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Impacts of emission trading scheme on technological progress: A case study in China

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ABSTRACT

Despite its significant role in mitigating climate change, technology was usually exogenously treated in evaluating climate policy, particularly emission trading scheme (ETS); such treatment cannot comprehensively reveal how ETS affects technological progress. To narrow this research gap, we attempt to endogenize ETS-induced technological change in this paper. A dynamic recursive Computable General Equilibrium (CGE) model is employed to quantify ETS-induced progress of clean technology (PCT) and efficiency improvement. The Chinese nationwide ETS is taken as a case study. The CGE model results show that PCT negatively affects anthropogenic emissions, while efficiency improvement decreases GDP loss or abatement cost. Simultaneously considering both technological progress increases emission abatement but slightly decreases GDP in the long term. The most interesting finding is that PCT moderates the relationship between efficiency improvement and emission abatement. Hence, PCT is crucial in emission abatement and economic growth under climate policy.

1. Introduction

Nowadays, the accelerating global warming has seriously affected lifestyles of human beings and posed significant threats to ecosystems. Until now, climate policy has been one of the most effective measures humans can take to decelerate global temperature rise. Unfortunately, implementing climate policy induces abatement cost, which causes reluctance or even opposition. Climate policy could have been more attractive worldwide if abatement cost had been lower.

One of the most important determinants of abatement cost is technology [1] because technology is rooted in mitigating climate change [2]. Without considering induced technological change, climate policy may seriously impede economic growth [3]. As technological progress of climate policy promotes carbon productivity [4], industrial structure upgrading [5], or firm innovation [6], it increases cost-effectiveness of emission abatement [7]. The Porter hypothesis postulates that strict environmental standard can incentivize technological progress [8]; therefore, the ability of climate policy to influence technological progress is one of the most essential criteria on which to judge its success [1].

Despite its significant impacts on emission abatement, technology was usually exogenous and excluded in policy design [9]. Within the climate policy domain, carbon tax was believed to affect technological progress endogenously [10] because it affects total factor productivity and energy efficiency [11]. Nevertheless, there is a paucity of research on induced technological change of emission trading scheme (ETS). In literature, technological progress of ETS was usually denoted by exogenous energy efficiency improvement

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[3]. For example, automatic energy efficiency index (AEEI) was used to model ETS-induced technological progress [12]. Exogenous treatment of technology cannot fully illustrate the role of technology and thus fails to establish an effective link between economy and environment [3]. To overcome the drawbacks of exogenously determining technological progress in ETS evaluation, some previous researchers endogenized ETS-induced technological progress, focusing on emission reduction technology [13] or green development efficiency [14]. Unfortunately, these two studies only partially captured induced technological change and thus cannot comprehensively reveal how ETS affects technological progress. This paper attempts to narrow the aforementioned research gap by endogenously and fully modeling ETS-induced technological advancement, namely progress of clean technology (PCT) and efficiency improvement.

The main contributions of this paper are presented as follows: Firstly, this paper improves Computable General Equilibrium (CGE) model by incorporating endogenous technological progress. Exogenous technical determination, like AEEI, cannot specify the role of technology in emission abatement. By endogenizing technological change, this paper helps develop CGE modeling to simulate socioeconomic system less biasedly. Secondly, this paper improves ETS evaluation framework by endogenously quantifying technological progress. Specifically, ETS-induced technological innovation is divided into PCT and efficiency improvement. Such division helps understand how ETS promotes technological progress thoroughly. Lastly, we compare economic and environmental impacts of the two types of technological advancement, concluding that PCT is crucial to emission mitigation and economic growth. This conclusion may enlighten future researchers to study how climate policy can effectively and efficiently promote PCT to achieve mitigation target and sustainable development.

As China has already become the biggest carbon emitter, it is worth researching how to reduce its anthropogenic emissions cost-effectively. In this paper, the Chinese nationwide emission trading scheme (CNETS) is taken as a case study because if appropriately designed and implemented smoothly, the CNETS may become one of China's most significant efforts to lessen its substantial CO_2 emissions. Nevertheless, to our knowledge, very few researchers have endogenized technological change under the CNETS; therefore, it is meaningful to study induced technological progress of the CNETS in this paper. To achieve this research target, we have adopted the method by Liang et al. (2022) [3] to quantify PCT, whereas efficiency improvement is modeled according to Chen (2021) [10].

This paper has six sections: Section 1 focuses on the research background and the existing research gap to be narrowed. Section 2 is the literature review section explaining the rationale for endogenizing technological progress in CGE model. Section 3 is the method section which describes the adopted CGE model, details of the designed ETS, ETS impact on clean technology, ETS impact on efficiency, and designed scenarios of this paper. Section 4 is the result section, which displays the major results of this paper. Section 5 is the discussion section where the major findings are compared to the relevant literature, and limitations are acknowledged. Section 6 is the conclusion section where this paper ends.

2. Literature review

Although climate-change-related issues have been hot in literature, climate change models are usually featured with exogenous technological change, even though coping with global warming requires more climate-change-related innovation [15]. Without governmental intervention, most innovation is directed at dirty technology because firms with much innovation in dirty technology in the past find it more profitable to innovate in dirty technology in the future [16]. To break such path dependency, climate policy needs to be implemented to redirect technological change. Evidence of carbon pricing redirecting innovation to climate-friendly technology can be found in the literature. For example, Aghion et al. (2016) [15] showed that the carbon tax would drive firms in the auto industry to innovate more in clean technology; Haas and Kempa (2018) [17] argued that increasing energy price would lead to lower energy intensity, and temporal energy price shock might induce a permanent redirection of innovation activity.

When studying how climate policy directs technological change, partial equilibrium (PE) model is usually employed to analyze equilibria of targeted markets at the price of omitting balances of other markets in the economy. Hence, PE model cannot fully capture the complicated socioeconomic system and thus fails to measure socioeconomic effects of climate policy unbiasedly. In contrast, general equilibrium (GE) model incorporates all the potential socioeconomic interactions [18], but it is criticized for its heavy reliance on parametric assumptions [4] and difficulties in interpretations, namely the "black box" [19]. If parameters are chosen from trusted sources and model mechanisms are interpreted comprehensively, GE model is likely to generate reliable results.

Within the domain of GE models, Computable General Equilibrium (CGE) model is widely adopted to evaluate climate policy, like carbon tax [20] and ETS [21]. Dating back to Johansen (1960) [22], CGE model enables researchers to endogenously quantify all the targeted variables in a series of equations. Nevertheless, previous CGE model was usually formed with exogenous technological determination [16]. Particularly, automatic energy efficiency index (AEEI) was usually adopted to exogenously define technological progress in studying ETS-related issues, like governmental fine [12] and sectoral coverage [23]. In these studies, the presumable AEEI was based on a governmental plan for energy saving; however, it cannot clearly distinguish between technological progress and long-term price effect [24]. Hence, AEEI measurement for technological advancement is problematic in climate policy evaluation.

As climate policy can increase R&D investment to promote carbon-saving innovation [25], technology should be incorporated as an endogenous variable in policy evaluation framework. In literature, CGE model was employed to endogenize technological progress using R&D variation. For example, Heggedal and Jacobsen (2011) [26] developed the CGE model with endogenous technological progress induced by new patents; Yang et al. (2016) [27] performed the CGE analysis to study how the carbon market affected R&D investment in China. Unfortunately, these two studies only modeled general technological change but cannot provide detailed content of technological progress, thereby failing to comprehensively measure induced technological progress of climate policy in CGE model.

This paper contributes to the CGE literature by detailing technological progress of climate policy. Specifically, we have divided policy-induced technological change into PCT, based on Liang et al. (2022) [3], and efficiency improvement, based on Chen (2021) [10]. Liang et al. (2022) [3] endogenously defined climate-friendly technology in CGE model; however, they overlooked potential efficiency improvement under climate policy, and thus their research method could be biased. Conversely, Chen (2021) [10] modeled efficiency improvement of climate policy but excluded the potential development of clean technology [28]. Hence, these two studies biasedly quantified induced technological progress of climate policy. With the research methods of these two studies combined, this paper may overcome the limitations of these two studies and unbiasedly measure policy-induced technological progress in CGE model.

3. Method

Fig. 1 shows the research framework in this paper. According to Fig. 1, technology affects labor, capital, and energy input, thereby varying economic output. In combination with carbon emission factor, energy input has unwanted environmental byproducts, namely carbon emissions. Soaring emissions cause climate change, which arouses global concerns, and thus climate policy (ETS) is implemented to curb emissions from energy consumption. As climate policy interrupts market mechanism, it causes deadweight loss and negatively affects GDP growth. Climate policy induces technological progress, namely progress of clean technology (PCT) and efficiency improvement. PCT affects emission factor and thus carbon emissions. Efficiency improvement includes improvement of energy-use efficiency, energy-production efficiency, and nonenergy-production efficiency; these efficiencies affect input of labor, capital, and energy.

Fig. 2 shows the research method of this paper in four steps. Step 1 shows the detailed content of the CGE model, including data source, sector division of the Chinese economy, and divided blocks. Step 2 displays the emission trading scheme (ETS) basics, like sectoral coverage, quota allocation method, and quota trading price. Step 3 focuses on ETS-induced PCT; specifically, a logistic curve is utilized to denote investment in clean technology which affects carbon emission factor. Step 4 details how ETS affects energy-use, energy-production, and nonenergy-production efficiency.

3.1. CGE model structure

The CGE model in this paper derives from our previous work [20]. The database of the CGE model is the social accounting matrix (SAM), which is built based on China Input-Output (IO) Table, and the SAM can be found in Chen (2021) [10]. The sectoral energy consumption data in the base year (2020) are from China Energy Statistical Yearbook. After sector aggregation and disaggregation, 29 sectors are left in Table A1 in Appendix. According to Table A1, the Chinese economy has 20 non-electricity sectors and nine electricity sectors. Like the CGE model in Liang et al. (2022) [3], the CGE model in this paper is formed by the top-down method to measure macro-level effect of climate policy [29].

The CGE model has a production, income-expenditure, and trade block. As the CGE model is related to an environmental issue (CO_2 emissions), it includes an environment block. The CGE model is dynamic recursive to study ETS effect on technological progress over time, and thus a dynamic block is incorporated to denote how the dynamic parameters and variables change over time. The detailed equations depicting the divided blocks are provided in Supplementary Materials.

In the production block, standing for all the enterprises in China, the representative enterprise covers all the divided sectors, each producing one type of commodity. Multi-layered productions occur within the enterprise: a Leontief function is employed to quantify the top production relation of intermediate input and added value [21], while constant elasticity of substitution (CES) functions are utilized to quantify the other production relations, shown in Eq. (1). The subscripts i and t denote a sector and year. $F1_{it}$ and $F2_{it}$ denote input of Factor 1 and Factor 2. $sf1_{it}$ and $sf2_{it}$ are the share parameters of $F1_{it}$ and $F2_{it}$. $OUTPUT_{it}$ is the output from $F1_{it}$ and $F2_{it}$. $scale$ and ρ are the scale parameter and elasticity parameter, respectively.

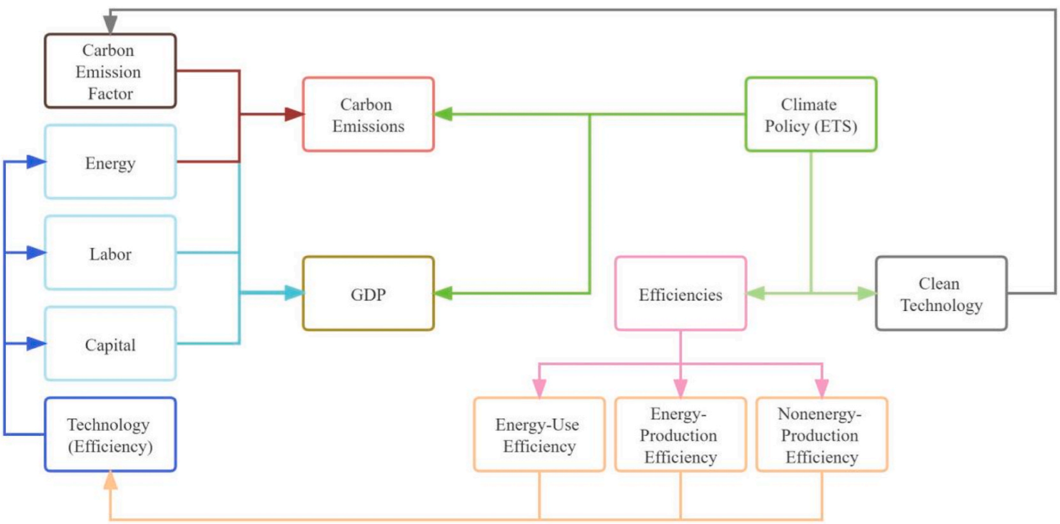

Fig. 1. Research framework.

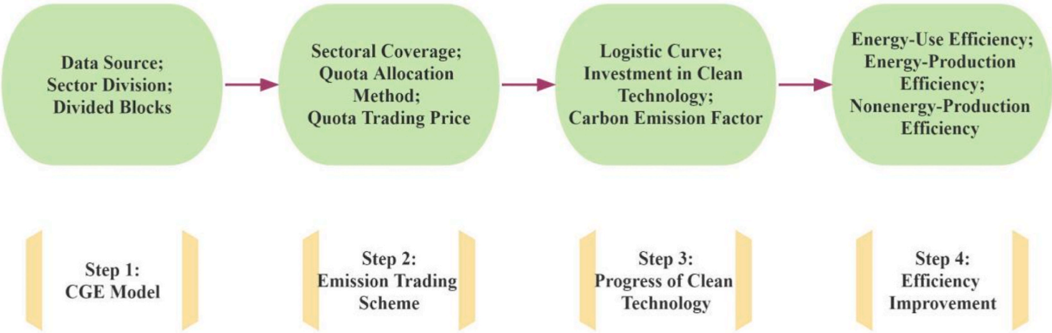

Fig. 2. Method overview.

$$OUTPUT_{it} = scale \times \left(sf1_{it} \times F1_{it}^{\frac{\rho-1}{\rho}} + sf2_{it} \times F2_{it}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{1}$$

The CES elasticity parameters are from Guo et al. (2014) [30] who have confirmed the robustness of the parameters; in addition, the parametric robustness is also confirmed in Chen (2022) [20]. Hence, sensitivity analysis is unnecessary to test the elasticity robustness in this paper. As climate policy increases consumption cost of fossil energy, rational entities tend to use less fossil energy under climate policy. With the fixed elasticity parameters, decreasing energy input reduces gross output even if nonenergy input remains unchanged.

In the income-expenditure block, the representative household, which denotes all the Chinese households, earns income from labor wage, capital return, and money transfer [31]; it consumes domestic or foreign commodities. The enterprise only has its income from capital return, whereas it buys labor to produce commodities and transfers money to the household [31]. The income sources of the representative government, denoting all the Chinese local and central governments, are foreign money transfer, climate policy implementation, and economic taxes (consumption tax, production tax, and tariff). Tax neutrality is applied to economic taxes. The governmental income is spent on commodity consumption and money transfer to the household and foreigner.

In the trade block, the representative foreigner, denoting all the countries in the rest of the world, consumes commodities that the domestic enterprise produces; at the same time, it produces commodities that are consumed by the domestic household and government. The enterprise and foreigner sell commodities in the domestic or foreign market to maximize profit. International trade occurs based on the Armington (1969) [32] assumption that commodities from different countries are imperfect substitutes. When aggregate export equals aggregate import in monetary value, trade balance is reached [31].

In the environment block, domestic commodity production and consumption generate CO_2 emissions, defined in Eq. (2). The subscript j refers to a type of energy. TCE_t denotes total CO_2 emissions; SEC_{ijt} is sectoral energy consumption; HEC_{jt} is household energy consumption. cef_j denotes CO_2 emission factor, and its time-invariant value is given by IPCC (2006) [33].

$$TCE_t = \sum_j \sum_i \left(SEC_{ijt} \times cef_j \right) + \sum_j \left(HEC_{jt} \times cef_j \right) \tag{2}$$

Increasing anthropogenic emissions arouse global concerns, and thus the government has to take measures, like ETS, to mitigate CO_2 emissions. The ETS implementation interrupts market mechanism in resource allocation and affects economic output; it also brings revenue to the government. The detailed ETS content can be found in Section 3.2 of this paper.

In the dynamic block, dynamic parameters are assumed to be exogenously determined regardless of the ETS implementation; by comparison, the ETS changes dynamic variables whose values are exogenously given in the business-*as*-usual (BAU) scenario only. This paper's dynamic parameter is the population growth rate from World Population Prospects. The dynamic variables are price, energy consumption growth rate, output growth rate, and capital accumulation. The price (export, import, and commodity price) is assumed to follow the price projection by OECD [21]. The growth rates of energy consumption and output are from International Energy Outlook and long-term GDP forecast by OECD [31]. The projected accumulation of physical capital is based on Long and Herrera (2016) [34], whereas China Human Capital Report shows the projected human capital accumulation in China [35].

To build the CGE model, we have simplified the complicated real world by several assumptions, otherwise too many variables increase model dimensionality and thus decrease degree of freedom. Firstly, labor and capital are assumed to be immobile internationally. This is because the magnitudes of international labor migration and capital flow are quite small, compared to the overall labor and capital supply, according to China Statistical Yearbook. Secondly, labor and capital are assumed to move freely between sectors within China; in other words, there are no labor training and capital installation costs. Thirdly, the ETS causes sectoral movement of labor and capital, but the overall labor and capital under the ETS implementation are assumed to equal that in the BAU scenario. Lastly, labor and commodity markets are balanced with no idle labor and commodity; therefore, labors are fully employed, and commodities are all consumed.

3.2. ETS basics

In July 2021, China officially launched the nationwide emission trading scheme (CNETS) after implementing the ETS pilots for many years; 2030 is the deadline to achieve the Chinese nationally determined contribution (NDC) target of peaking emissions [36]. Hence, this paper's study period is 2021–2030 [37].

Currently, the CNETS covers electricity firms only; carbon quotas of electricity firms were allocated based on firms' emissions in 2020 [38]. In the Chinese ETS pilots, 90 % of carbon quotas were freely distributed, and other quotas were auctioned [39]; the quota decline factor was 0 %, 0.5 %, 1 %, and 2 % [39]; the penalty price of emission noncompliance was three times the quota trading price [31]. Currently, the quota trading price of the CNETS is around 60 $CNY/t\ CO_2$ [40] or approximately 8.5 $USD/t\ CO_2$.

The ETS in this paper is designed based on the CNETS and Chinese ETS pilots; more details about the designed ETS can be found in Chen (2023) [41]. The ETS is targeted to regulate electricity generation only; however, as the sectors generating electricity from renewable energy are assumed to have zero fossil energy consumption, these electricity sectors are exempted by the ETS. Sectoral carbon quotas are based on sectoral emissions in 2020, which is the base year of this paper. Regarding the quota allocation method, 90 % of carbon quotas are freely allocated, and the remnants are auctioned. Impact of quota decline factor is unrelated to this paper's research scope, so the ETS is designed with the zero decline factor.

The government cancels an auction when the highest bid is much lower than quota trading price [42]; therefore, quota auction price is assumed to equal trading price [31]. The quota trading price in this paper is fixed at the current price in the CNETS. Such exogenous price determination avoids quota trading price severely deviating from actual price, unlike some previous researchers arguing for exorbitant prices to accelerate low-carbon transition [43] or achieve NDC targets [44].

Because of the exogenous price determination, the ETS market is unbalanced in this paper, contrary to Mu et al. (2018) [45] who endogenously defined the equilibrium price to equate permit supply and demand. More details on how to quantify an unbalanced ETS market in CGE model can be found in Chen and Wang (2023a) [21]. In an unbalanced ETS market, quota demand is unequal to supply [37]. When quota demand is lower than supply, untradeable surplus quotas exist in market. Conversely, in most cases, when quotas are in shortage, quota-uncovered emissions are regulated by ETS penalty. Existing in the EU ETS [42], Korean ETS [46], and Chinese ETS pilots [47], ETS penalty is usually implemented through penalty price of emission noncompliance. In this paper, the ETS penalty price is assumed to be three times the quota trading price [31].

The ETS brings about revenue from auctioning carbon quotas and penalizing quota-uncovered emissions. As revenue recycling is not considered in this paper, ETS revenue is assumed to be kept by the government [31], which is akin to no revenue recycling in Li et al. (2019) [48]. Equivalently, from the sector perspective, ETS revenue can be regarded as mitigation cost paid to the government.

3.3. ETS impact on clean technology

As ETS increases consumption cost of fossil energy, rational entities have incentives to develop clean technology to reduce fossil energy combustion; therefore, ETS may promote progress of clean technology. Corresponding to the life cycle of technology [49], logistic curve that overcomes shortcomings of learning curve can better describe cost reduction induced by technological progress [50]. This paper shows the logistic curve in Eq. (3).

$$PCT_t = \alpha_{lo} + \frac{\alpha_{up}}{\left\{1 + \theta \times e^{-\beta \times \left[ORD_t \times (1+ICT_t) - \frac{mt}{1+ICT_t}\right]}\right\}^{\frac{1}{\theta}}} \tag{3}$$

In Eq. (3), PCT_t denotes progress of clean technology. α_{lo} and α_{up} refer to the lower and upper asymptote of PCT_t, and their values are 0.02 and 0.98, respectively [50]. θ is the parameter to determine whether maximum growth occurs early or late, and its value is set to one to denote symmetric change; β stands for average growth rate of clean technology, and it is equal to 0.3 [50]. ORD_t refers to the relative position of a research year in the ordinal set t. mt is the year of maximum growth, and its value is 40 [50]. ICT_t is proportion of investment in clean technology [3]. Higher output usually induces higher income, which results in more R&D investment [51]; therefore, ICT_t is assumed to equal the ratio of the renewable electricity sectors' outputs to the overall economic output in this paper.

PCT_t affects emissions because it reduces CO_2 emission factor [3], shown in Eq. (4). $CCEF_{jt}$ refers to CO_2 emission factor influenced by PCT_t. In the base year (2020), $CCEF_{jt}$ is assumed to equal cef_j.

$$CCEF_{jt} = \begin{cases} cef_j, t = 2020 \\ CCEF_{j,t-1} \times (1 - PCT_t), t > 2020 \end{cases} \tag{4}$$

3.4. ETS impact on efficiency

ETS endogenously affects energy efficiency because it increases consumption cost of fossil energy, and thus rational entities have incentives to raise energy efficiency to reduce fossil energy consumption. Energy efficiency improvement could be achieved through R&D investment in energy sectors; therefore, resources may flow to energy sectors under ETS. Nevertheless, ETS may also cause resource inflow to nonenergy sectors because it increases the comparative advantages of nonenergy commodities over energy commodities.

In this paper, ETS impact on efficiency is modeled based on the quantification method in Chen (2021) [10]. During ETS implementation, energy cost share (ECS_t) is defined in Eq. (5). PE_{ijt} is energy price; GDP_t is gross domestic product; $COST_t$ refers to abatement cost.

$$ECS_t = \frac{\sum_i \sum_j \left(PE_{ijt} \times SEC_{ijt}\right) + COST_t}{GDP_t} \tag{5}$$

Eq. (6) defines energy-use efficiency (EUE_t). TEC_t is consumed energy commodities in total. σ is the substitution elasticity between energy commodities and nonenergy commodities, and its value is 0.4 [28]. Hence, the exponent in Eq. (6) is negative, implying that EUE_t is negatively related to ECS_t.

$$EUE_t = ECS_t^{\frac{\sigma-1}{\sigma}} \times \frac{GDP_t}{TEC_t} \tag{6}$$

Eqs. (7) and (8) define energy-production efficiency (EPE_t) and nonenergy-production efficiency (ENE_t), respectively. The subscripts e and ne denote an energy sector and a nonenergy sector. QM_{it} and QE_{it} are import and export. TEP_t and $TNEP_t$ are produced energy and nonenergy commodities in total. TEC_t and $TNEC_t$ are consumed energy and nonenergy commodities in total. $SGDP_{it}$ is sectoral output.

$$EPE_t = \frac{TEP_t}{GDP_t \times ECS_t} = \frac{TEC_t}{GDP_t \times ECS_t} \times \frac{\sum_e SGDP_{et}}{\sum_e SGDP_{et} + \sum_e QM_{et} - \sum_e QE_{et}} \tag{7}$$

$$ENE_t = \frac{TNEP_t}{GDP_t \times (1 - ECS_t)} = \frac{TNEC_t}{GDP_t \times (1 - ECS_t)} \times \frac{\sum_{ne} SGDP_{ne,t}}{\sum_{ne} SGDP_{ne,t} + \sum_{ne} QM_{ne,t} - \sum_{ne} QE_{ne,t}} \tag{8}$$

According to Wang et al. (2019) [28], overall efficiency index (OEI_t) is defined as a function of EUE_t, EPE_t, and ENE_t, shown in Eq. (9). Nonenergy-use efficiency is assumed to be one [28]. As higher overall efficiency increases economic output, $SGDP_{it}$ is assumed to change proportionally to OEI_t, shown in Eq. (10). $OEI0_t$ and $SGDP0_{it}$ are overall efficiency index and sectoral output in the BAU scenario. The embedded assumption of Eq. (10) is that efficiency improvement occurs evenly across sectors, and thus this paper cannot measure disparities of efficiency improvement at sector level during ETS implementation.

$$OEI_t = \left[(EUE_t \times EPE_t)^{\sigma-1} + ENE_t^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{9}$$

$$SGDP_{it} = \frac{OEI_t}{OEI0_t} \times SGDP0_{it} \tag{10}$$

3.5. Scenario design

In this paper, the designed scenarios are displayed in Table 1. The business-*as*-usual (BAU) scenario is the reference scenario where no ETS is implemented. In the non-efficiency and non-clean-technology (NEC) scenario, the ETS is implemented without considering efficiency improvement and progress of clean technology. In the efficiency (EFC) scenario, the ETS is implemented incorporating efficiency improvement, whereas in the clean technology (CLT) scenario, the ETS is implemented with progress of clean technology. In the efficiency and clean technology (ECT) scenario, both types of technological progress are considered during the ETS implementation.

4. Result

4.1. Progress of clean technology

ETS impact on investment in clean technology (ICT) is shown in Fig. A1 in Appendix. The ETS increases ICT; however, this ETS impact is quite minimal because ICT only occupies a small proportion of the overall investment. According to Fig. A1, ICT is quite close in the CLT and ECT scenario, and thus the curves for these two scenarios overlap in Fig. 3 which shows ETS impact on CO_2 emission factor (CEF). In the NCE and EFC scenario, CEF is exogenous and equal to that in the BAU scenario; therefore, these two scenarios are excluded in Fig. 3. In summary, although the ETS has a minimal impact on ICT, its impact on CEF is significant.

Table 1
The designed scenarios in this paper (unit: $CNY/t\ CO_2$).

Scenario	ETS Implementation	Clean Technology	Efficiency
BAU			
NEC	×		
EFC	×		×
CLT	×	×	
ECT	×	×	×

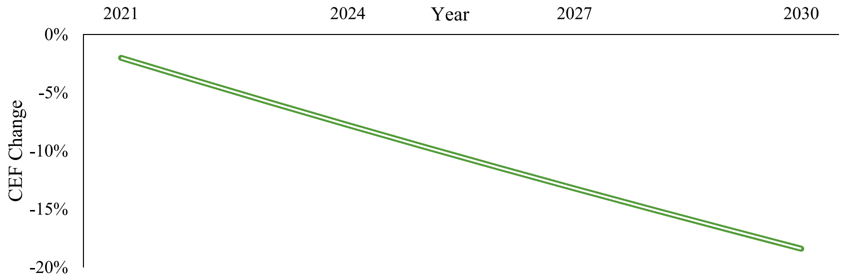

Fig. 3. ETS impact on CO_2 emission factor (CEF).

4.2. Efficiency improvement

Fig. A2–A4 in Appendix shows ETS impact on EUE, EPE, and ENE, respectively. The ETS increases EUE in the NEC scenario, but this impact is uncertain in the other scenarios. This result implies that the ETS increases EUE without induced technological progress; however, this impact is uncertain considering induced technological progress.

The ETS decreases EPE over time except in 2021 which was the first year of the ETS implementation because, in the short term, energy sectors need to increase EPE to counteract rising cost of energy production caused by the ETS. Nevertheless, in the long term, energy sectors become comparatively disadvantageous and thus experience capital outflows; therefore, EPE declines owing to capital outflows under the ETS.

The ETS positively affects ENE irrespective of induced technological progress because it increases comparative advantages of nonenergy production over energy production and thus stimulates capital inflows to nonenergy sectors. Hence, the ETS promotes R&D and increases ENE in nonenergy sectors.

ETS impact on overall efficiency index (OEI) is shown in Fig. 4. The ETS positively affects OEI over time, implying that efficiency loss in energy sectors can be compensated by efficiency gain in nonenergy sectors under the ETS.

4.3. Economic impact

According to Fig. 5, the ETS negatively affects GDP. Although progress of clean technology (PCT) is assumed to have no direct impact on GDP, it affects carbon emissions through emission factor, thereby changing abatement cost. PCT decreases ETS-induced GDP loss, and this impact is stable in the long term. By comparison, efficiency improvement decreases GDP loss, but this impact diminishes over time. The curve for the ECT scenario is close to that for the CLT scenario in the short term, but it is slightly below the curve for the NEC scenario in the long term. This result implies that simultaneously considering both technological progress brings about GDP benefit temporarily, but such GDP benefit eventually disappears; in other words, efficiency improvement outperforms PCT to affect GDP in the long term. The economic intuition to explain the result is that efficiency improvement may increase fossil energy consumption owing to the rebound effect [52]; consequently, rational entities may become reluctant to adopt clean technology in the long term.

4.4. Emission abatement

Negative ETS impact on anthropogenic CO_2 emissions is displayed in Fig. 6. Emission abatement in the NEC scenario is higher than that in the EFC scenario but lower than that in the CLT scenario, implying that efficiency improvement decreases emission abatement, and PCT increases emission abatement. Compared to the CLT scenario, the ECT scenario has slightly lower emission abatement in the short term but higher abatement in the long term. This finding implies that without PCT, efficiency improvement reduces emission

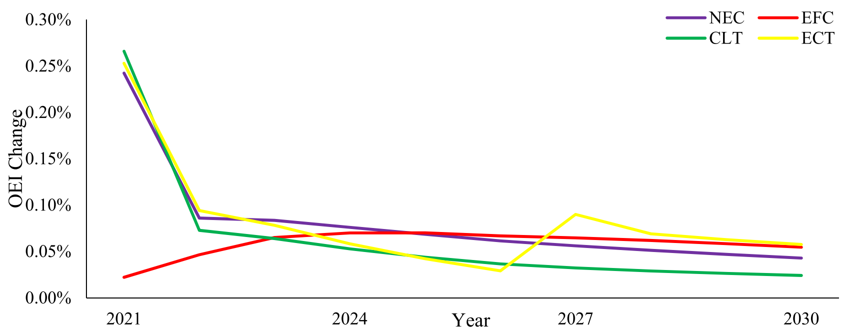

Fig. 4. ETS impact on overall efficiency index (OEI).

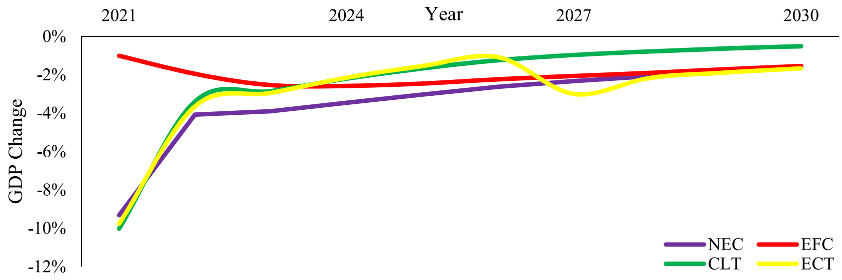

Fig. 5. ETS impact on GDP

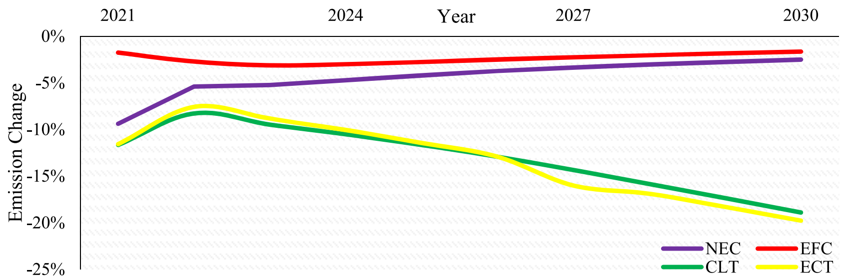

Fig. 6. ETS impact on anthropogenic CO_2 emissions.

abatement; considering PCT, it temporarily reduces abatement effort but eventually promotes emission mitigation. This is because clean technology enhances green innovation, and efficiency improvement may speed up low-carbon transition in the long term. Hence, clean technology can be regarded as a moderator between efficiency improvement and emission abatement under the ETS.

5. Discussion

Targeted at electricity generation only, the designed ETS induces clean technology innovation, which is denoted by investment in clean technology (ICT). The ETS promotes ICT because it increases advantages of clean technology over dirty or energy-intensive technology, thereby incentivizing decarbonization of power sector and reducing carbon intensity of coal and gas power [53]. Similarly, Lin et al. (2018) [54] argued that the CNETS would help redirect technological innovation onto a cleaner path. Unfortunately, ETS impact on ICT is quite minimal because attributes, like compliance period, quota banking, and policy stability, significantly influence the possibilities of corporate investments in low-carbon technology [55]. In addition, the trading price of the CNETS is too low, compared to the current EU ETS price; low carbon pricing cannot sufficiently mobilize additional financing for new investments in lower carbon modes of production [56]. Nevertheless, ETS-induced progress of clean technology (PCT) significantly decreases CO_2 emission factor and thus abates carbon emissions. This finding agrees with Chen et al. (2020) [57] who concluded that the ETS stimulated clean innovation and thus curbed anthropogenic emissions.

Without considering induced technological progress, the ETS increases energy-use efficiency (EUE) because it raises consumption cost of fossil energy, and thus rational entities have more incentives to increase efficiency in energy use. Similarly, Zhang and Fan (2019) [58] argued that the ETS implementation stimulated firms to improve EUE in China proactively. With induced technological progress, the positive ETS impact on EUE diminishes and even turns negative as the ETS spurs green innovation [59] and thus reduces fossil energy consumption; consequently, sectors are disincentivized to improve EUE.

The ETS decreases energy-production efficiency (EPE) because it increases production cost of fossil energy and thus reduces competitivity of energy sectors [60], thereby stimulating resources to move from energy sectors to nonenergy sectors. Consequently, influenced by the ETS, energy sectors have fewer incentives to raise EPE, and energy products become less favorable, which complies with the argument that climate policy induces less carbon-intensive input [61]. Conversely, the ETS positively impacts nonenergy-production efficiency (ENE) as it increases the comparative competitivity of nonenergy sectors and thus causes resource inflow to these sectors. Similar evidence could be found in the EU ETS which positively impacted the economic performance of the regulated manufacturing firms [62].

The ETS increases overall efficiency because sectors with surplus quotas have incentives to reduce sectoral emissions to sell more quotas [8]; for sectors needing extra quotas, compliance cost is helpful to supersede inefficient technology and raise production efficiency [63]. Owing to rising overall efficiency, ETS-induced efficiency loss in energy sectors can be compensated by efficiency gain in nonenergy sectors. Evidence of efficiency improvement under climate policy could be found in the literature. For example, Hu et al. (2020) [8] investigated the emission reduction effects of the Chinese ETS pilots, concluding that the ETS pilots improved technological efficiency; Zhang et al. (2021) [64] empirically found that the Chinese ETS pilots significantly improved green development efficiency.

The ETS decreases GDP, and a similar ETS effect on GDP could be found in the Vietnamese ETS [65]. PCT decreases ETS-induced

GDP loss, as clean technology significantly decreases CO_2 emissions and thus abatement cost. This finding agrees with the previous research showing that a firm could invest in clean capital to reduce its abatement cost [66]. Efficiency improvement also decreases GDP loss because it increases productivity and thus stimulates GDP growth. Nevertheless, considering both ETS-induced technological progress slightly impedes economic growth in the long term, which agrees with the previous research showing that the carbon price increased R&D level but did not increase industrial sales and profits [67]. One reason to explain this finding is that ETS-induced technological progress may cause high energy-consuming industries to improve efficiency at distribution and marketing stage rather than production stage of value creation chain [67].

The ETS abates anthropogenic emissions, and PCT further increases emission abatement. This finding agrees with Hu et al. (2020) [8] who showed that the ETS induced closure of firms with severe pollution and stimulated capital inflow to firms with high emission efficiency, thereby achieving emission reduction. Efficiency improvement partially counteracts ETS emission abatement because it boosts GDP growth [68], and this economic boom is accompanied by increasing energy consumption [52]. The Jevons Paradox [69] or energy rebound effect [70] also implies that efficiency improvement may increase energy consumption to undermine the effectiveness of climate policy in achieving mitigation targets [71]. Nevertheless, considering PCT, efficiency improvement reduces CO_2 emissions in the long term, implying that PCT moderates the relation between efficiency improvement and emission abatement. Similarly, clean innovation was regarded as the key to reconciling the relationship between emission abatement and economic growth for the Chinese carbon market [54].

To summarize, this paper shows that clean technology can solve the Jevons Paradox or avoid energy rebound effect to harmonize conflicts between environment and economy to achieve sustainable development. Unfortunately, clean technology usually has limited impacts on emission mitigation in reality because there is a path dependency on dirty technology in the past [16], and thus clean technology is usually costlier than dirty technology. Adoption of clean technology is related to consumers' willingness to pay for clean products, and private and public incentives to adopt clean technology differ [72]. In addition, clean technology may not be quickly diffused by climate policy because there are factors other than policy important to clean technology diffusion, like characteristics of clean technology, absorptive capacities of potential adopters, and age structure of capital [73]. Hence, despite its significance in emission mitigation, clean technology is usually underplayed, owing to restrictive factors in the real world.

In the current Chinese nationwide emission trading scheme (CNETS), the government has clear regulations on sectoral coverage, quota allocation method, and quota trading price [38]; however, regulations on technological progress are lacking. Many previous researchers explored the historical data to confirm that the Chinese ETS pilots promoted green development efficiency [14], green technology innovation [74], or progress of emission abatement technology [13]. This paper further confirms that the CNETS also stimulates PCT and efficiency improvement. To ensure the potential roles of the CNETS in promoting technological progress, the Chinese government may adopt ETS complementary measures, like ETS revenue recycling. Compared to a single climate policy, a hybrid one may induce lower economic loss or energy utilization cost [75], making it more likely to be smoothly implemented.

This paper has some limitations that need to be addressed in future research. Firstly, owing to the lack of sectoral data, this paper only shows how the ETS affects efficiency at country level by assuming that each sector experiences the same percentage change of efficiency under the ETS. There could be sectoral disparities in ETS-induced efficiency improvement. Secondly, clean technology is assumed to affect CO_2 emission factor only in this paper. Nevertheless, clean technology can have direct economic impacts, such as industrial upgrading towards low-carbon industries. Increasing innovation of clean technology may also crowd out innovation of other technology, and thus ETS effect on overall R&D could be negative [54]. Thirdly, in the CGE model of this paper, capital is immobile internationally, implying that R&D investment cannot flow across countries. In reality, technology can be imported and exported. Lastly, international technology spillover is not considered in this paper. Technological progress in the rest of the world may help achieve low-carbon transition in China; meanwhile, spurred green innovation in China may also help decrease anthropogenic emissions elsewhere.

6. Conclusion

This paper employs a dynamic recursive CGE model to quantify ETS-induced technological progress, namely progress of clean technology (PCT) and efficiency improvement. The model results show that PCT negatively affects anthropogenic emissions, while efficiency improvement decreases GDP loss or abatement cost. Simultaneously considering both technological progress increases emission abatement but slightly decreases GDP in the long term. The most interesting finding is that PCT moderates the relationship between efficiency improvement and emission abatement, and thus it plays a crucial role in emission abatement and economic growth under climate policy. Future research may address this paper's limitations in the following four aspects: ETS-induced efficiency improvement at sectoral level, economic impact of clean technology, international technology flow, and international technology spillover.

Data availability statement

The model results are calculated based on the following data sources: China Input-Output Table (https://data.stats.gov.cn/files/html/quickSearch/trcc/trcc01.html), China Statistical Yearbook (http://www.stats.gov.cn/sj/ndsj/), China Energy Statistical Yearbook (http://cnki.nbsti.net/CSYDMirror/area/Yearbook/Single/N2022060061?z=D26), World Population Prospects (https://population.un.org/wpp/), OECD Data (https://data.oecd.org/), and International Energy Outlook (https://www.eia.gov/outlooks/ieo/).

Additional data will be made available on request.

CRediT authorship contribution statement

Shuyang Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix. Additional Tables and Figures

Table A1
Divided Sectors in This Paper

Non-electricity Sector	Non-electricity Sector	Electricity Sector
Agriculture	Construction	Electricity Transmission and Distribution
Mining	Transport and Storage	Supercrit-coal Generation
Food and Tobacco	Service	USC-coal Generation
Textile	Coal Mining	Subc-coal Generation
Furniture	Coking	Natural-Gas Generation
Chemical Industry	Petrol Mining	Nuclear Generation
Mineral Production	Petrol Processing	Hydro Generation
Metal Production	Gas Mining	Wind Generation
Machinery	Gas Production	Solar Generation
Water Production	Fire Power	

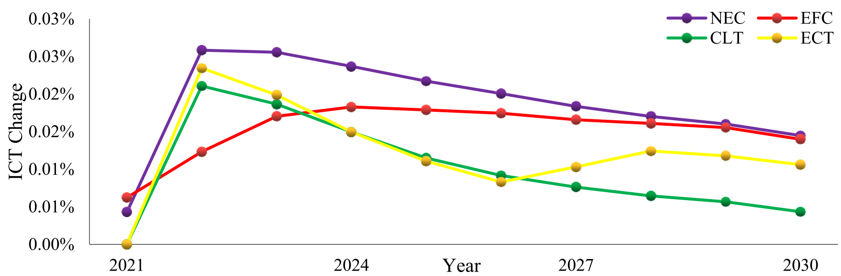

Fig. A1. Investment in Clean Technology (ICT) Influenced by the ETS

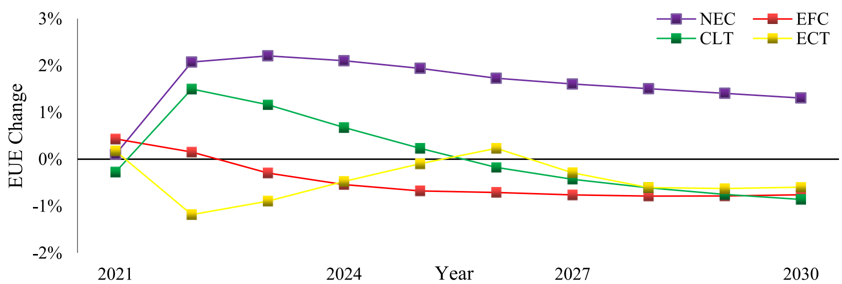

Fig. A2. ETS Impact on Energy-use Efficiency (EUE)

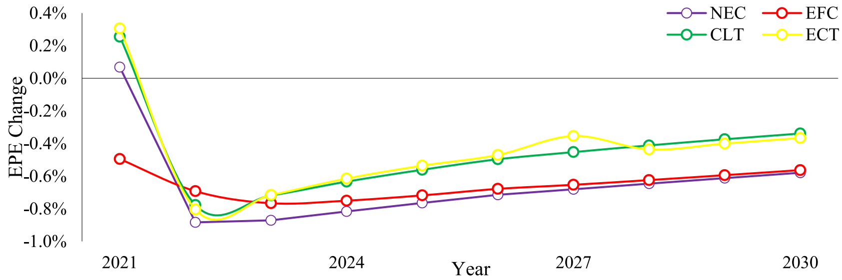

Fig. A3. ETS Impact on Energy-Production Efficiency (EPE)

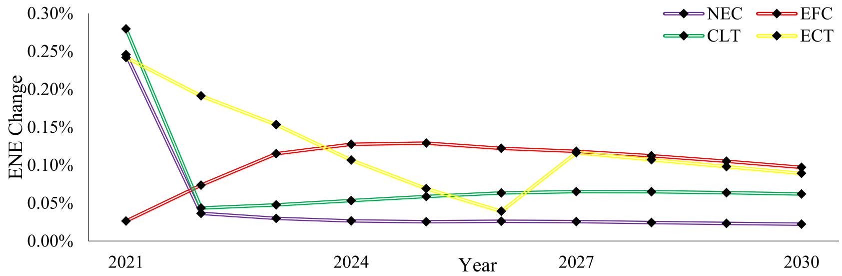

Fig. A4. ETS Impact on Nonenergy-Production Efficiency (ENE)

Nomenclature

Set	Meaning
e	energy sector
i	sector
j	energy
ne	nonenergy sector
t	year

Parameter

cef_j	CO_2 emission factor
mt	year of maximum growth 40
$scale$	scale parameter
$sf1_{it}$	share parameter of $F1_{it}$
$sf2_{it}$	share parameter of $F2_{it}$
α_{lo}	lower asymptote of PCT_t 0.02
α_{up}	upper asymptote of PCT_t 0.98
β	average growth rate of clean technology 0.3
θ	parameter to determine whether max growth occurs early or late 1
ρ	elasticity between $F1_{it}$ and $F2_{it}$
σ	elasticity between energy and nonenergy commodities 0.4

Variable

$CCEF_{jt}$	CO_2 emission factor influenced by PCT_t
$COST_t$	abatement cost CNY (yuan)
ECS_t	energy cost share
ENE_t	nonenergy-production efficiency
EPE_t	energy-production efficiency
EUE_t	energy-use efficiency
$F1_{it}$	input of Factor 1
$F2_{it}$	input of Factor 2
GDP_t	gross domestic product CNY (yuan)
HCE_{jt}	household energy consumption
ICT_t	proportion of investment in clean technology
OEI_t	overall efficiency index
$OEI0_t$	overall efficiency index in the BAU scenario

ORD_t relative position of a year in the ordinal set t
$OUTPUT_{it}$ output from $F1_{it}$ and $F2_{it}$
PCT_t progress of clean technology
PE_{ijt} energy price
QE_{it} export CNY (yuan)
QM_{it} import CNY (yuan)
SEC_{ijt} sectoral energy consumption
$SGDP_{it}$ sectoral output CNY (yuan)
$SGDP0_{it}$ sectoral output in the BAU scenario CNY (yuan)
TCE_t total CO_2 emissions ton CO_2
TEC_t consumed energy commodities in total CNY (yuan)
TEP_t produced energy commodities in total CNY (yuan)
$TNEC_t$ consumed nonenergy commodities in total CNY (yuan)
$TNEP_t$ produced nonenergy commodities in total CNY (yuan)

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e23126.

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