a power-sector-only ETS. Zhang et al. [21] developed a dynamic Computable General Equilibrium (CGE) model to assess the impacts of the ETS in China’s power generation sector. They found that a quicker decline of the carbon cap would decrease electricity supply and would have a spill-over effect that is expected to the output of other industries such as those primary energy production sectors and construction sector. Zhao et al. [22] examined the differences and potentials of combining carbon tax and ETS in China’s power sector by applying a CGE model. Their main finding is that carbon tax can effectively reduce carbon emissions in the power sector, but it does not significantly change energy structure of the power sector, while combining ETS would achieve a more significant carbon emissions reduction. Lanz and Rausch [23] evaluated an power-sector-only ETS in the United States by develop a CGE model and using operator level data. They focus on comparing economic efficiency between free allocation and auction in a partially regulated electricity market.

In addition, several studies focused on the sectoral coverage of China’s ETS [24–27], some of which included one or several scenarios of ETS in the power generation sector alone. For instance, Lin et al. [27] developed a dynamic CGE model to evaluate the impacts of sectoral coverage in China’s national ETS. They found that covering the whole energy production sector, instead of only the power generation sector, would lead to better performance in terms of emissions reduction as well as emission intensity.

From another perspective, several studies assessed the interactions between ETS and renewable energy development, which could also reflect the interactions between ETS and the power generation sector. These studies centred around combining ETS with mandatory renewable energy targets [28], renewable energy quotas [29], subsidies and feed-in tariffs [30,31], as well as revenue recycling into the renewable energy industry [32,33]. However, these studies usually apply a conventional mass-based ETS, covering all sectors.

In summary, these relevant studies either lack the consideration of regional disparities or the consideration of the power generation sector itself such as different generation technologies and renewable energy. Moreover, studies combining renewable generation and ETS do not assess the impacts of either a rate-based ETS or a power-sector-only ETS. Given that renewable resource endowments have large geographical disparities in China, it is crucial to assess how ETS would promote regional renewable energy development. From a broader perspective, a rate-based design is rarely implemented in the emissions trading markets around the world. There is also a lack of understanding about the impacts of such a rate-based ETS, especially on a developing economy experiencing a rapid transition. Thus, it is crucial to assess the pros and cons of such design.

With these factors in mind, there is a crucial need to investigate the impacts of such an unconventional ETS. This study applies a regional dynamic CGE model to evaluate the potential impacts of China's national ETS in the power generation sector in 2030. In response to China's unconventional market design, this study aims at assessing the economic implications of a rate-based ETS compared with a conventional mass-based system. Special attention is given to the impacts of such a rate-based ETS on the provincial power system transition. Moreover, this study contributes to current literature by providing valuable insights to other economies who would consider a rate-based ETS.

This paper is organised as follows. Section 2 introduces research methods, data, and scenarios development. Section 3 presents the results of model simulation. Section 4 discusses these research results and summarizes research limitations. Section 5 draws research conclusions and propose policy recommendations to those policy makers.

2 Methods and data

2.1 Overview of the CGE model

CGE models have been widely used for impact assessment of climate policies at global [34,35], national [36,37], and regional levels [11–14]. Given its feature of reflecting price adjustment mechanisms behind supply and demand equilibrium, CGE models have been particularly useful in emissions trading studies [8].

CGE models assume that the interaction of supply and demand will eventually result in an overall general equilibrium so that costs of producers are minimised and welfares of consumers are maximised. In this regard, CGE models use historical data to describe an economy and estimate how the economy may react to policy interventions. A standard CGE model can be solved as a Non-Linear Programming (NLP) problem [38], while a modern approach is to turn it into a Mixed Complementarity Problem (MCP). Mathiesen [39] found that one Arrow-Debreu economic equilibrium model can be formulated and solved as an MCP as long as three complementarity conditions are satisfied. These conditions include zero-profit condition, market clearance condition, and income balance condition. The following algorithms are summarised and modified from Paltsev [40].

Assuming a simple economic system where there are i commodities in the market at price P_i. These commodities are produced by factors of supplies of labour (L) and capital (K), at price ω and ν, respectively. The utility W is produced at price P_w when consuming commodity i .The unit cost of commodity i is calculated by function $f_i^c(\omega, \nu)$. The unit expenditure of utility W is calculated by function $f^w(P_i)$. The consumer obtains income I from labour and capital.

Assuming the production of commodities and utility is subject to Constant Elasticity of Substitution (CES) functions. When the costs are minimised and the utility is maximised, the unit cost and unit expenditure functions are given by the following equations.

$$f_i^c(\omega, \nu) = \frac{1}{\phi_i^c}\left[\alpha_i^{\sigma_i^c}\omega^{1-\sigma_i^c} + (1-\alpha_i)^{\sigma_i^c}\nu^{1-\sigma_i^c}\right]^{\frac{1}{1-\sigma_i^c}} \quad (1)$$

$$f^W(P_i) = \frac{1}{\phi^W}\left(\sum_i \beta_i^{\sigma^W} P_i^{1-\sigma^W}\right)^{\frac{1}{1-\sigma^W}} \quad (2)$$

$$\sum_i \beta_i = 1 \quad (3)$$

Where:

$f_i^c(\omega, \nu)$ refers to the unit cost function of commodity i.

$f^w(P_i)$ refers to the unit cost function of utility commodity W.

ω refers to the price of labour.

ν refers to the price of capital.

P_i refers to the price of commodity i.

σ_i^c, σ^W refer to the elasticities of the production of commodity i and utility W.

α_i, β_i and ϕ_i^c, ϕ^W refer to share parameters and productivity parameters. They can be calibrated by using base year data.

The three complementarity conditions are listed below. Those equations linked by the symbol "⊥" means that they are complementary[2].

(1) Zero-profit condition

This zero-profit condition ensures that any production activity must earn a zero profit, which means when the output of an activity is positive, the producers must spend all profits on producing their commodities.

This zero-profit condition can be represented by:

$$P_i \geq f_i^c(\omega, \nu) \quad \perp \quad Q_i \geq 0 \tag{4}$$

$$P_w \geq f^w(P_i) \quad \perp \quad W \geq 0 \tag{5}$$

Where:

P_w refers to the price of utility commodity W.

Q_i refers to the supply of commodity i.

W refers to the supply of utility commodity.

(2) Market clearance condition

This market clearance condition ensures that if there is excess supply in the market, the price of the commodity or factor must be zero.

This market clearance condition can be represented by:

$$Q_i \geq \frac{\partial f^w(P_i)}{\partial Pi} \cdot W \quad \perp \quad P_i \geq 0 \tag{6}$$

$$L \geq \sum_i \left(\frac{\partial f_i^c(\omega, \nu)}{\partial \omega} \cdot Q_i \right) \quad \perp \quad \omega \geq 0 \tag{7}$$

$$K \geq \sum_i \left(\frac{\partial f_i^c(\omega, \nu)}{\partial r} \cdot Q_i \right) \quad \perp \quad \nu \geq 0 \tag{8}$$

$$W \geq \frac{I}{P_w} \quad \perp \quad P_w \geq 0 \tag{9}$$

Where:

[2] Consider two simple complementary conditions:

$$x \geq 0 \quad \perp \quad y \geq 0$$

Complementarity means either $x = 0\, and\, y > 0$ or $x > 0\, and\, y = 0$ holds.

L refers to the supply of labour.

K refers to the supply of capital.

(3) Income balance condition

This income balance condition ensures that the consumer spends all income on obtaining utility.

This income balance condition can be represented by:

$$\omega L + \nu K \geq I \quad \perp \quad I \geq 0 \tag{10}$$

Where:

I refers to the income.

In total, there are $2i + 5$ variables, which are $P_i, P_w, Q_i, W, \omega, \nu, I$, and there is an equal number of complementarity equations (Equation 4 to Equation 10). These equations formulate an MCP, and these variables can be solved. In practice, these equations may be more complex, including multiple regions and agents, tax and subsidies, input substitutions, etc., but the three complementarity conditions hold.

We developed a China-based multi-regional recursive dynamic CGE model. The basic structure of this CGE model comprises a production block, a trade block, and a final demand block. Fig. 1 illustrates supply and demand relations among producers and consumers. In the production block, products are produced with two factors (labour and capital) and other intermediates. The output enters the trade block and is divided into export and locally consumed goods. The locally consumed goods partly loop back to the production block as intermediates, and the rest enters the final demand block. The two consumers, namely household and government, receive income from labour wages and capital rents, and expend their income on consumptions and investment. In addition, we introduced two types of taxes in the model structure, both of which are received by the government. The direct tax, also known as the income tax, comes from household. The indirect tax, also known as the output tax, is implemented on the output of production sectors and passed to consumers through price mechanism. All the inputs are nested by constant elasticity of substitution (CES) functions. This model is characterised by disaggregated electricity sector which includes eight power generation technologies (Table S2 in the Supplementary Materials). This model uses existing energy model results [41] on the development of renewable energy generation in the future to base the transition on insights from specialised bottom-up energy models. These features contribute to a more realistic representation and simulation of China's power system. More details on the CES structure and the power sector disaggregation are available in the Supplementary Materials. All monetary values in this model are calculated based on the 2015 price. The CNY/USD exchange rate is 6.23. This model is written in the General Algebraic Modelling System (GAMS) by Mathematical Programming System for General Equilibrium (MPSGE) syntax [42]. It is solved as an MCP by the PATH/MCP solver [43]. This model is solved for the period of 2015-2030 by using one-year interval.

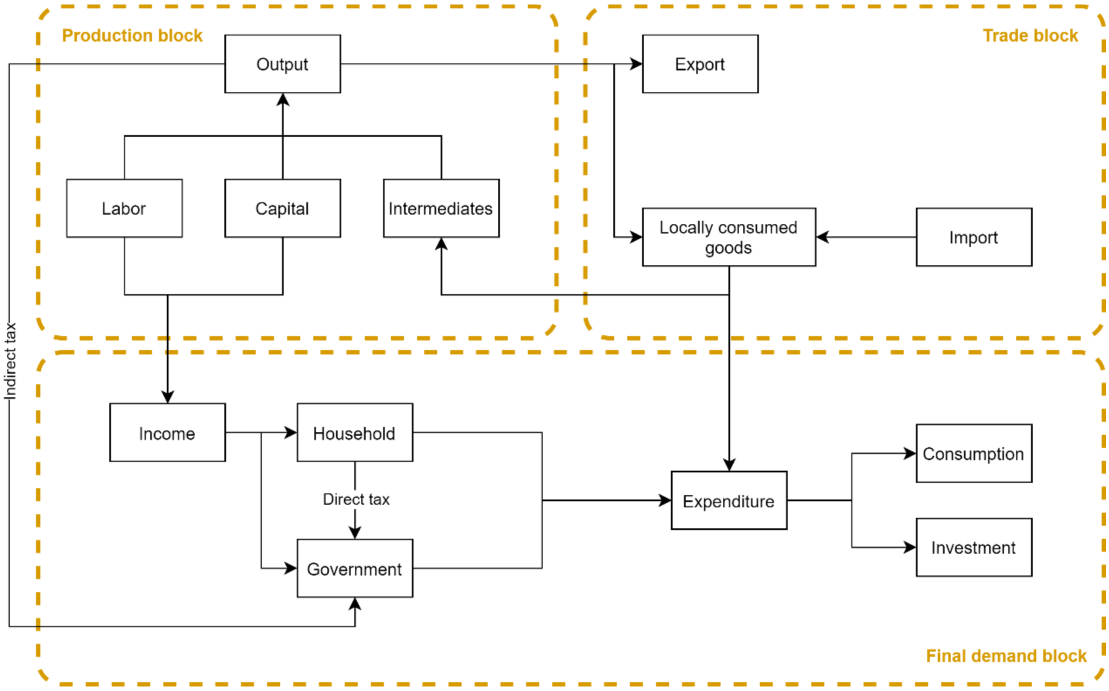

Fig. 1 Basic structure of the CGE model in this study

2.2 Multi-region mechanism

This model covers 30 Chinese provinces and 13 sectors (Table S2, Supplementary Materials). Hong Kong, Macao, Taiwan, and Tibet are not covered due to data unavailability.

Production and consumption are province-specific. The commodities are allowed to be traded both interprovincially and internationally. The interprovincial and international trade follows the Armington assumption [44], which means local and imported goods are assumed to be imperfect substitutes. The substitutions between local and imported goods are subject to CES functions. More details about the CES structure of trade flows are available in the Section 1.1.2 of Supplementary Materials. Labour endowment and capital stock are also provincial-specific, but they are not allowed to transfer across provinces.

In total, there are 30 sets of complementarity equations (Equation 4 to Equation 10). Instead of setting a single and universal objective that maximises the total utility of all provincial consumers in NLP-based CGE models, MCP-based CGE models allow optimisation of multiple provincial consumers, thus equations for all provinces in this CGE model are solved all at once.

2.3 Emissions trading module

Provincial and sectoral carbon emission inventories are derived from the CEADs database [45]. It should be noticed that process emissions are excluded in this study.

As shown in Fig. 2, if a certain sector is covered in the emissions trading, the fossil fuel input will be first combined with carbon permits with an elasticity of zero. A dummy production block is activated to produce the fuel-permit bundle. The scarcity of carbon permits will increase the cost of producing the fuel-permit bundle, creating incentives to reduce the use of fossil fuels. Carbon permits can be freely traded among regions and sectors, consequently minimising the total abatement cost. Given that only coal and gas power are covered in the emissions trading, the nesting of carbon permits (Fig. 2) will only apply to these two technologies.

In this model, the free allocation of permits is realised indirectly by recycling the revenue of permit auction [4]. Specifically, we first assume that a full permit auction is taking place and the revenue of permits auction is collected by the government. Then the revenue is recycled to the sectors depending on which specification is adopted (Equation 11 to Equation 14). The parameter with a bar on top hereafter represents that it is given exogenously.

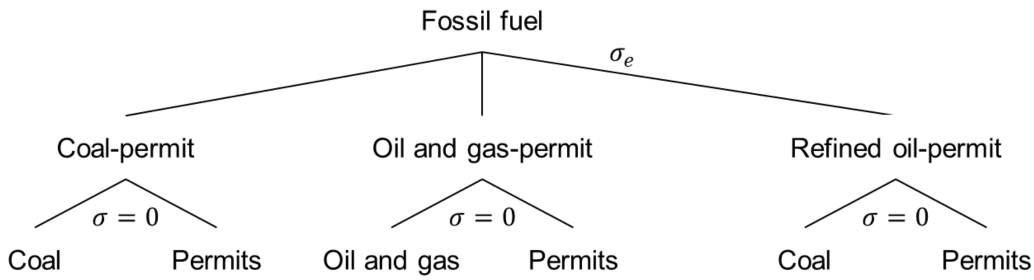

Fig. 2 CES structure of carbon permits

2.3.1 Rate-based specification

Under a rate-based specification, the initial permits are calculated according to the latest National Carbon Emissions Trading Permit Setting and Distribution Implementation Plan 2019-2020 (Power Generation Industry) [3] [47].

[3] There are three different levels of benchmarks for coal power according to the plant type, while we only use the benchmark for "conventional coal power plants above 300MW" due to the lack of data of type-specific generation. This benchmark is the lowest, namely most stringent, among the three levels. The plants in this category account for more than 91% of the total coal power capacity in China in 2015

$$permit_{r,elet} = GEN_{r,elet}^{E} \cdot \overline{BMK_{elet}^{E}} \cdot \overline{Fl_{r,elet}} \cdot \overline{Fr_{r,elet}} \cdot \overline{Ff_{r,elet}} + GEN_{r,elet}^{H} \cdot \overline{BMK_{elet}^{H}} \quad (11)$$

Where:

$GEN_{r,elet}^{E}$ and $GEN_{r,elet}^{H}$ refer to electricity and heat generation in region r from technology $elet$, respectively.

$\overline{BMK_{elet}^{E}}$ and $\overline{BMK_{elet}^{H}}$ refer to benchmarks of electricity and heat generation from technology $elet$ (Table 1). Since the benchmarks are exogenous, thus the initial permit is subject to electricity and heat generation which are both endogenous.

$\overline{Fl_{r,elet}}$ and $\overline{Ff_{r,elet}}$ are cooling correction factor and load correction factor, respectively, which both have a default value of 1. $\overline{Fr_{r,elet}}$ is heat supply correction factor, which can be calculated by the following equations (2) and (3).

$$\overline{Fr_{r,ELE_{col}}} = 1 - 0.22 \times \overline{Q_{r,ELE_{col}}^{H}} \quad (12)$$

$$\overline{Fr_{r,ELE_{gas}}} = 1 - 0.60 \times \overline{Q_{r,ELE_{gas}}^{H}} \quad (13)$$

Where:

$\overline{Q_{r,elet}^{H}}$ refers to the share of energy input that is used to produce heat, which is assumed to be constant during the dynamic process.

Table 1 Benchmarks for coal and gas power generation

	Electricity generation (tCO_2/MWh)	Heat generation (tCO_2/GJ)
Coal power	0.877	0.126
Gas power	0.392	0.059

2.3.2 Mass-based specification

The mass-based cap is determined by carbon emissions from the results of corresponding rate-based scenarios. The initial permits of different provinces and power technologies are calculated according to the share of carbon emissions in the previous year, which is also known as the grandfathering method.

$$permit_{r,elet,t} = \overline{CAP_t} \times \frac{CE_{r,elet,t-1}}{\sum_{r,elet} CE_{r,elet,t-1}} \quad (14)$$

Where:

[46].

$\overline{CAP_t}$ refers to the mass-based cap in year t.

$CE_{r,elet,t}$ refers to the carbon emission of region r from technology $elet$ in year t.

2.4 Scenarios development

Apart from a *Business-as-Usual* (BaU) scenario, we design three *rate-based* emissions trading scenarios with *Low, Medium, High* level of benchmark reduction rates (RB_L, RB_M, and RB_H) and one *mass-based* scenario (MB_M) with the same carbon emission level as RB_M for comparisons. The details of these scenarios are listed in Table 2.

The BaU scenario, namely the baseline, is a reference case where the emissions trading is not activated. Cost reduction of renewable energy is applied in the BaU scenario (Supplementary Materials, Section 1.2), thus the transition to renewable energy will still occur. In addition, the electrification of the economy is considered in the BaU scenario, which is reflected by electricity input substituting fossil fuel energy input in sectoral production. The elasticity between electricity and fossil fuels (σ_{elee}) increases by 2% annually in the BaU scenario so as to depict the existing trend of electrification [48].

Rate-based emissions trading is activated in scenarios RB_L, RB_M, and RB_H. The benchmarks in Table 1 are applied in all three rate-based scenarios in the first year of emissions trading (2020). Afterwards, the benchmarks are designed to have three levels of linear annual reduction rate of 1%, 2%, 3% during the 2020-2030 period, in the RB_L, RB_M, and RB_H scenarios respectively. This formulates an increasingly stringent carbon abatement target. We set these three levels based on the historical trend. The average annual reduction rate of the carbon intensity of coal power in the previous five years was approximately 0.6% [49]. We intentionally designed larger reduction rates in order to avoid carbon constraint becoming insufficient during simulation. To the best of our knowledge, there is only one existing study focusing on the benchmark trajectory design in China's rate-based power-sector-only ETS [18]. Their reduction rate of the benchmark for coal power is 3% from 2020 to 2025, and 6% from 2025 to 2030, which can be roughly converted into a 0.6% and 1.2% annual reduction rate respectively.

The MB_M scenario corresponds to the RB_M scenario. A mass-based cap is applied in the MB_M scenario. The result of national carbon emission in the RB_M scenario is used as the absolute carbon cap in the MB_M scenario. Furthermore, the grandfathering method is applied to allocate the initial permits. Comparisons between the results in the RB_M and MB_M scenarios can reveal the difference between a rate-based method and a mass-based method in emissions trading.

Table 2 Summary of scenarios

Code	TFP	AEEI	ETS	Benchmark/Cap
BaU	4% from 2016 to 2019; 3% from 2020 to 2030.	1% (specific settings in coal power)	None	None
RB_L	Same as BaU	Same as BaU	Rate-based	Benchmark, annual reduction rate of 1%
RB_M	Same as BaU	Same as BaU	Rate-based	Benchmark, annual reduction rate of 2%
RB_H	Same as BaU	Same as BaU	Rate-based	Benchmark, annual reduction rate of 3%
MB_M	Same as BaU	Same as BaU	Mass-based	Carbon cap corresponding to the emission in RB_M

Note: TFP refers to Total Factor Productivity, which is calibrated so that the model can produce a realistic baseline GDP growth in China. AEEI refers to Annual Energy Efficiency Improvement, which has a default value of 1% [29]. A comparison of baseline GDP growth in this study and other China-based models and specific AEEI assumptions for coal power can be found in the Supplementary Materials.

2.5 Data sources

The base year input-output data and energy consumption data are derived from the input-output table and energy inventory of China from CEADs in 2015 [50]. Provincial power generation data are derived from China Electric Power Yearbook [51]. The transfer of payments among the households, the central government, and foreign accounts are derived from the national and provincial Statistical Yearbooks [52], Fiscal Yearbooks [53], Tax Yearbooks [54], and Social Statistical Yearbooks [55]. Provincial and sectoral carbon emission inventories are derived from CEADs database [45].

3 Results

3.1 Baseline results

The baseline simulation results show the normal development trend when the current policy remains unchanged and no further policy is implemented (Business as Usual, BaU). These results serve as the base of the relative changes in the emissions trading scenarios. Main indicators are summarised in Table 3.

Population is exogenously given according to Chen et al. [56]. Its growth slows down overtime, stabilising around 1.44 billion in 2030. GDP will reach 22,397 billion USD in 2030, indicating an average annual GDP growth rate of 4.91% since 2015. As a result, per capita GDP will reach 15.55 kUSD in 2030. Primary energy consumption will experience a steady growth since 2015 and will reach 10.04 tce in 2030, of which 18.18% comes from non-fossil fuels sources. Power generation will increase steadily since 2015 and reach 12196 TWh in 2030, of which 47.06% is from renewable energy. Provincial distributions of power generation from two major renewable sources, namely wind and solar power, are shown in Fig. S7 of Supplementary Materials, which is in line with the geographical distribution of wind and solar endowments in China. Without policy intervention, the total carbon emission will reach 16.74 Gt in 2030. The share of carbon emission from power generation will be 36.68% in 2030.

Coal power will remain to be the dominant electricity source in China in 2030 (Fig. 3). The share of coal power in total power generation will be 46.3%, following by solar (18.7%), wind (17.3%), hydro (8.3%) and other power technologies (9.4%). Both wind power and solar power in the BaU scenario are driven by the existing trend of cost reduction which is exogenously given [57]. With current policies, the total carbon emission will grow quickly, while carbon emission from power generation sector will grow slowly due to renewable energy development, especially from wind and solar power. Provincial distributions of wind and solar power are illustrated in Fig. S7 of the Supplementary materials. On the other hand, carbon intensities of coal and gas power generation will not have significant improvements in the BaU scenario. Also, the national average carbon intensity of gas power will increase in the BaU scenario. Such an increase at the national level is not induced by increases in carbon intensities of gas power at the provincial level. Instead, it is induced by the increases of gas power generations from provinces with relatively higher carbon intensities.

Table 3 Baseline simulation results at the national level (Business as Usual scenario)

	Unit	2015	2020	2025	2030
Population	Billion	1.37	1.41	1.44	1.44
GDP	BillionUSD	10907	14744	18404	22397
Per capita GDP	kUSD	7.98	10.46	12.82	15.55
Primary energy consumption	Billion tce	4.52	6.39	8.15	10.04
Non-fossil fuel share in primary energy consumptions	%	10.80	15.36	17.57	18.18
Power generation	TWh	5736	8009	10048	12196
Renewable energy share in power generation	%	26.75	38.52	44.82	47.06
Carbon emissions	Gt	8.95	11.51	13.91	16.74
Carbon emissions from power generation	Gt	4.19	4.74	5.31	6.14
Carbon intensity of coal power	gCO2/kWh	892	892	886	874
Carbon intensity of gas power	gCO2/kWh	472	477	476	475

Note: Population is exogenously given according to Chen et al. [56] (See Supplementary Materials Section 1.3). The unit tce refers to tonnes of coal equivalent. The unit Gt refers to billion tonnes.

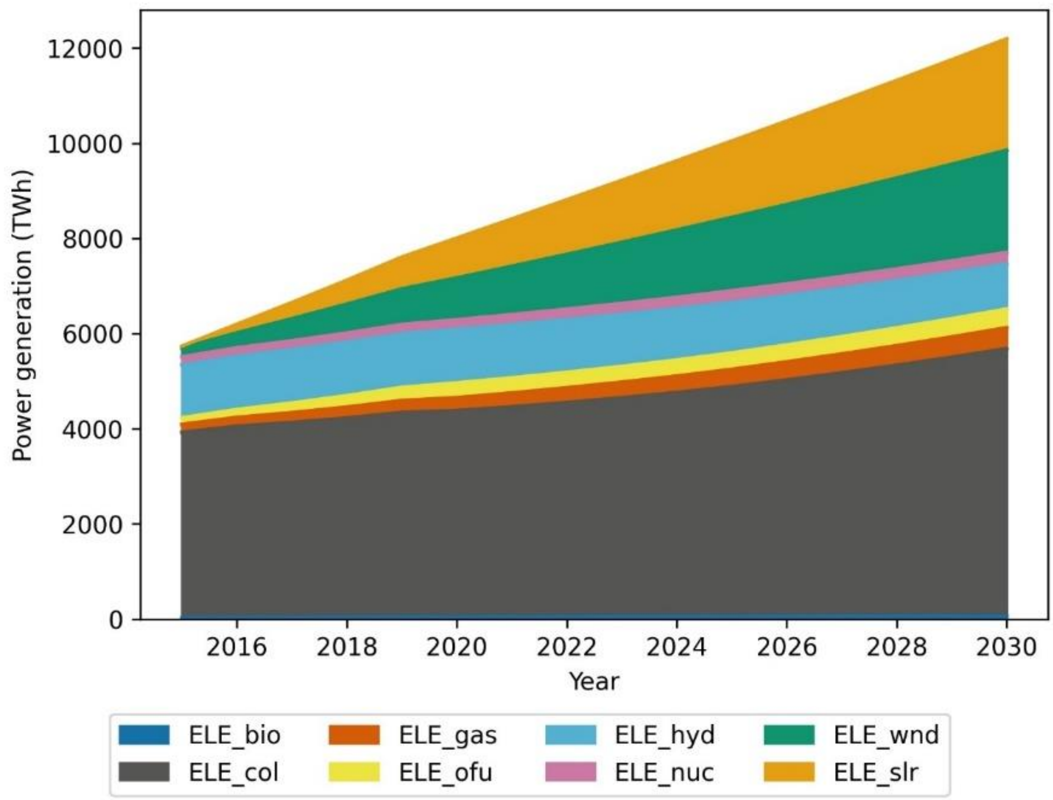

Fig. 3 Power generation in China from 2015 to 2030 in the BaU scenario

Note: The abbreviations in the legend are presented in Table S2 in the Supplementary Materials.

~~3.3~~3.2 Results for ETS scenarios

~~3.3.1~~3.2.1 Energy mix

The total primary energy consumption will increase in all emissions trading scenarios (Fig. 4). The total primary energy consumptions are 0.9%, 1.7%, 3.0% higher in the rate-based scenarios than those in the BaU scenario, respectively. The changes in the mass-based scenario are close to the results in the rate-based scenario. Intuitively, the ETS should have reduced the total energy consumption of the economy because it increases the cost of energy input by adding a price on carbon emissions. There are two reasons for the counterintuitive results in this study.

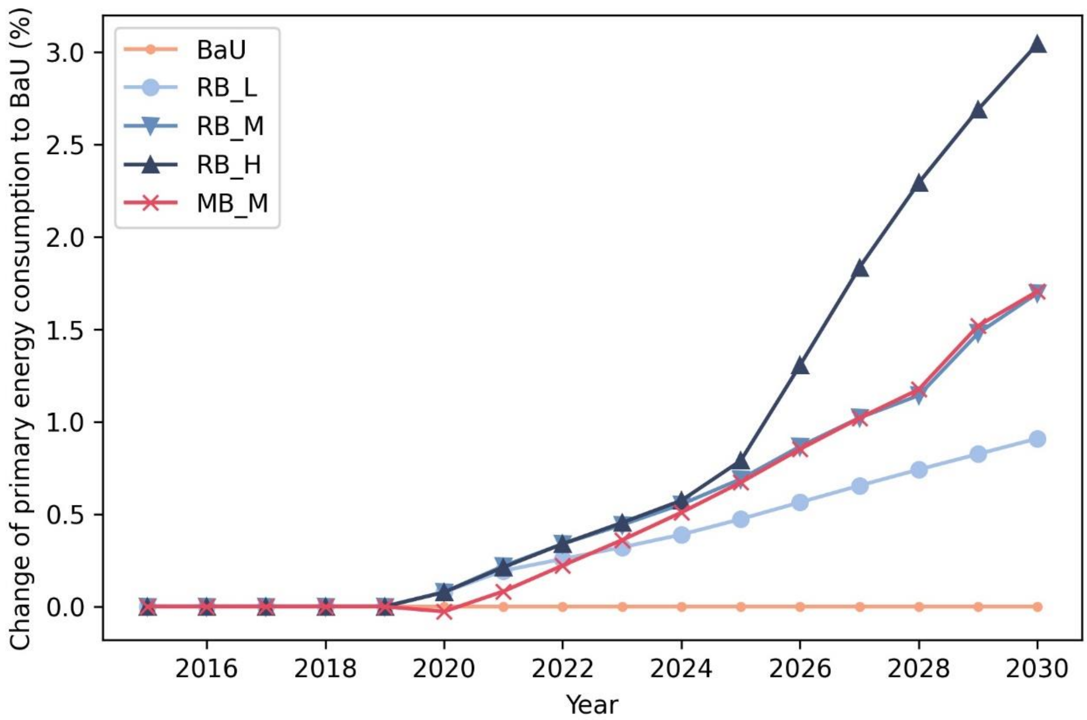

Fig. 4 Changes of primary energy consumption in China

One reason is China's limited coverage of ETS - only coal and gas power more specifically. Since the consumptions of other fossil fuels are not covered, electricity input could be substituted by other fossil fuels which may have lower costs under ETS, such as coal, oil, and gas. This trend can be observed in Fig. 5. All the sectors, except water production and supply sector (WATR), have a notably lower share of electricity input among all the energy inputs. The share of electricity will further decline when the carbon constraints of the emissions trading become stricter. This trend is observed not only in the energy consumptions of the industries, but also in the final demands (FD), namely household energy consumptions. Therefore, China's power-sector-only ETS would incentivise such a trend against electrification.

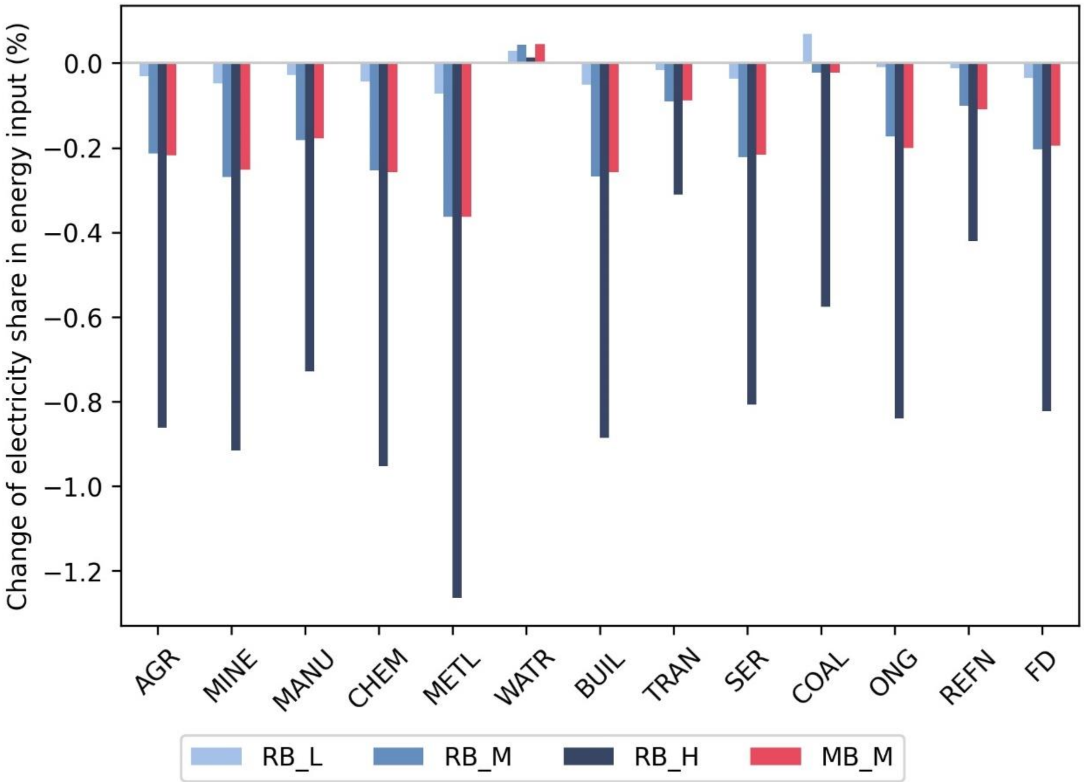

Fig. 5 Share changes of electricity input in China in 2030

Note: The share of electricity input is accounted based on the total energy input of each sector, all converted into tonnes of coal equivalent.

Another reason is the limited development of renewable energy. This can be seen from the shares changes of non-fossil fuels in primary energy consumption (Fig. 6). In the BaU scenario, the main incentive is the continuous cost reduction of renewable energy. The share of non-fossil fuels will be 18% in the BaU scenario in 2030. In contrast, the shares of non-fossil fuels will range from 19.5 to 22.7% in the emissions trading scenarios. This indicates a relatively limited effect of China's ETS on promoting the transition to non-fossil fuels. If China keeps promoting ETS under the current settings – with a limited coverage and a rate-based cap, then China would achieve the Nationally Determined Contribution (NDC) target of the non-fossil fuels share (approximately 20% in 2030), but there is still a noticeable gap to achieve the updated target (25% in 2030) that China announced at the Climate Ambition Summit 2020 [47]. More details about provincial disparities of renewable energy development will be shown with further illustrations in Section 3.3.

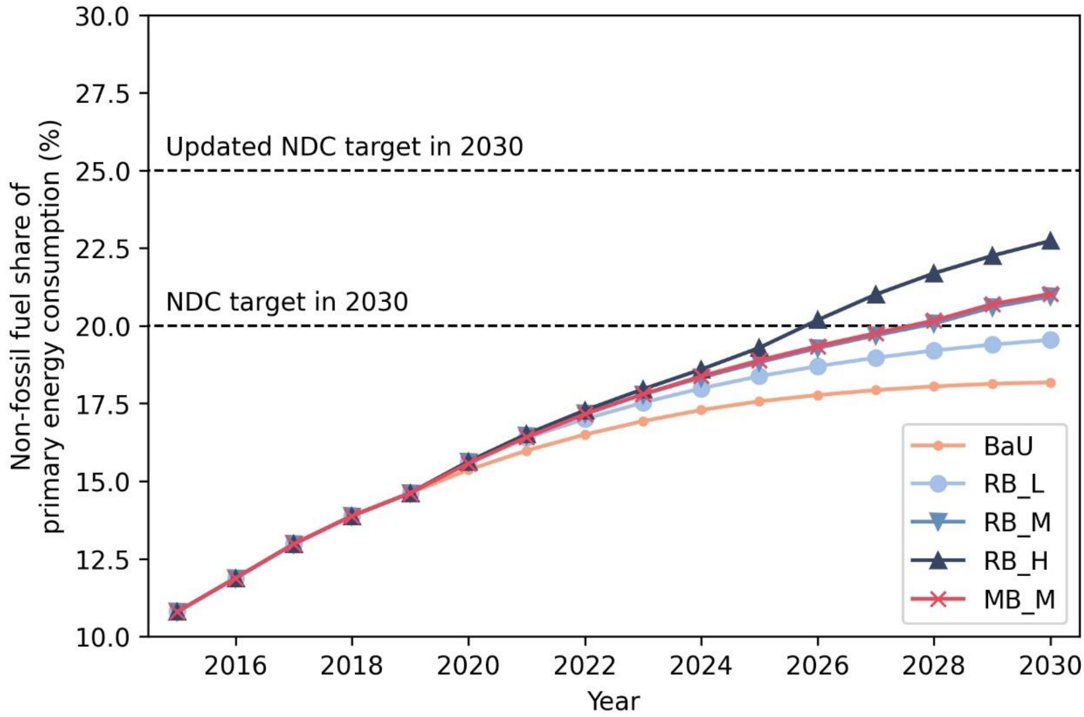

Fig. 6 Non-fossil fuels shares in primary energy consumption

~~3.3.2~~3.2.2 Power mix

Emissions trading leads to significant reductions in coal power generation (Fig. 7) in both rate-based and mase-based scenarios, while the responses of gas power are quite different in these two scenarios. One key feature of China's rate-based emissions trading is that coal and gas power are controlled based on their own benchmarks. Thus, even though gas power plants are generally less carbon intensive than coal power plants, gas power plants are only subject to its own benchmark. This results in a significant power generation loss from gas power in the rate-based scenarios. In RB_M scenario, coal and gas power generation will decrease by 1174 TWh and 191 TWh in 2030, respectively. In contrast, the generation from coal power plants in the MB_M scenario have a larger reduction (1368 TWh), while the gas power slightly declines (7 TWh). This indicates that China's current benchmarks would be stricter for the gas power than that for the coal power.

The benchmark method in a rate-based ETS also leads to the result that reducing production does not alleviate the burden of carbon abatement because less production leads to less carbon permits allocated to this sector. The only way is to improve energy efficiency so that less permits are needed per unit of production. Fig. 7 shows that rate-based emissions trading improves carbon intensity of coal and gas power significantly. The national average carbon intensity of coal power will decrease by 19.1% in 2030 in the RB_M scenario. A more significant reduction will be achieved in the gas power (37.6%).

This indicates a strong incentive for phasing out inefficient coal and gas power plants and transferring to more advanced and efficient ones in China's future power system. In comparison, conventional mass-based emissions trading leads to less carbon intensity improvement in both coal and gas power plants (this can be seen in the MB_M scenario in Fig. 7). The carbon intensity reductions of coal and gas power in the MB_M scenario will be 19.0% and 21.4%, respectively.

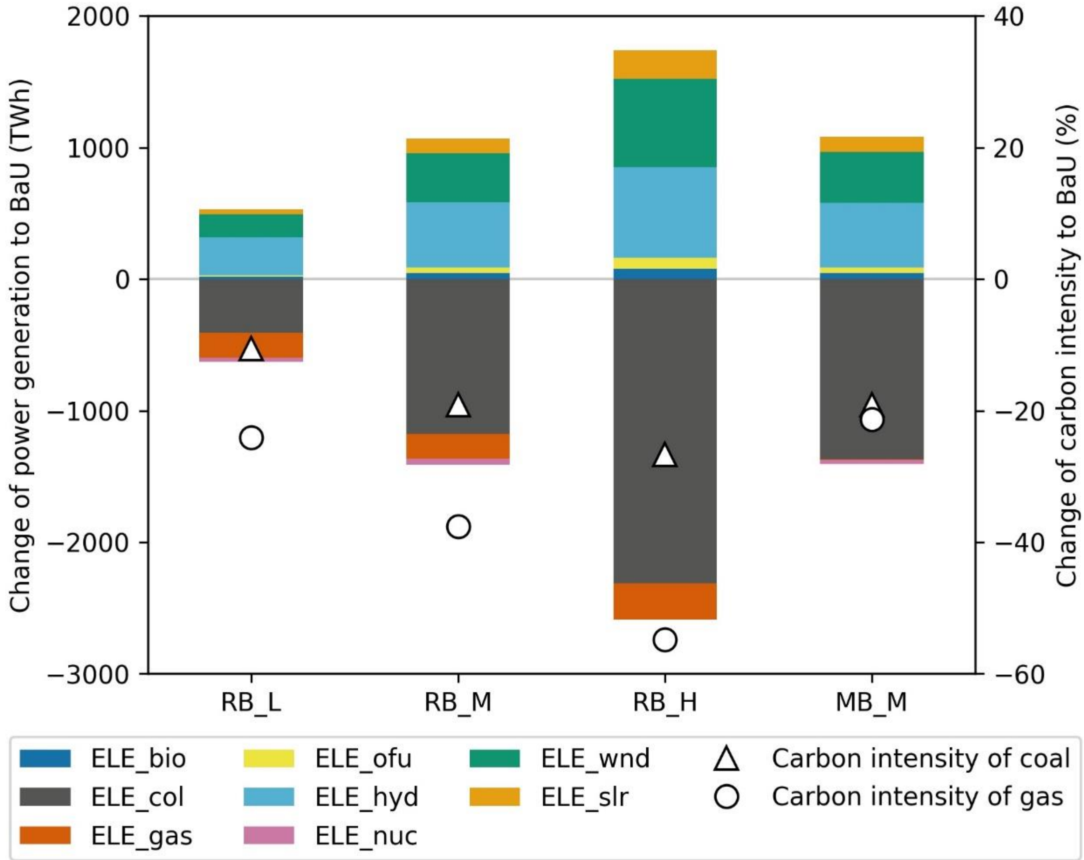

Fig. 7 Comparisons of power generation and carbon intensity changes between different scenarios in 2030

Note: The abbreviations in the legend are presented in Table S2 in the Supplementary Materials.

Renewable energy cannot fully fill– power generation gap from the reduction of coal and gas power. The shortage in renewable energy can be attributed to similar reasons for the increase in primary energy consumption (Fig. 4), which are the limited ETS coverage in power sector and the limited incentive from ETS. Furthermore, the transition from coal and gas power to renewable energy will experience significant regional disparities (Fig. S8 in Supplementary materials). The emissions trading will facilitate the phaseout of coal power in most provinces, especially in Hubei (R17), Sichuan (R23), and Yunnan (R26). However, Shanghai (R09), Zhejiang (R11), Guangdong (R19) will experience noticeable growth in coal power generation, which will substitute other fuels and renewable energy in the power mix. The main reason is that coal power generation in east Chinese provinces is generally more advanced [58], leading to lower carbon intensities. In a rate-based ETS, each unit of power generation from a plant having a carbon intensity below the benchmark will receive more free permits than it actually needs – end up being subsidised. Consequently, the growth of coal power restricts power generation from other technologies in those provinces. An obvious example is the reduction in nuclear power. Guangdong (R19) and Zhejiang (R11) will have reductions of 46 TWh and 16 TWh in the RB_M scenario compared with the BaU scenario, which contribute to a total reduction of 44 TWh of nuclear power generation at national level (Fig. 7).

Compared with the significant changes in provincial power mix, the electricity balance, namely the trade of electricity, seems to be less affected by the emissions trading. The electricity balances are calculated based on the difference between provincial electricity production and consumption, and are then aggregated at the grid levels. Positive values represent the surplus of electricity generation (export), while negative values represent the deficit of electricity generation (import). As shown in Fig. 8 (provincial results are illustrated in Fig. S9 of the Supplementary Materials), the southwest and northwest grids are the two main electricity exporters, while the north grid is the main electricity importer. A general trend across these grids is that emissions trading can reduce electricity transfer. Both north and east grids increase their total power generation in the RB_M and MB_M scenarios, leading to less electricity import. The reduction of electricity import will mainly come from Beijing and Tianjin (North grid), Zhejiang and Shanghai (East grid). In contrast, both central and southwest grids will reduce their total power generation, thus having lower electricity exports. The reduction of electricity export will mainly come from Sichuan (Central grid) and Yunnan (Southwest grid), which is related to the significant reduction of coal power (Fig. S8 of the Supplementary Materials).

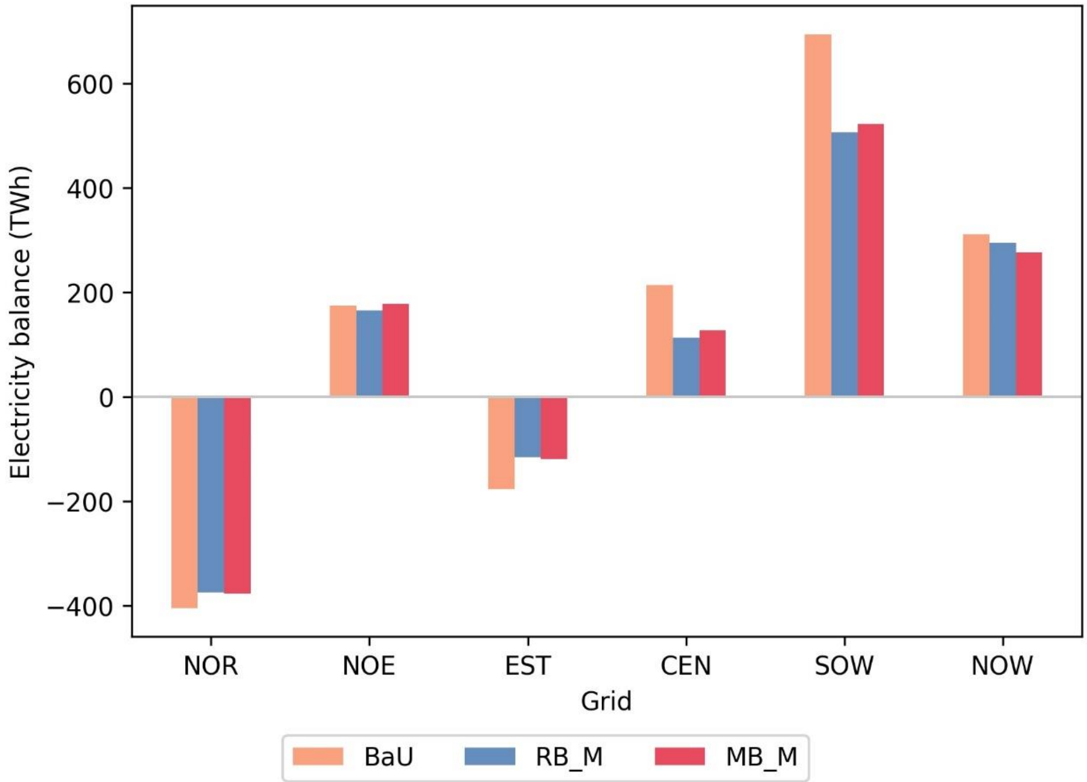

Fig. 8 Grid electricity balances in China in 2030

Note: A positive value represents the surplus of electricity generation, while a negative value represents the deficit of electricity generation.

The electricity prices will increase in most Chinese provinces in both rate-based and mass-based scenarios in 2030 (Fig. 9). The emissions trading system puts a price on carbon, thus increasing the cost of fossil fuels to generate electricity. Those provinces with the largest electricity price increases are the same provinces that are previously identified having larger generation losses in coal power, such as Hubei (R17), Sichuan (R23), and Yunnan (R26). In contrast, Shanghai (R09), Zhejiang (R11), Guangdong (R19), which are found to have advantages in coal power generation, will experience electricity price decreases compared with BaU.

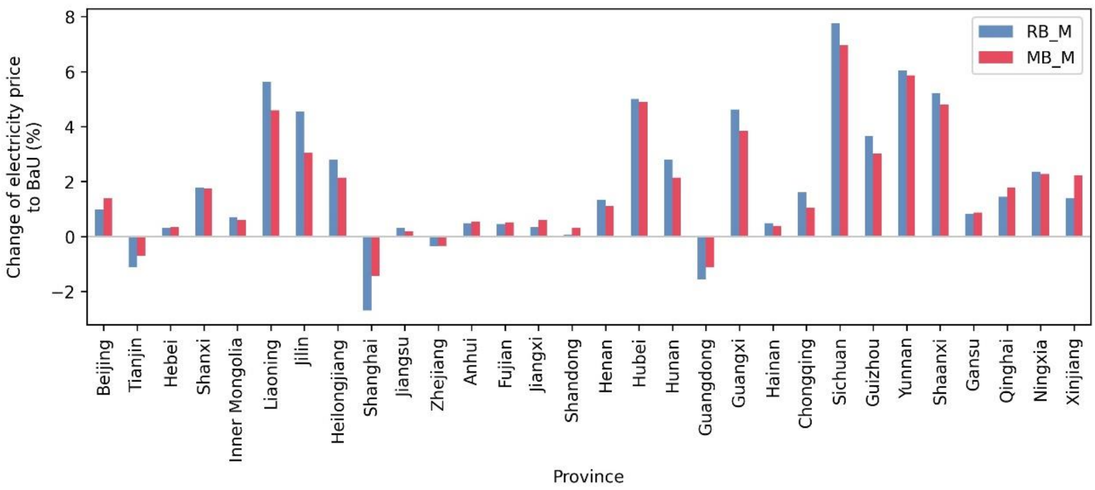

Fig. 9 Changes of provincial electricity price in 2030

~~3.3.3~~3.2.3 Carbon emissions and emissions trading

Fig. 10 shows that carbon emission reduction from power sector is significant. The three different benchmarks will lead to emission reductions of 19.0%, 38.5%, and 59.2% in 2030 compared with BaU, respectively. The mechanism of carbon reduction under a rate-based ETS is different from a mass-based ETS where all participants face the same and direct incentives of reducing their carbon emissions. The free permit allocation in a rate-based ETS would be a production subsidy. Thus, concerns may rise upon whether enough incentives of decarbonisation can be generated. However, sectors/technologies with lower carbon intensities will have clear advantages in comparison to others in the ETS. If more production is carried out by less carbon-intensive sectors/technologies, then more emissions can be reduced.

The carbon price shows a high sensitivity to the changes of benchmarks. The carbon price is relatively low in 2020, which is the first year of ETS. However, this carbon price will rise rapidly overtime. Taking RB_M as a representative scenario, such a carbon price will rise from 1.6 USD/tCO_2 in 2020 to 30.6 USD/tCO_2 in 2030. In the most stringent scenario RB_H, the annual reduction rate of the benchmark is 1% higher than that in RB_M, while the carbon price will be 127.5 USD/tCO_2 – four times compared with RB_M in 2030. For scenarios RB_M and MB_M, the carbon prices are similar. Since carbon emission in RB_M is the same as the one in MB_M, the main factor affecting carbon prices is the different allocation of initial permits.

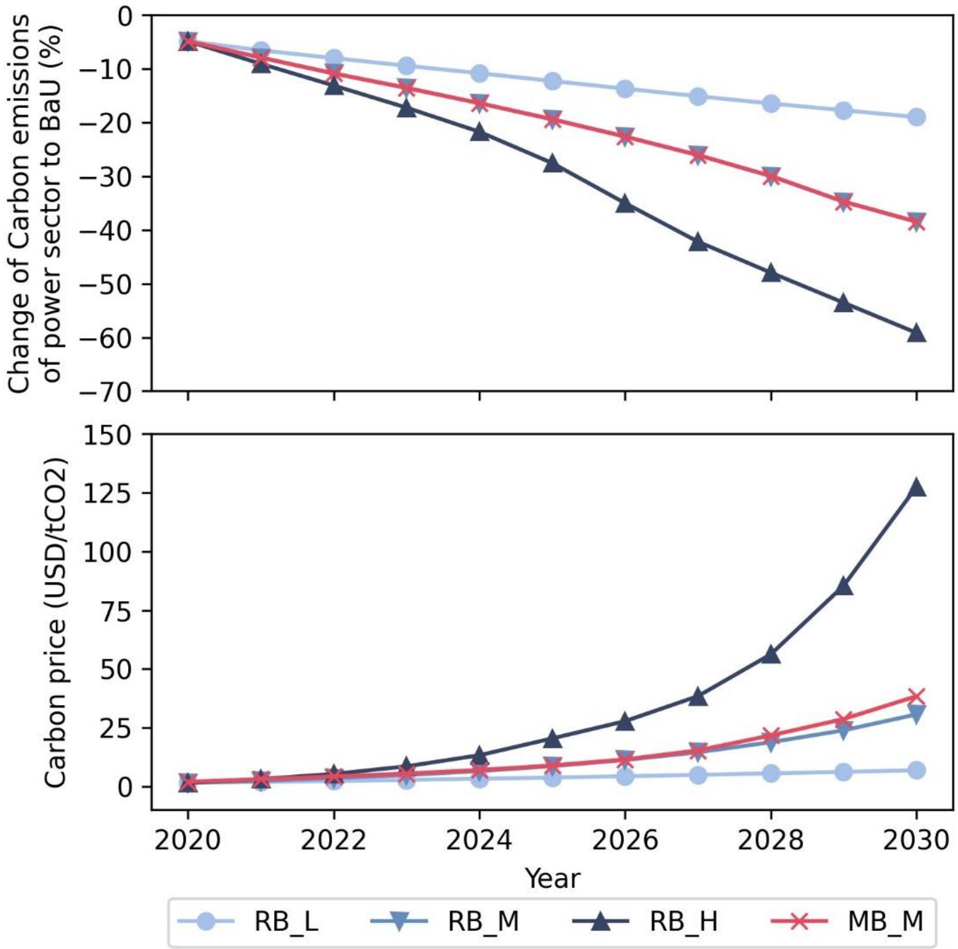

Fig. 10. Changes of carbon emission from power sector and carbon price

Note: The MB_M scenario uses the emission trajectory of the RB_M scenario as the carbon cap.

The results of permit trading show that those east and northwest provinces would have permit surplus, while those central provinces would have permit deficits (Fig. 11). By comparing rate-based ETS and mass-based ETS, the choice between buying and selling permits remains the same in most provinces. However, a rate-based ETS has a smaller market scale than a mass-based ETS (155 Mt in the RB_M scenario and 113 Mt in the MB_M scenario). Guangdong (R19), Shanghai (R09), Shandong (R15) are the top permit sellers, while Liaoning (R06), Inner Mongolia (R05), Guangxi (R20) are the top permit buyers. The permit buyers are mainly located in east China, where they have increasing coal power generations (Fig. S8) and relatively lower electricity prices (Fig. 9) in the emissions trading scenarios.

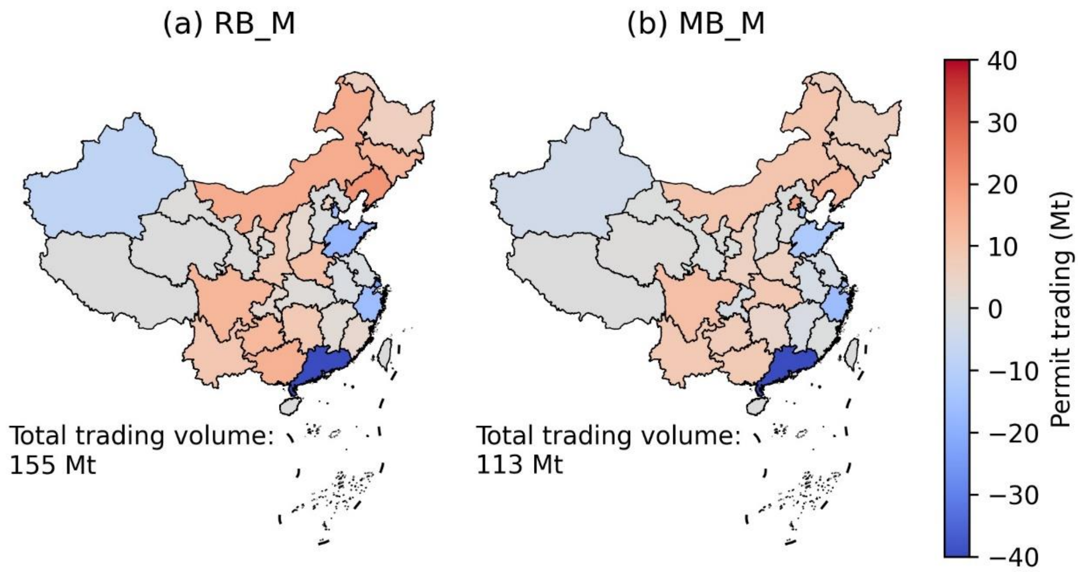

Fig. 11 Permits trade in China in 2030

Note: A positive value represents buying permits. A negative value represents selling permits.

Provincial carbon emission changes can be decomposed into changes in power generations and changes in carbon intensities. Fig. 12 shows the changes of these two indicators in coal power generation. Each bubble represents one provincial result. The bubble size represents the change in the provincial carbon emission (Mt) compared with BaU. More than 90% of carbon emission reduction from this power sector comes from coal power in our simulation (RB_M scenario), thus we focus on the coal power when analysing these indicators. The results show that provinces having larger generation reductions tend to have larger carbon emission reductions, while provinces having power generation increases tend to have carbon emission increases. In both rate-based and mass-based scenarios, the top three provinces having carbon emission reductions are Yunnan, Sichuan, Hubei, while the top three provinces having carbon emission increases are Guangdong, Zhejiang, Shanghai. In contrast, the changes in carbon intensity have great regional disparities, but they do not seem to have a close relation with the change in carbon emission reduction. These results indicate that carbon emission reductions in the power sector are mainly driven by power generation reductions.

~~3.3.4~~3.2.4 GDP and welfare

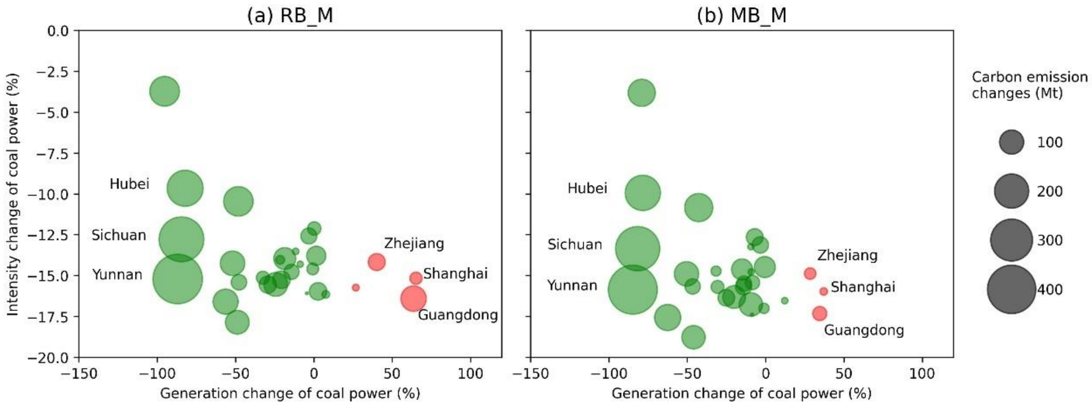

Fig. 12 Provincial change in generation vs. change in intensity of coal power in 2030

Note: Each bubble represents one provincial result. One bubble size represents the change in the provincial carbon emissions of coal power (Mt) compared with BaU. Bubbles in green refer to emission reductions. Bubbles in red refer to emission increases.

At the national level, emissions trading in the power sector leads to notable GDP losses (Fig. 13). In 2030, the GDP loss rates in the RB_L, RB_M, RB_H scenarios will be 0.03%, 0.12%, and 0.40%, respectively. GDP loss rate in the MB_M scenario will be 0.11% in 2030, which is slightly lower than the one in the RB_M scenario. The welfare in this study is defined as the household income (the sum of consumption and investment). The results of welfare change have a similar trend as GDP. In 2030, the welfare loss rates in the RB_L, RB_M, RB_H scenarios will be 0.03%, 0.13%, and 0.42%, respectively. The welfare loss rate in the MB_M scenario will be 0.11% in 2030. As the medium carbon constraint scenarios (RB_M and MB_M) share exactly the same total carbon emission, such results indicate that a mass-based ETS results in higher economic efficiency than a rate-based ETS.

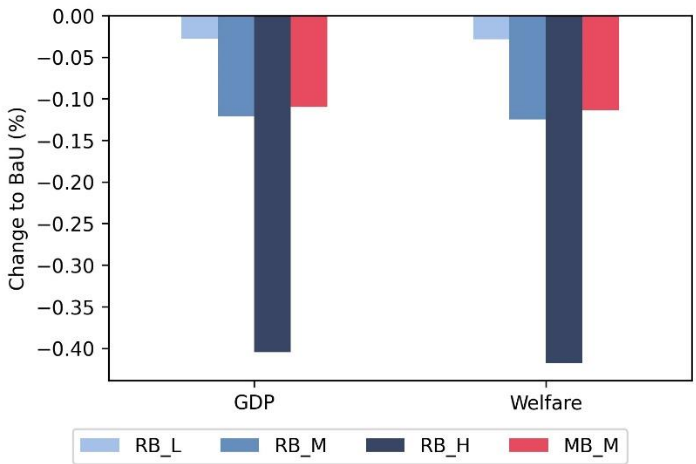

Fig. 13 Changes in GDP and welfare in China in 2030

Note: Welfare is defined as the income of the household, which equals the sum of consumption and investment.

At the provincial level, most provinces experience notable GDP losses (Fig. 14). Provincial GDP changes range from -0.30% to 0.06%. The GDP losses in the RB_M scenario are generally larger than those in the MB_M scenario., Tianjin, Shandong, Qinghai. Hubei, Shaanxi, Sichuan, Yunnan, Guangxi will exprience more GDP losses than other provinces. Moreover, the GDP of Beijing, Fujian, and Gansu seem to be hardly affected by the emissions trading.

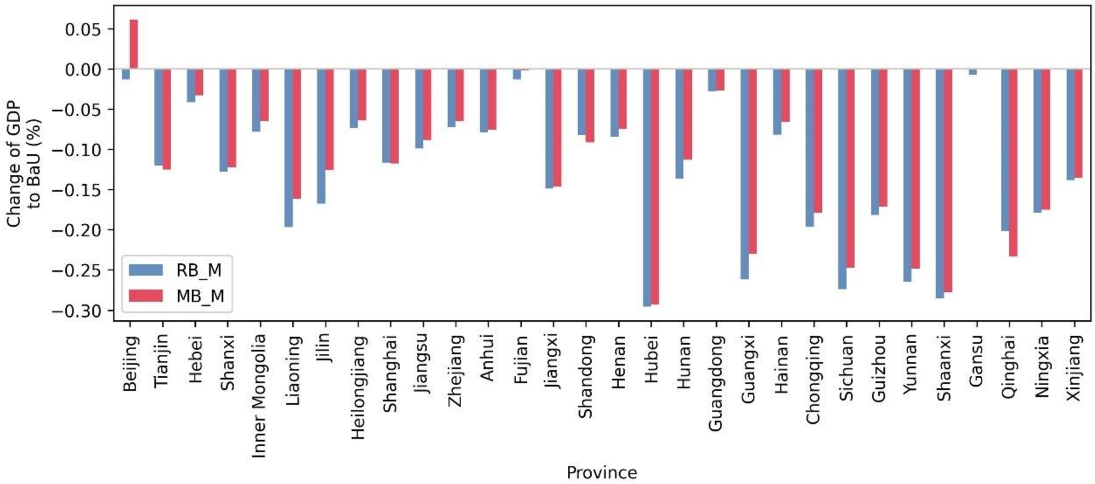

Fig. 14 Provincial GDP changes compared with BaU in China in 2030.

GDP changes can be attributed to the changes in consumption, investment, and net export. The decomposition results of these factors are illustrated in Fig. S10 (Supplementary Materials). These results show that the consumption loss is the main driving factor of GDP losses in most provinces. Hubei, Sichuan, Liaoning will have the largest consumption losses, with figures of 2.6, 2.4, and 2.1 billion USD (RB_M scenario), respectively. These provinces are also identified with more coal power generation losses (Fig. S8) and increasing electricity prices (Fig. 9).

We further analyse the co-relations between provincial consumption losses and other three possible driving factors through linear regression (Fig. 15). First, provincial renewable energy shares do not have strong relations with consumption losses (Fig. 15 (a)). Provinces with higher renewable energy shares would still face more consumption losses, leading to corresponding more GDP losses. Second, coal phaseout has a noticeable relation with provincial consumption losses (Fig. 15 (b)). The reduction of provincial coal power generation can explain 38% of the consumption changes. Provinces that have more coal power generation losses would have more consumption losses as well. Third, permit scarcity is another important factor affecting provincial consumptions. Fig. 15 (c) shows the relations between permit trading and consumption losses. Permit trading behaviours can explain 47% of the consumption changes. Therefore, those provinces having permit shortages would experience more consumption losses, leading to corresponding more welfare and GDP losses.

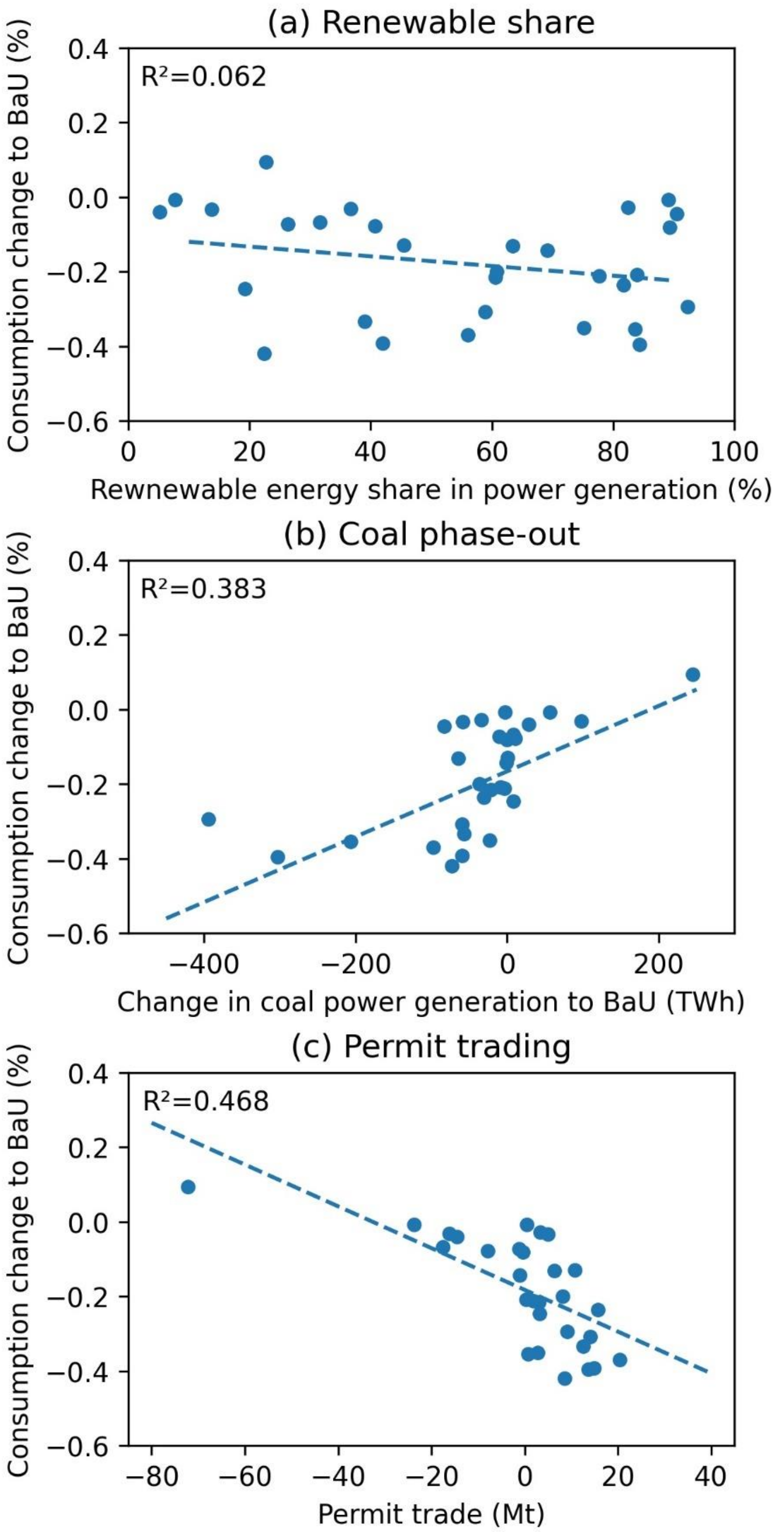

Fig. 15 Influencing factors of provincial consumption changes in RB_M

scenario in 2030. The y-axis refers to provincial consumption changes compared with the BaU scenario. The x-axis refers to (a) renewable energy share in total power generation, (b) change in coal power generation, (c) permits trade (a positive value refers to buying permits, a negative value refers to selling permits). The dashed line refers to the results of linear regression.

4 Discussion

4.1 Interpretation of research results

One feature of this model is that it considers the trend of cost reduction in renewable energy. This means that promoting renewable energy already has been considered in the BaU scenario, which should be taken into consideration when interpreting research results. Specifically, the growth of renewable energy in the BaU scenario is regarded to be faster than other studies, leading to a smaller difference between the emissions trading scenarios and the BaU scenario. For example, Lin et al. [32] applied a recursive dynamic CGE model to study the effect of China's emission trading on promoting renewable energy, in which they estimated that the annual growth rate of total renewable energy will be 3.83% and 8.28% in the reference and emissions trading scenarios from 2017 to 2030 respectively, while such an annual growth rate will be 6.42% and 7.91% from 2020 to 2030 in the similar scenarios of our study (BaU and RB_M).

This study compares the impacts between a rate-based cap and a mass-based cap. The results show that a rate-based cap can achieve significant carbon reduction at the national level. However, the GDP loss in the scenario with a rate-based cap is slightly higher. These differences are mainly due to different allocation methods of initial permits. Theoretically, a rate-based cap can lead to an identical result as a mass-based cap, but China is going to apply multiple benchmarks for coal and gas power when allocating initial permits – even for coal power plants with different technologies and capacities. Power plants in different categories are therefore competing unevenly although there is only one universal permit market. Our results indicate that the multiple benchmarks in China would be stricter with gas power than coal power, which would lead to gradual phaseout of coal power. This would be preferable especially considering the key role of coal power in China's current power mix. Gradual phaseout of coal power would facilitate China's economy to better adapt to the new situations, such as alleviating the impacts of stranded assets and job losses [59]. Furthermore, a rate-based system would be preferable in the short term in China's climate mitigation. China, as a developing country, has been framing its climate goals in intensity terms, such as its NDC. The benchmarks in a rate-based system can better coordinate sectoral climate targets with national climate targets. From a long-term perspective, China has pledged to achieve carbon neutrality by 2060, which is an absolute target. This rate-based ETS might be switched to a mass-based one at a certain point, such as a carbon emission peak, to cooperate with the national development strategy [60].

Nevertheless, policy makers should still be careful because a stringent benchmark would lead to a sharp phaseout of fossil fuels power in certain provinces, such as coal power in Hubei, Sichuan, and Yunnan, where GDP and welfare would be lost. As a characteristic of the benchmark method, if the carbon intensity of one power plant is higher than the benchmark, reducing production will not help permit compliance at all. A more stringent benchmark will have its impact on a power generation technology, turning from a subsidy to a tax at a certain point and leading to a sharp drop of power generation from that power plant. Although such a sharp phaseout may not occur in the reality, it indicates a potential risk of increasing stringencies at the provincial level. Furthermore, if free allocation in China's current ETS is replaced by auction, it might also increase the stringency of the policy, consequently increasing energy prices and leading to more GDP and welfare losses.

Provinces with higher shares of renewable energy would not necessarily benefit in the emissions trading market (e.g. Sichuan and Yunnan). They could still suffer from considerable economic losses, which is more closely related to coal phaseout and permit scarcity. However, developing renewable energy is still necessary in these provinces because ETS would accelerate coal phaseout in these provinces and thus create large power generation gaps. Policy makers should make sure that local renewable energy capacity can fill such a generation gap. In addition, improving local power grid capacity and importing clean electricity from other provinces would also help coal phaseout [61] although this exceeds the capability of this model.

Another factor limiting renewable energy development is the limited coverage of ETS. The ability to switch to other fossil fuels instead of electricity would weaken the advantage of having a higher share of renewable energy in their power system. This would lead to an opposite trend of electrification, which has been considered a key step in climate mitigation and has a considerable potential of air quality and human health co-benefits [62]. More broadly, although air quality and human health co-benefits of ETS are not considered in this study, substantial co-benefits can be achieved with the implementation of ETS [63]. For instance, carbon permits trade could lead to less air pollutants emissions at regional level, as well as improved health benefits [64].

4.2 Policy recommendations

The nationwide ETS will be a major policy instrument for China to achieve carbon peak by 2030 and carbon neutrality by 2060. The following policy recommendations are proposed by considering the Chinese realities.

First, promoting renewable energy development is critical. ETS would bring a significant generation gap due to the phaseout of coal and gas power. Earlier deployment of renewable energy infrastructure would help speed up the expansion of such capacity. Both national and local governments should prepare appropriate policies to encourage more enterprises to engage in renewable energy fields, such as financial subsidies, preferable tax rates, research & development support, and capacity building efforts. Power generation enterprises should take a leading role to promote renewable energy deployment, while financial enterprises should facilitate their actions through green finance.

Second, it is crucial to expand the coverage of ETS, especially to cover fossil fuels use in those carbon intensive industries so as to prevent the opposite trend of electrification and carbon leakage. Such an economic instrument can provide incentives to those energy intensive enterprises so that they can actively engage in energy saving and emission reduction efforts.

Third, provincial governments should initiate their efforts to engage in ETS. On one hand, supportive policies should be made in those provinces with higher risks of a sharp phaseout in coal and gas power (Hubei, Sichuan, Yunnan). Their policy makers should restrict the construction of new coal and gas power plants. Also, they should prepare their plans on retiring their conventional coal and gas power plants so that these companies can respond such a transition request asap [65]. On the other hand, those provinces with lower carbon intensities (Shanghai, Guangdong, Zhejiang) should not delay to phase out their coal and gas power plants since they will receive carbon permits as a subsidy that encourages the development of coal and gas power. Their policy makers should be aware of the risk of such a delay and actively engage in developing renewable and clean energy so that national carbon neutrality target will be achieved in due time.

4.3 Limitations

One limitation of this study is the lack of available data, including data of provincial carbon intensities from coal and gas power generators, data of generators with different capacities, etc. We applied aggregations and estimations to solve these issues although more accurate simulations can be conducted with more real data.

Another limitation is a methodological issue. This CGE model was built based on various assumptions. Elasticities of substitution between key inputs are particularly important and would influence research results. The disaggregation of power generation sector is a simple reflection of current power system, which could lead to deviations when simulating energy system transition. This can be improved by linking it with bottom-up energy models, because bottom-up energy models have advantages in depicting different cost structures and emission intensities of power generation units that have different scales and technologies.

Furthermore, this study did not consider China's state-controlled electricity price and power market reform [66,67]. These factors would hinder price pass-through mechanism from power generation industries to those power consumers, thus reducing the effectiveness of ETS.

5 Conclusions

This study developed a multi-regional recursive dynamic CGE model which considers disaggregated power generation technologies. This model was applied to evaluate the impacts of a rate-based emissions trading system (ETS) with the benchmark method in the power sector in China. The main findings are concluded as follows.

1) There would be a notable gap to reach the non-fossil fuels share target described in China's NDC pledge if the limited emissions trading coverage continues until 2030. Such results also indicate a noticeable fallback in electrification in most industrial sectors as well as final consumption, which may be attributed to the limited coverage and the limited incentive of emissions trading markets.

2) The total power generation from two power generation technologies covered by China's ETS, namely coal and gas power, will be reduced. However, renewable energy cannot fully fill this generation gap. In addition, carbon intensities of both coal and gas power will be significantly improved.

3) ETS has a significant effect on decarbonising the entire power system. The main driving factor of provincial carbon reduction is reduced power generation (mainly from coal power), while the reduction of carbon intensity only plays a limited role.

4) The estimated GDP loss from a rate-based ETS is slightly higher than the one from a conventional mass-based cap-and-trade scheme. From a provincial perspective, a higher renewable share in the power system does not result in less GDP loss. Coal power phaseout and permit scarcity are the two main factors leading to provincial consumption loss, which further contribute to provincial GDP loss.

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