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What will China's carbon emission trading market affect with only electricity sector involvement? A CGE based study

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ABSTRACT

On December 29, 2017, China's Carbon Trading Scheme (ETS) was officially launched, and it may be the largest emission trading platform in the world. This paper establishes 5 counter-measured scenarios based on the recently launched China's national ETS market and constructs a dynamic recursive Computable General Equilibrium model to study the impact of national ETS on the economy, energy, and environment. We find that the national ETS will have a negative impact on GDP by 0.19%–1.44%. The national ETS can significantly increase the price of electricity, however, the increase in the prices of other commodities will be much lower than that of electricity. As long as the mechanism of the ETS market remains unchanged, emission reduction per year will increase linearly. Economic output and CO_2 emission are sensitive to Annual Decline factor (ADF). This paper argues that China's national ETS market is an effective tool to reduce CO_2 emission, and we suggest that ADF could be 0.5% when allocating carbon allowance for the electricity sector. This could balance economic output and CO_2 reduction. Also, it is easy to achieve the goal of "double control" (total amount and intensity) in China.

1. Introduction

Energy shortage, environmental degradation, and global warming have become global issues since the industrial revolution, and greenhouse gas (GHG) emissions are the major cause. There is a strong correlation between carbon dioxide (CO_2) emission and other GHG emissions. Many scholars have made several efforts to solve the problem of global warming (Lin and Chen, 2018; Li and Jia, 2017a). They have been working on measures for sustainable development (Ang and Goh, 2016; Lin and Wu, 2018). The studies mainly focus on two aspects: the low-carbon economy and low carbon technology. For the former, carbon tax (CT) (Zhang et al., 2016; Li and Jia, 2017b), forest carbon sinks (Song et al., 2018; Gren et al., 2012), green electricity certificate trading system (Bunn and Yusupov, 2015; Suo et al., 2017) and clean development mechanism (Koo, 2017; Chen et al., 2017) (especially Emission Trading Scheme (ETS) (Liu et al., 2016a, 2016b; Z. Liu et al., 2016; Creti and Joets, 2017; Viskovic et al., 2017; Liu et al., 2016a, 2016b)) are the current feasible policies to reduce emissions. For the latter, smart grid, grid energy storage (Zetterberg, 2014; Kapsali and Anagnostopoulos, 2017), electric vehicle (Wang et al., 2018; DeForest et al., 2018), new power generation technologies (Shrivastava and Prabu, 2016) and carbon capture and storage (Ha-Duong and Nguyen-Trinh, 2017; Viskovic et al., 2014) are now relatively key technologies for emissions reduction. With respect to the low-carbon economy, forest carbon sinks require higher land use, and the maintenance costs are highest. Most researchers argue that carbon tax may be a rough mean to reduce CO_2 emission with lower reduction efficiency, which means if the emission reductions are the same, the loss of Gross Domestic Product (GDP) may be higher than in ETS (Bruvoll and Larsen, 2004; Qian et al., 2017).

The National Development and Reform Commission (NDRC) of China issued *Construction Program of National Carbon Emissions Trading Market* (*Power Generation Industry*) (NDRC, 2017) (Hereinafter referred to as *Construction Program*) on December 18, 2017, indicating that national ETS market had been formally established in China. Therefore, studying the issue of carbon trading in China is critical for the country's efforts to achieve emission reduction and sustainable development.

There are many studies with respect to the construction, impact mechanism, and efficiency evaluation of the carbon emissions trading market. Oh et al. (2017) described the background for design characteristics of emissions trading schemes (ETS) in developing and emerging economies, with a particular focus on Korea. Wang and Zhou (2017) theoretically investigates how emission permit allocation affects CO_2 cost pass-through rate and found that the magnitude of CO_2 cost pass-through rate is relevant to the type of definition, product market structure and average carbon intensity of the industry. Zhu et al. (2017) predicted carbon prices using empirical model decomposition and evolutionary least-squares support vector regression. Perino and Willner (2017) used an analytically tractable simulation model of the EU-ETS to project the proposals' impacts on allowance price paths, and the number of allowances reserved for future use. They found that all three proposals have virtually the same impact on allowances

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prices during Phase IV. Koch et al. (2014) explored the reasons for the declining carbon price in EU-ETS and found that the changes in economic activity and the growth of wind power and solar electricity production greatly affect the carbon trading price. Mehling and Haites (2009) analyzed the mechanisms for linking emissions trading schemes. Liu et al. (2015) introduced and analyzed the status of China's carbon trading market in the international market, examined the Chinese government's drive to start the carbon market, and traced the development of mandatory carbon emissions trading and voluntary emission reduction trading.

Carbon price (or ETS price) in ETS markets is also a well-researched topic. For instance, Tang et al. (2017) compared and analyzed the factors of carbon price volatility of the EUA and sCER. This study argued that carbon price volatility is mainly affected by the market mechanism and the external environment. Fan et al. (2017) studied what policy adjustments in the EU-ETS will truly affect carbon prices. Zhang et al. (2016) investigated the impacts of different factors on ETS prices. Pradhan et al. (2017) estimated the GHG emissions from the agriculture, forestry and other land use sectors in Nepal and identifies the economically attractive countermeasures to abate GHG emissions from the sectors at different carbon prices. Tu and Mo (2017) explored the interaction between carbon pricing and renewable electricity subsidies. Rooney and Paul (2017) assessed policy and carbon price settings for incentivizing reforestation activities in a carbon market in Australia. Egli and Lecuyer (2017) quantified the net cost of a carbon price floor in Germany, and find that with the 40(sic)/tCO_2 carbon price floor, median prices increase by 37(sic)/MWh and average price peaks by 50(sic)/MWh. Chang et al. (2017) examined the spot price dynamics, asymmetric clustering and regime-switching behaviors of CO_2 emissions allowances in the new China-wide emissions trading scheme pilots, and indicated that the spot prices of regional emissions allowances exhibit significant dynamic behaviors, asymmetric leverage effects, and regime-switching behaviors in the entire period considered.

The *Construction Program* which the NDRC issued on December 18, 2017, indicates that national ETS market has been formally established in China. However, due to data collection challenges, regulation, and other reasons, only the power sector is involved in the carbon trading market (The setting method is introduced in Section 2.1.4). Thus, this paper studies the possible economic, energy and environmental impacts of ETS based on the current carbon trading market in China.

The innovations of this paper are as follow:

1) An improved dynamic recursive Computable General Equilibrium (CGE) model is established to analyze the impact of ETS. This model can be applied by other modelers to analyze other issues related to carbon trading. The benchmark model in this CGE model is from Hosoe et al. (2010). We have enriched the sector classification, separated the energy input from the intermediate input, separated rural and urban residents, added the energy-policy block, and added a dynamic method into the sector, which model is used in Lin and Jia (2018b).
2) This paper closely follows the current government strategy to study the possible economy-energy-environment impact of China's carbon trading market with the involvement of the power industry, as most literatures have so far focused on the impact of ETS market with assumed coverage industries.
3) We analyze the impact of two key factors of the carbon trading allocation mechanism on economic output and CO_2 emission and their impact mechanism. Then we provide our suggestion for China's national ETS market.

The basic structure of this paper is: the introduction and literature review are presented in Section 1. The CGE model, Social Accounting Matrix (SAM) and model dynamics are introduced in Section 2. The scenario design is described in Section 3. The simulation results and discussions are provided in Section 4. The conclusions and suggestions are proposed in Section 7. In order to make this paper more concise and easy to read, the main abbreviations in this paper are shown in Table B.1.

2. Methodology

2.1. CGE model

CGE model is widely used in policy analysis (Lin and Ouyang, 2014; Paroussos et al., 2015; Lu et al., 2017). The construction of all CGE models is based on traditional Walras paradigm, which means that the model can be described as a system of simultaneous equations deduced by all actors' maximizing behavior. CGE model simulates the behavior of social subjects, such as residents, enterprises, government, and foreigners (Bohringer et al., 2017; He and Lin, 2017). It consists of five blocks: production block, income-expenditure block, trade block, energy-policy block, and macroscopic-closure & market-clearing block (Lin and Jia, 2018a). The utility function of residents is Cobb-Douglas function. The general framework of the CGE model is illustrated in Fig. 1. The elasticity of production function is from *AIM/CGE 2.0* (Fujimori et al., 2012). The suggested elasticity in AIM/CGE is shown in Table 1.

2.1.1. Production block

We assume that one sector produces only one product in the CGE model. Moreover, the output consists of policy cost, Value-Added & Energy (VAE) and intermediate input following a Leontief function. VAE is a bundle that consists of value-added (VA) and energy following a Constant Elasticity of Substitution (CES) function. The next level is VA bundle and energy bundle, which consist of capital and labor, electricity and non-electricity energy (fossil energy) input following a CES function, respectively. The non-electricity energy bundle consists of coal and non-solid fuel (oil and gas) following a CES function. Because China's 139 sector input-output table does not separate the oil and gas industries, and the main energy consumption in China is coal, this paper does not subdivide oil and gas. Several literatures did separate intermediate input, labor and capital input of oil and gas industries only by production. The method is inappropriate and has no obvious economic significance. So this paper doesn't follow this pattern.

2.1.2. Income-expenditure block

The four social subjects are government, enterprise, household (both rural residents and urban residents), and foreigner. The CGE model embodies the balance and relationship between the four subjects. For the government, it gets fiscal revenue through direct tax, indirect tax, and tariff; and all the revenue are used for transfer payments, consumption, and savings. For domestic enterprises, they get sales revenue from consumption by the government, residents, other enterprises and foreigners to support their own expenditure: indirect tax, households' income, and savings. For the households, they get income through remunerations from enterprises and transfer payments by the government, and the income is equal to the sum of their consumption, direct tax and savings. The trade deficit is given by exogenous, which is according to *Textbook of Computable General Equilibrium Modeling: Programming and Simulations* (Hosoe et al., 2010).

2.1.3. Trade block

CGE model assumes that both domestic and foreign products of an industry are homogeneous. Thus, for one kind of product, imports and exports cannot exist at the same time. However, imports and exports do exist at the same time in one type of commodity in the real world. Therefore, like most of the literature, the Armington assumption is introduced into the CGE model (Lin and Li, 2012; Hosoe, 2014) by using CES and CET (Constant Elasticity of Transformation) functions to simulate import and export in the real world.

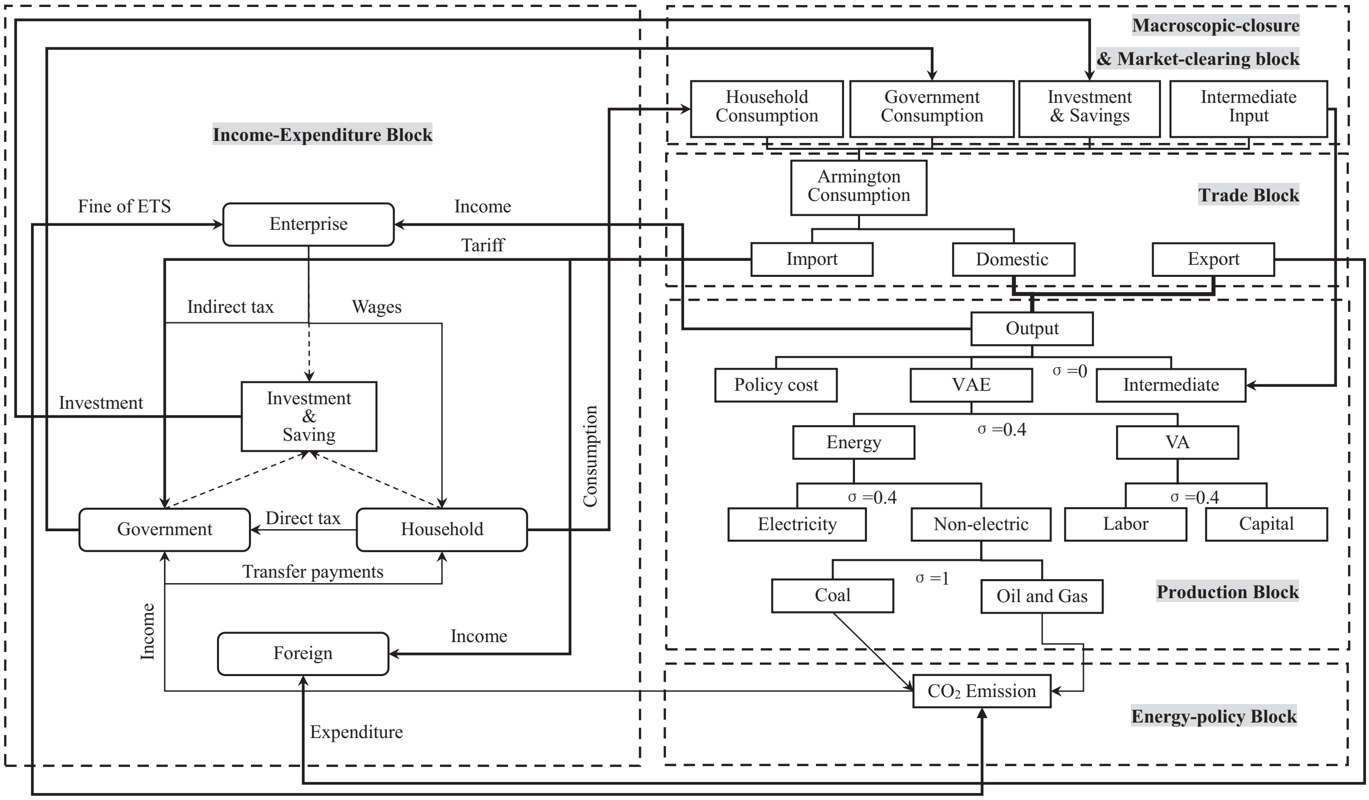


Fig. 1. General framework of the CGE model.

2.1.4. Energy-policy block

CGE model assumes that ETS market is a perfectly competitive market; hence, the auction price of ETS is equal to the trading price of carbon emissions allowances (or carbon rights we called) in an equilibrium state in modeling. If CO_2 emissions of enterprises are greater than their carbon emission allowances, the over-emitting enterprises should pay a fine (ETS fine), which is 3 times the ETS price, to the government. The government will transfer all ETS' revenue to the residents. The Rate of Free Payment (RFP) will be 0.5 in the period 2017–2030, and this is set in accordance with the seven pilot cities in China as well as the period I in EU-ETS, as there is no relative detail description in *Construction Program*. In addition, this model assumes that FP cannot be traded or transferred, which means only the paid parts of Carbon Rights (CR) can be traded in the carbon trading market. This block can be explained by the following three equations.

$$EM_i = COAL_i \times \gamma^{coal} + O\_G_i \times \gamma^{o\text{-}g} \tag{1}$$

$$\begin{aligned} PLC_{ei} &= p^t(CR_{ei} - FP_{ei}) + p^f(EM_{ei} - CR_{ei}), EM_{ei} \geq CR_{ei} \\ PLC_{ei} &= p^t(CR_{ei} - FP_{ei}), EM_{ei} < CR_{ei} \end{aligned} \tag{2}$$

$$fpr = \textstyle\sum_{ei} FP_{ei} / \sum_{ei} CR_{ei} \tag{3}$$

where EM_i represents total emission of a sector. $COAL_i$ and O_G_i represents fossil consumption of the sector i. γ^{coal} and $\gamma^{o\text{-}g}$ represent the carbon emission coefficients of coal, oil and gas. PLC_{ei} depicts the policy cost (ETS cost) in the sector *ei*. The subscript *ei* represents the coverage industries under the ETS, and the electricity industry is the only sector participating in the ETS in this paper. p^t is carbon price while p^f represents the fine for over-emission. CR_{ei} denotes CR of the sector *ei*. FP_{ei} represents the free payment of the carbon allowances, while *fpr* shows the rate of free payment.

This paper assumes that carbon emission allowances are calculated using the output of sector *ei* in the current period, last year's CO_2 emission intensity and coefficient of decreasing carbon intensity per year. The free payment of sector *ei* can be explained by the following equation.

$$FP_{ei,t} = Z_{ei,t} \times \frac{EM_{ei,t-1}}{Z_{ei,t-1}} \times (1 - \omega) \times fpr \tag{4}$$

where $FP_{ei,\,t}$ is free payment rate of sector *ei* in the current period. $EM_{ei,\,t-1}$ represents the CO_2 emission of sector *ei* in last period. ω represents annual decline factor (ADF) which is set as 0.5% in accordance with Guangdong's experience (the pilot city in China), which set the factor as 0% or 1% (Carbon emissions trading network, 2016). $Z_{ei,\,t}$ and $Z_{ei,\,t-1}$ represent the sectoral output of sector *ei* in the current and last period respectively. The reason why we set ADF according to Guangdong's experience is that Guangdong's ETS is similar to the National Carbon Trading Plan of the National Development and Reform Commission of China, and the market is relatively mature.

Table 1
Elasticity in AIM/CGE.

Objective	Function	Elasticity
Output	Leontief function	0
Energy and value added	CES function	0.4
Value added	CES function	0.5
Capital (new or old)	CES function	5.0
Energy aggregate	CES function	0.5
Fossil fuel	CES function	1.0

2.1.5. Macroscopic-closure & market-clearing block

Three principles of market closure are considered in this model: government budget balance, foreign trade balance, and investment-saving balance. The first two balances are introduced in Section 2.1.2. As for investment-saving balance, CGE model assumes that all the savings are transformed into investment, which means that total investment is equal to total savings. Two principles are considered in the market clearing. One is the market clearing of Armington composite commodity. The other is factor market clearing. The former shows that all Armington commodities are used for consumption of household and government, intermediate input and savings, without surplus. The latter assumes that there is no unemployment in the market.

2.2. Social accounting matrix

The most important basic data of the CGE model is the social accounting matrix, which can be compiled by an input-output table. The 2010 Input-Output Table of China (CIOT) is used in this paper. The energy data of the SAM is from China Statistical Yearbook (NBS, 2014) and the economic data is from China Input-Output Association (CIOA) (CIOA, 2014). The SAM is balanced by using SG-RAS method (Wang et al., 2012). An important point worth noting is that CO_2 emissions in this paper are only from fossil fuel combustion, implying this paper does not consider CO_2 emissions generated by microbial decomposition, animal, and plant respiration. We reclassify sectors in the CIOT into 14 departments in SAM, as shown in Table 2.

2.3. Model dynamics

Capital depreciation (capital input) is determined by the capital stock in the current period and the rate of capital depreciation. Capital stock is determined by capital stock in the last period, capital depreciation and investment in the last period. Capital stock is endogenous except for the first period, while investment is endogenous. Labor endowment is exogenous and determined by *National Population Development Plan (2016–2030)* (CPGPRC, 2017). Autonomous Energy Efficiency Improvement (AEEI) in CGE model is considered in this study according to Li et al. (2017).

3. Scenario design

The main purpose of this paper is to analyze the impact of ETS with only electricity sector participation on the economy, energy, and environment in China. However, the details of the distribution plan for the power industry have not been completely set. This paper first simulates the mode of Guangdong experience and phase II of EU-ETS (whose free payment rate, government fine, annual decline factor and allowance calculating method is introduced in Section 2.1.4) as ETS scenario. We then set the CM scenarios by changing some parameters of the ETS scenario. F1 and F2 scenarios are the scenarios which the Annual Decline Factor (ADF) is changed, while R1 and R2 scenarios are the scenarios in which the rate of free payment is changed. The parameters this paper set, is shown in Section 2.1.4 and Table 3. Other ETS settings in detail can be referred to in Section 2.1.4.

Table 2
Description and coverage of sector classification and population classification.

Sectors	Description	Coverage in ETS
AGR	Agriculture, forestry, animal husbandry and fishery	–
COL	Coal mining and washing industry	–
O_G	Petroleum and natural gas exploitation	–
PAP	Paper industry	–
CMT	Cement	–
FER	Chemical fertilizer	–
CMC	Chemicals	–
STL	Steel smelting and rolling processing industry	–
EQU	Equipment manufacturing industry	–
ELC	Electricity	Yes
CST	Construction industry	–
TRA	Transportation	–
OTH	Other industry	–
SER	Service	–
RUR	Rural population	–
CTZ	Urban population	–

Table 3
The scenario design in this paper.

Scenarios	Annual decline factor	Rate of free payment
BaU	–	–
ETS	0.5%	50%
F1	0%	50%
F2	1%	50%
R1	0.5%	40%
R2	0.5%	60%

4. Results and discussion

4.1. Economic impact

4.1.1. GDP

Gross Domestic Product (GDP) in all the scenarios in 2030 is illustrated in Fig. 2. GDP discussed in this paper is at the price level of 2010, so the GDP in 2030 is the real GDP at 2010 price level. GDP will be 86.86 trillion yuan in the BaU scenario in 2030. But in the ETS scenario, GDP will be 86.25 trillion yuan, a 0.70% or 0.61 trillion yuan decrease compared with the BaU scenario. In the F1 and F2 scenarios, GDP will be 86.70 and 85.63 trillion yuan, respectively, which will decrease by 0.19% and 1.44%, or 0.16 and 1.23 trillion yuan compared with the BaU scenario. GDP in the R1 and R2 scenarios will be the same as in the ETS scenario. We find that the national ETS will have a negative impact on GDP by 0.19% to 1.44%, or 0.16 trillion yuan to 1.23 trillion yuan. A real GDP loss of more than 1% is huge. GDP is sensitive to annual decline factor: lower ADF will result in lower GDP loss. However, the rate of free payment can hardly impact GDP, which will be discussed in Section 5.

4.1.2. Commodity price

Fig. 3 depicts the commodity price in the CM scenarios in 2030 compared with the BaU scenario in 2030. As can be seen, China's national ETS can significantly increase the price of electricity. The reason is simple: ETS with only electricity sector participation will directly increase the total cost of the electricity sector, which will increase the price of electricity. Electricity price will increase 6.47–16.02%, while the price of other commodities will increase by 1.07–2.93%. The positive impact on the commodity prices of coal-intensive or electricity-intensive industries (such as construction, coal mining, agriculture, chemical, and steel etc.) will be slightly greater than other industries. The increased cost of electricity input will directly affect the cost and the price of other industries, especially in energy-intensive industries. For example, the rate of increase in prices in the agriculture and coal industries (2.93% and 2.80% in ETS scenario) are greater than that in the service industry (2.55% in ETS scenario). Moreover, ADF will

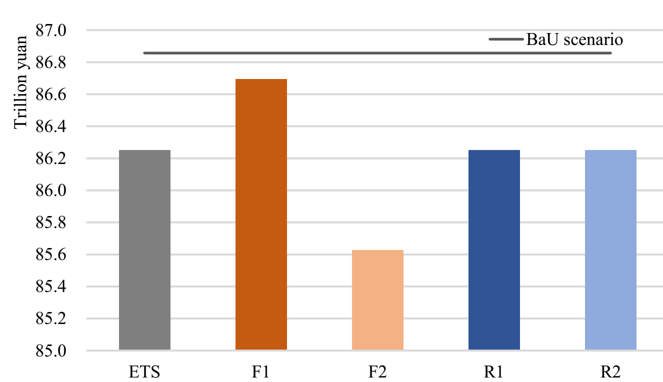
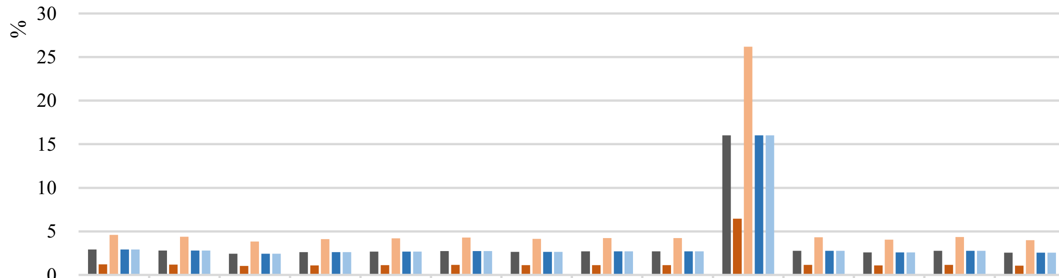


Fig. 2. GDP in BaU scenario and CM scenarios in 2030.



	AGR	COL	O_G	PAP	CMT	FER	CMC	STL	EQU	ELC	CST	TRA	OTH	SER
ETS	2.93	2.80	2.44	2.62	2.68	2.73	2.64	2.70	2.70	16.02	2.76	2.59	2.78	2.55
F1	1.23	1.17	1.03	1.10	1.12	1.14	1.11	1.13	1.13	6.47	1.16	1.09	1.17	1.07
F2	4.60	4.39	3.84	4.12	4.21	4.28	4.14	4.23	4.23	26.20	4.33	4.06	4.36	3.99
R1	2.93	2.80	2.44	2.62	2.68	2.73	2.64	2.70	2.70	16.02	2.76	2.59	2.78	2.55
R2	2.93	2.80	2.44	2.62	2.68	2.73	2.64	2.70	2.70	16.02	2.76	2.59	2.78	2.55

Fig. 3. Commodity price in CM scenarios compared with BaU scenario in 2030.

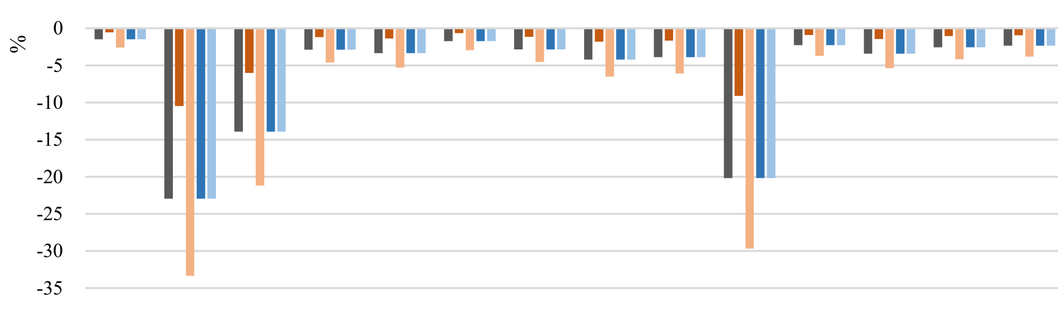
significantly impact the results of commodity price but RFP will not. Higher ADF will result in higher commodity price. The main reason is that higher ADF will increase the ETS cost of electricity enterprises so that the commodity price of electricity will increase more.

4.1.3. Sectoral output

Sectoral output in the CM scenarios in 2030 compared with the BaU scenario is illustrated in Fig. 4. The output of coal, oil & gas, and electricity will significantly decrease under the context of China's national ETS market. The output of coal will decrease by 10.49–33.34%, while the output of oil and gas will reduce by 6.03–13.93%. The output of electricity will also decrease by 9.11–29.70%. Except for energy industries, several energy-intensive industries, such as steel (the reduction is 1.80–6.53%) and equipment (the reduction is 1.65–3.91%), will experience greater output loss than others. We find that energy sectors, especially the coal and electricity industries, are highly influenced by China's national ETS. The price of coal, oil, and gas will increase by no more than 5%, however, the output will reduce by 10–35%. The main reason is that ETS market with only electricity participating will reduce the output of electricity, causing the demand for fossil energy to decrease immediately. That's why there will be decrease in output more than the increase in commodity price. Energy-intensive industries will also experience loss to the tune of 6.5%. Other industries, such as agriculture and service, will have their output reduce by 0.54–3.82% due to the increasing commodity prices. The output is sensitive to annual decline factor: higher ADF will result in higher output loss. The reason is that higher ADF will increase the demand for carbon emission allowance, and the changes in supply and demand will inevitably affect the price of carbon trading. Carbon trading prices will further directly affect the cost of electricity enterprises, resulting in an increase in electricity prices. This will eventually lead to changes in the output of the entire industries. However, the output will not be influenced by RFP and the reason will be discussed in Sections 4.3.2 and 5.

4.2. Energy impact

Fossil energy consumption of industries in all the scenarios in 2030 is illustrated in Fig. 5. The bar represents the amount of direct fossil energy consumption in different industries, while the polyline denotes the variation of fossil energy consumption in the CM scenarios compared with the BaU scenario. China's national ETS could significantly reduce the energy consumption of energy industries. The energy consumption of energy industries will reduce by 6.54%–44.61%. The decline in coal and electricity industries is higher than in other industries. Compared with the results of Section 4.1.3, the reduction in fossil energy consumption is greater than the reduction in industrial output, indicating that



	AGR	COL	O_G	PAP	CMT	FER	CMC	STL	EQU	ELC	CST	TRA	OTH	SER
ETS	-1.49	-22.95	-13.93	-2.89	-3.35	-1.75	-2.85	-4.22	-3.91	-20.20	-2.29	-3.43	-2.58	-2.35
F1	-0.54	-10.49	-6.03	-1.19	-1.39	-0.65	-1.16	-1.80	-1.65	-9.11	-0.92	-1.44	-1.04	-0.94
F2	-2.60	-33.34	-21.21	-4.61	-5.31	-2.98	-4.55	-6.53	-6.09	-29.70	-3.71	-5.38	-4.17	-3.82
R1	-1.49	-22.95	-13.93	-2.89	-3.35	-1.75	-2.85	-4.22	-3.91	-20.20	-2.29	-3.43	-2.58	-2.35
R2	-1.49	-22.95	-13.93	-2.89	-3.35	-1.75	-2.85	-4.22	-3.91	-20.20	-2.29	-3.43	-2.58	-2.35

Fig. 4. Sectorial output in CM scenarios compared with the BaU scenario in 2030.

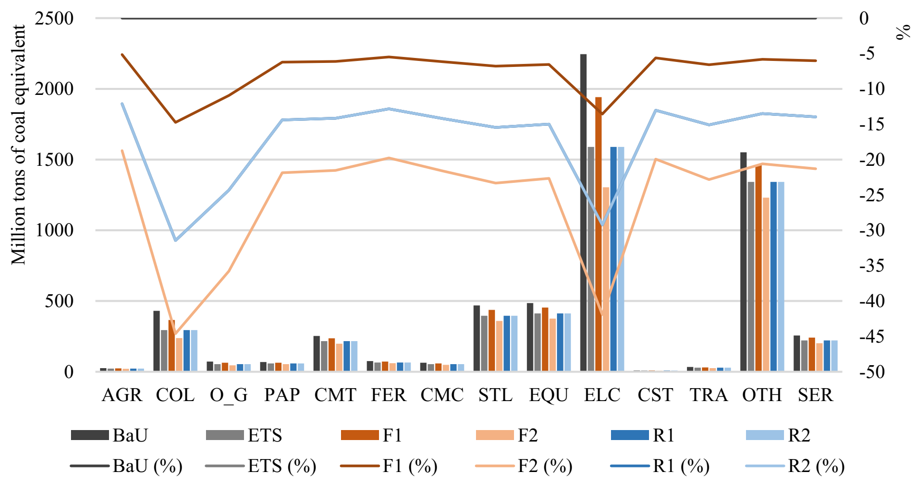


Fig. 5. Fossil energy consumption of industries in all scenarios in 2030.

China's national ETS is somehow useful for energy savings. Other industries will reduce their energy consumption by 5.15%–21.59%. We also find that higher ADF can reduce energy consumption. Energy consumption is significantly sensitive to ADF, but not to RFP.

Fossil energy structure in all CM scenarios in 2030 is illustrated in Fig. 6. Coal consumption accounts for 78.68% in 2030 BaU scenario. However, it will reduce to 77.01%, 77.96%, 76.12%, 77.01% and 77.01% in ETS, F1, F2, R1 and R2 scenarios, respectively. Compared with BaU scenario, the proportion of coal consumption will reduce by 2.13%, 0.92%, 3.25%, 2.13% and 2.13% in ETS, F1, F2, R1 and R2 scenarios, respectively. We found that ETS will help to reduce the proportion of coal consumption and to optimize the energy structure. Higher ADF will reduce much more the proportion, as the proportion will reduce by 0.92% in F1 scenario compared with BaU scenario while it will reduce by 3.25% in the F2 scenario. We, therefore, considered that ETS markets with lower allowances have a stronger positive significance for reducing energy consumption and optimizing energy structure.

4.3. Environment impact

4.3.1. CO_2 emission

CO_2 emission in all the scenarios during 2012–2030 is depicted in Fig. 7. The emission in the BaU scenario will increase from 8.06 Billion tons of CO_2 (Bt-CO_2) to 12.63 Bt-CO_2 in 2030. When China's national ETS market is established in 2017, the emission will be different: in 2030, CO_2 emission will be 9.96 Bt-CO_2 in the ETS, R1 and R2 scenarios; 11.42 Bt-CO_2 in the F1 scenario; and 8.73 Bt-CO_2 in the F2 scenario, respectively. We find that if ADF is set at 1%, emission reaches a peak in 2017 and decreases as time goes by. However, the GDP loss is great in such scenario (refer to Fig. 2). The reason why the CO_2 emission will reduce immediately when starting ETS with the setting of F2 scenario is that too low carbon allowance will lead to lower fossil energy consumption (see Section 4.1.3), while energy efficiency improvements due to advances in technology will jointly lead to a downward trend in carbon emissions in the F2 scenario. ADF has a significant impact on CO_2 emission. Lower ADF will directly increase CO_2 emission compared with the ETS scenario, while higher ADF will decrease it. In the ETS, R1 and R2 scenarios, emission will increase slowly: from 8.06 Bt-CO_2 to 8.73 Bt-CO_2 in 2030. If China adopts other emission reduction policies simultaneously (such as new energy generation, improving energy use efficiency, and carbon sinks), it is quite possible to peak carbon emissions before the year of 2030, which will meet the goal of *Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions* (*the Action*) (NDRC, 2015).

4.3.2. CO_2 abatement

Table 4 depicts a CO_2 reduction in all the CM scenarios compared with the BaU scenario during 2017–2030. In 2017, the reduction will be 0.07 Bt-CO_2 in the F1 scenario; 0.16 Bt-CO_2 in the ETS, R1 and R2 scenarios; and 0.25 Bt-CO_2 in the F2 scenario. In 2030, the reduction effect will increase to 2.66, 1.21, 3.90, 2.66 and 2.66 Bt-CO_2 in the ETS,

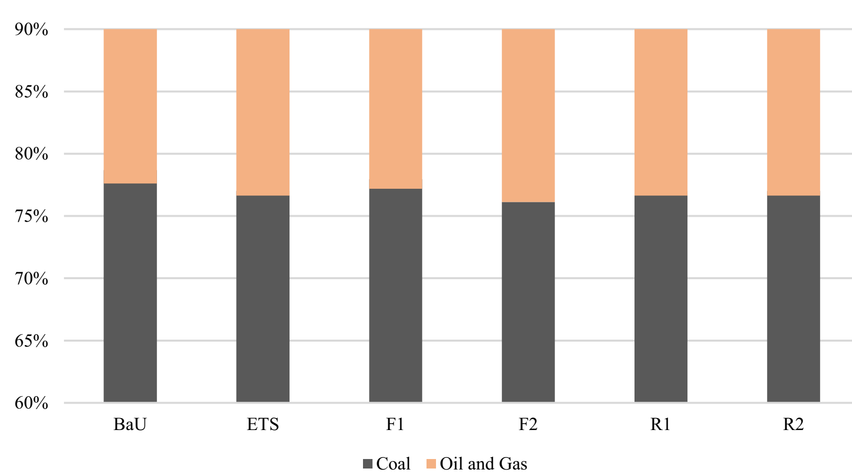


Fig. 6. Fossil energy structure in all CM scenarios in 2030.

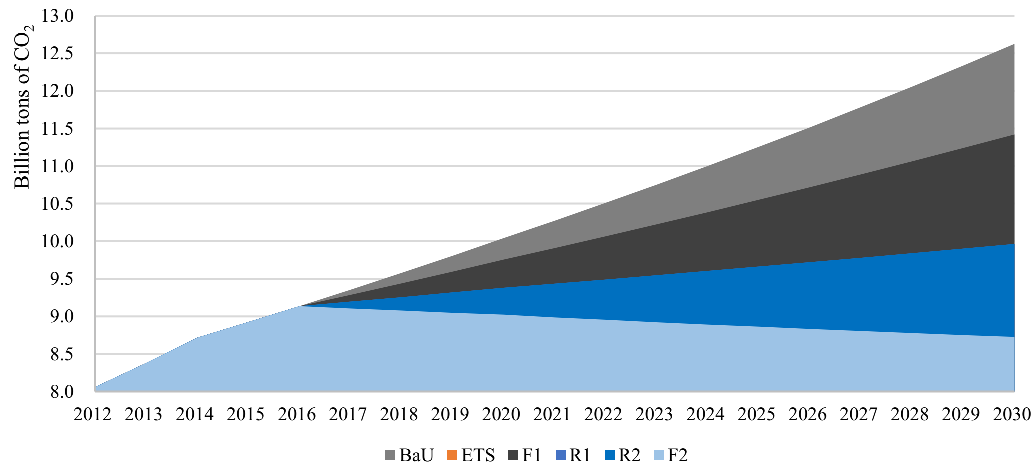


Fig. 7. CO_2 emission in all scenarios during 2012–2030.

F1, F2, R1 and R2 scenarios, respectively. The cumulative emission reduction will be 18.80, 8.35, 28.14, 18.80 and 18.80 Bt-CO_2 in the ETS, F1, F2, R1 and R2 scenarios, respectively. Then, we draw a few straightforward conclusions:

1) The emission reduction effect of China's national ETS will increase with time, due to the reduction of carbon emission allowances each year.
2) As long as the mechanism of the ETS market remains unchanged, the annual emission reductions will increase linearly.
3) Annual decline factors can significantly influence CO_2 emission reduction: the higher the ADF, the higher the CO_2 abatement will be. In contrast, the rate of free allowance cannot impact the effect. Because ADF will affect the cap, while the rate will not.

The emission reduction effect of China's national ETS is very significant. For example, China will reduce 2.66 Bt-CO_2, or 6.81% of 2030's global emission in the ETS scenario in 2030 (IPCC, 2007). The cumulative CO_2 reduction in the ETS scenario will be 18.80 Bt-CO_2, or 268.42% of 2010's China's total CO_2 emission, or 48.13% of 2030's global emission. Even if only the power industry participates in the ETS market, the emission reduction effect of China's national ETS will be very impressive.

4.3.3. Carbon intensity

Fig. 8 illustrates the carbon intensity (CI) in all the scenarios during 2016–2030. CI, calculated by CO_2 emission and GDP, is an indicator of energy efficiency. Carbon intensity is 0.168 tons of CO_2/thousand yuan in 2016 in the BaU scenario and it will reduce to 0.145 tons of CO_2/thousand yuan in 2030. CI will reduce by 0.030 tons of CO_2/thousand yuan or 20.53% in the ETS, R1 and R2 scenarios compared with the BaU scenario. It will reduce by 0.014 tons of CO_2/thousand yuan or 9.38% in the F1 scenario relative to the BaU scenario, and 0.043 tons of CO_2/thousand yuan or 29.89% in the F2 scenario compared with the BaU scenario. We find that China's national ETS market will significantly reduce CO_2 emission intensity, indicating that China's national ETS is an effective tool to reduce CO_2 emission. According to *the Action*, carbon intensity will be 0.112 tons of CO_2/thousand yuan in 2030. If the average inflation per year is above 0.15% during 2010–2030, the CI target of *the Action* will be achieved in ETS, R1 and R2 scenarios. In fact, based on past experience, the inflation rate in each year will be more than 1%. Thus, this paper argues that the CI goal of *the Action* will be easily realized.

5. Paid CR, free payment, and ETS cost

This section explores several issues in the results, which are:

1) Why will higher ADF cause higher emission reduction and higher GDP loss?
2) Why does RFP have no influence on emission reduction and economic output?
3) What is the carbon trading price level in China's national ETS market? And what is the impact of RFP and ADF on carbon price?

Table 4
CO_2 reduction and the reduction proportion in all scenarios compared with the BaU scenario during 2017–2030.

Scenario	ETS		F1		F2		R1		R2	
(Unit)	(Bt-CO_2)	(%)	(Bt-CO_2)	(%)	(Bt-CO_2)	(%)	(Bt-CO_2)	(%)	(Bt-CO_2)	(%)
2017	0.16	1.69	0.07	0.72	0.25	2.66	0.16	1.69	0.16	1.69
2018	0.32	3.36	0.14	1.44	0.50	5.24	0.32	3.36	0.32	3.36
2019	0.49	4.99	0.21	2.15	0.76	7.74	0.49	4.99	0.49	4.99
2020	0.66	6.59	0.29	2.85	1.02	10.17	0.66	6.59	0.66	6.59
2021	0.84	8.16	0.36	3.54	1.29	12.52	0.84	8.16	0.84	8.16
2022	1.02	9.70	0.44	4.23	1.56	14.81	1.02	9.70	1.02	9.70
2023	1.21	11.21	0.53	4.91	1.83	17.02	1.21	11.21	1.21	11.21
2024	1.40	12.70	0.62	5.59	2.11	19.18	1.40	12.70	1.40	12.70
2025	1.59	14.16	0.70	6.26	2.39	21.27	1.59	14.16	1.59	14.16
2026	1.80	15.60	0.80	6.93	2.68	23.31	1.80	15.60	1.80	15.60
2027	2.00	17.01	0.89	7.59	2.98	25.28	2.00	17.01	2.00	17.01
2028	2.22	18.39	0.99	8.25	3.28	27.20	2.22	18.39	2.22	18.39
2029	2.44	19.75	1.10	8.90	3.59	29.07	2.44	19.75	2.44	19.75
2030	2.66	21.09	1.21	9.55	3.90	30.88	2.66	21.09	2.66	21.09
Total	18.80		8.35		28.14		18.80		18.80	

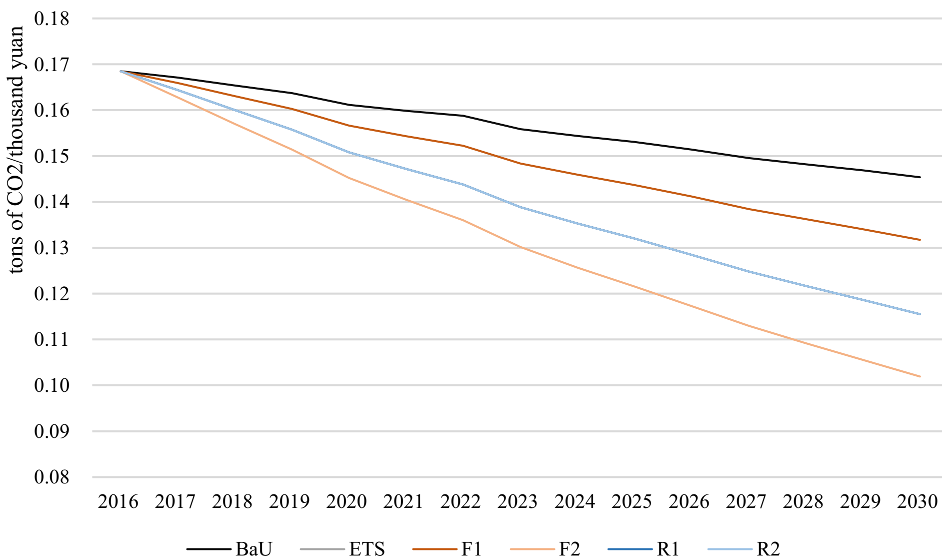


Fig. 8. Carbon intensity in all scenarios during 2016–2030.

Table 5 shows paid carbon allowances, free carbon allowances (free payment), total CR, carbon price and ETS cost in the electricity sector in 2030. First, this paper introduces the ETS cost: ETS cost means the direct cost of participating in ETS market by the coverage industries, which is equal to A multiplied by B. We find that high ADF could directly reduce CO_2 allowance. Then the demand for CR will increase, which will increase the carbon price. Moreover, the elasticity of the ETS price with respect to paid CR is greater than 1, so that ETS cost will be significantly higher. High ETS cost will lead to high electricity price (Fig. 3), resulting in a low output level and huge GDP loss, as well as high emission reduction.

If ADF does not change, RFP has no influence on total CR. RFP only changes the rate of paid CR and FP, not the total carbon emission allowance. The same total carbon rights in the R1 and R2 scenarios means that the total amount of carbon emissions will remain unchanged. In the same technical level, the same emission reductions (because of the same total CRs) have the same emission reduction costs, while in a perfectly competitive market, the emission reduction costs will be the same as ETS cost. So the ETS cost will not be affected by the RFP.

Moreover, in Table 5, we find that the ETS price in the national ETS in 2030 will be 118.69–562.79 yuan/t-CO_2. With only the power sector participating in the carbon market, carbon trading prices will not be low (Lin and Jia, 2017). The increase in ADF will lead to an increase in the carbon price, and the increase in the RFP will also drive up the price. However, the elasticity of the ETS price with respect to ADF is lower than that of ETS price with respect to RFP. Moreover, we find that the latter is always 1, which makes ETS cost remain unchanged. The reason why RFP and ADF have positive correlations with the carbon price is that the increase of RFP and ADF will directly increase the demand of paid CR, and carbon prices will rise accordingly due to demand and supply relationship changes.

Table 5
Paid CR, Free payment, and ETS cost in ETS market in 2030.

	Paid CR (billion ton)	FP (billion ton)	Total CR (billion ton)	Carbon price (yuan/t-CO_2)	ETS cost (billion yuan)
ETS	1.66	1.66	3.32	317.95	528.22
F1	2.03	2.03	4.06	118.69	240.91
F2	1.36	1.36	2.73	562.79	767.64
R1	1.99	1.33	3.32	264.96	528.22
R2	1.33	1.99	3.32	397.44	528.22

6. Sensitivity analysis

Table 6 shows the sensitivity analysis of the BaU scenario. A CGE model can be influenced by some key parameters, such as elasticity, population growth rate, depreciation rates and AEEI. Thus, a sensitivity analysis of the above 4 parameters is provided in this paper. We test the variations of CO_2 emissions and GDP and carbon intensity, assuming that these variables increase or decrease by 10%.

According to Table 6, we found that the elasticity can have an effect on CO_2 emissions, GDP, and carbon intensity, especially on emissions and carbon intensity by 3.03–3.95% and 2.92–3.85% respectively. The increase of AEEI can increase both emissions and GDP, as well as carbon intensity, while population growth rate and depreciation rates can hardly impact on emissions and GDP. In general, if all the parameters increase or decrease by 10%, GDP, CO_2 emissions, and carbon intensity will increase or decrease by no more than 3.95%, indicating a modest change.

7. Conclusions and policy implications

This paper establishes 5 counter-measured scenarios based on the recently launched China's national ETS market and constructs a dynamic recursive Computable General Equilibrium model to study the impact of national ETS on the economy, energy, and environment. The findings are meaningful for the establishment and modification of future national ETS market in China. The study reached the following conclusion:

The national ETS in China will have a negative impact on GDP, by 0.19%–1.44%, or 0.16 trillion yuan to 1.23 trillion yuan. GDP is sensitive to annual decline factor. China's national ETS can significantly increase

Table 6
Sensitivity analysis of BaU scenario (unit: %).

Item	Changes	CO_2 emissions	GDP	Carbon intensity
Elasticity in production block	−10	−3.0305	−0.1162	−2.9193
	+10	3.9542	0.0966	3.8520
Population growth rate	−10	0.1323	0.1321	0.0000
	+10	0.1100	0.1099	0.0001
Depreciation rates	−10	0.0433	0.0432	0.0001
	+10	−0.0400	−0.0431	0.0000
AEEI	−10	−2.8335	−1.3631	−1.5011
	+10	2.9476	1.3701	1.5458

the price of electricity, however, the increase in the price of other commodities will be much lower than the electricity price. The output of fossil energy and electricity will significantly reduce. Higher ADF will result in higher output loss, but RFP doesn't affect output loss. The reduction of fossil energy consumption is greater than the reduction of industrial output, indicating that China's national ETS is somehow useful for energy savings.

We find that the emission reduction effect of China's national ETS will increase with time. As long as the ETS market mechanism remains unchanged, the annual emission reductions will increase linearly. Even if only the power industry participates in the ETS market, the emission reduction effect of China's national ETS will be very significant. If China adopts other emission reduction policies simultaneously, it is quite possible to peak carbon emissions in the year of accomplishing synergistic emission reduction in the ETS scenario. Moreover, the CI goal of *the Action* will be easily realized.

This paper argues that China's national ETS market is an effective tool to reduce CO_2 emission, and the authors suggest that the annual decline factor could be 0.5% when allocating carbon allowance for the electricity sector. This could balance economic output and CO_2 reduction. It is also easy to achieve the goal of "double control" (total amount and intensity) in China.

This paper also explains why ADF will significantly have an impact on the society while RFP will not. This is because ADF could increase the ETS cost while RFP could not. We also find that ETS price in the national ETS will be 118.69–562.79 yuan/t-CO_2 in 2030. With only the power sector participating in the carbon market, carbon trading prices will not be low.

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Conflicts of interest

We declare no conflict of interest.

Appendix A. Equation system of the dynamic CGE model

A.1. Production block

$$NOE_i = \alpha_i^{noe}\left[\delta_i^{noe}COAL_i^{\rho_i^{noe}} + (1-\delta_i^{noe})NOS_i^{\rho_i^{noe}}\right]^{1/\rho_i^{noe}} \tag{A.1}$$

$$\frac{PCOAL_i}{PNOS_i} = \frac{\delta_i^{noe}}{1-\delta_i^{noe}}\left(\frac{NOS_i}{COAL_i}\right)^{(1-\rho_i^{noe})} \tag{A.2}$$

$$NOE_iPNOE_i = COAL_iPCOAL_i + NOS_iPNOS_i \tag{A.3}$$

$$ENE_i = \alpha_i^{ene}\left[\delta_i^{ene}ELE_i^{\rho_i^{ene}} + (1-\delta_i^{ene})NOE_i^{\rho_i^{ene}}\right]^{1/\rho_i^{ene}} \tag{A.4}$$

$$\frac{PELE_i}{PNOE_i} = \frac{\delta_i^{ene}}{1-\delta_i^{ene}}\left(\frac{NOE_i}{ELE_i}\right)^{(1-\rho_i^{ene})} \tag{A.5}$$

$$ENE_iPENE_i = ELE_iPELE_i + NOE_iPNOE_i \tag{A.6}$$

$$VA_i = \alpha_i^{va}\left[\delta_i^{va}LAB_i^{\rho_i^{va}} + (1-\delta_i^{va})CAP_i^{\rho_i^{va}}\right]^{1/\rho_i^{va}} \tag{A.7}$$

$$\frac{PLAB_i}{PCAP_i} = \frac{\delta_i^{va}}{1-\delta_i^{va}}\left(\frac{CAP_i}{LAB_i}\right)^{(1-\rho_i^{va})} \tag{A.8}$$

$$VA_iPVA_i = LAB_iPLAB_i + CAP_iPCAP_i \tag{A.9}$$

$$VAE_i = \alpha_i^{vae}\left[\delta_i^{vae}VA_i^{\rho_i^{vae}} + (1-\delta_i^{vae})ENE_i^{\rho_i^{vae}}\right]^{1/\rho_i^{vae}} \tag{A.10}$$

$$\frac{PVA_i}{PENE_i} = \frac{\delta_i^{vae}}{1-\delta_i^{vae}}\left(\frac{ENE_i}{VA_i}\right)^{(1-\rho_i^{vae})} \tag{A.11}$$

$$VAE_iPVAE_i = ENE_iPENE_i + VA_iPVA_i \tag{A.12}$$

$$INT_{i,j} = a_{i,j}^{INT}Z_j \tag{A.13}$$

$$FVAE_j = a_j^{VAE}Z_j \tag{A.14}$$

$$PZ_j = a_j^{vae}PVAE + \sum_i a_{i,j}^{INT}PQ_i \tag{A.15}$$

A.2. Income-expenditure block

$$SP_l = ss_l^p\sum_i\left(\gamma_l^{lab}LAB_i\cdot PLAB_i + \gamma_l^{cap}CAP_i\cdot PCAP_i\right) \tag{A.16}$$

$$SG = ss^g\left(\sum_l TD_l + \sum_i TZ_i + \sum_i TM_i\right) \tag{A.17}$$

$$XG_i = \frac{\mu_i}{PQ_i}\left(\sum\nolimits_l TD_l + \sum_i TZ_i + \sum_i TM_i - SG\right) \tag{A.18}$$

$$XP_{i,l} = \frac{\beta_{i,l}{}^{xp}}{PQ_i}\left(\sum_i\left(\gamma_l^{lab}LAB_i\cdot PLAB_i + \gamma_l^{cap}CAP_i\cdot PCAP_i\right) - SP_l - TD_l\right) \tag{A.19}$$

$$TD_l = \tau_l^d\sum_i\left(\gamma_l^{lab}LAB_i\cdot PLAB_i + \gamma_l^{cap}CAP_i\cdot PCAP_i\right) \tag{A.20}$$

$$TZ_i = \tau^zPZ_iZ_i + PLC_i \tag{A.21}$$

$$TM_i = \tau^mPM_iM_i \tag{A.22}$$

A.3. Trade block

$$PE_i = \varepsilon PWE_i \tag{A.23}$$

$$PM_i = \varepsilon PWM_i \tag{A.24}$$

$$\sum_i PWE_iE_i + SF = \sum_i PWM_iM_i \tag{A.25}$$

$$Q_i = \gamma_i\left(\delta m_iM_i{}^{\eta_i} + \delta d_iD_i{}^{\eta_i}\right)^{1/\eta_i} \tag{A.26}$$

$$M_i = \left[\frac{\gamma_i{}^{\eta_i}\delta m_iPQ_i}{(1+\tau_i^m)PM_i}\right]^{\frac{1}{1-\eta_i}}Q_i \tag{A.27}$$

$$D_i = \left[\frac{\gamma_i{}^{\eta_i}\delta d_iPQ_i}{PD_i}\right]^{\frac{1}{1-\eta_i}}Q_i \tag{A.28}$$

$$Z_i = \theta_i\left(\xi e_i E_i^{\phi_i} + \xi d_i D_i^{\phi_i}\right)^{\frac{1}{\phi_i}} \tag{A.29}$$

$$E_i = \left[\frac{\theta_i^{\phi_i}\xi e_i\left[\left(1+\tau_i^z\right)+PLC_i/PZ_i/Z_i\right]PZ_i}{PE_i}\right]^{\frac{1}{1-\phi_i}} Z_i \tag{A.30}$$

$$D_i = \left[\frac{\theta_i^{\phi_i}\xi d_i\left[\left(1+\tau_i^z\right)+PLC_i/PZ_i/Z_i\right]PZ_i}{PD_i}\right]^{\frac{1}{1-\phi_i}} Z_i \tag{A.31}$$

A.4. Energy-policy block

$$EM_i = ENE\_COAL_i \times \gamma^{coal} + ENE\_O\_G_i \times \gamma^{o-g} \tag{A.32}$$

$$COAL_i = \chi_i^{coal} \times ENE\_COAL_i \tag{A.33}$$

$$NOS_i = \chi_i^{nos} \times ENE\_O\_G_i \tag{A.34}$$

$$\begin{aligned} PLC_{ei} &= p^t(CR_{ei}-FP_{ei}) + p^f(EM_{ei}-CR_{ei}), EM_{ei} \ge CR_{ei} \\ PLC_{ei} &= p^t(CR_{ei}-FP_{ei}), EM_{ei} < CR_{ei} \end{aligned} \tag{A.35}$$

$$fpr = \sum_{ei} FP_{ei} \Big/ \sum_{ei} CR_{ei} \tag{A.36}$$

A.5. Macroscopic-closure & market-clearing block

$$XV_i = \frac{\lambda_i}{PQ_i}\left(\sum\nolimits_l SP_l + SG + \varepsilon SF\right) \tag{A.37}$$

$$Q_i = \sum_l XP_{i,l} + XG_i + XV_i + \sum_j X_{i,j} \tag{A.38}$$

$$\sum_i LAB_i = \sum_l FF_l^{lab} \tag{A.39}$$

$$\sum_i CAP_i = \sum_l FF_l^{cap} \tag{A.40}$$

Appendix B. Abbreviations in this paper

Table B.1
The main abbreviations in this paper.

Abbreviation	Full name
ETS	Emissions trading scheme
VA	Value-added
VAE	Value-Added & Energy
CES	Constant Elasticity of Substitution
CET	Constant Elasticity of Transformation
CO_2	Carbon dioxide
GDP	Gross Domestic Product
CIOT	China input-output table
AEEI	Autonomous Energy Efficiency Improvement
SAM	social accounting matrix
CGE	Computable General Equilibrium
BaU	Business as usual scenario
CM	Counter-measured scenario
ADF	Annual decline factor
RFP	Rate of free payment
Construction Program	Construction Program of National Carbon Emissions Trading Market (Power Generation Industry)

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