The optimal industrial carbon tax for China under carbon intensity constraints: a dynamic input–output optimization model

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Abstract
To reduce carbon emissions, the Chinese government is considering introducing a differentiated industrial carbon tax on enterprises outside the carbon trading market in the future. An efficient carbon tax must consider not only how carbon taxes impact the current economy but also how the size of the tax should be adjusted across time due to external changes. To calculate the optimal industrial carbon tax for China which is subject to certain constraints, this paper investigates the economic and environmental effects of four possible industrial carbon tax rate models under carbon intensity constraints from 2021 to 2030 by a dynamic input–output optimization model. The results show that the dynamic tax rate model leads to larger fluctuations in GDP growth than the other tax models, with a low initial tax rate in the beginning and a high tax rate exceeding ¥180/t in 2030. Second, a large quantity of capital stock is distributed across the energy-intensive industries, which leads the existing capital investment structure to be path-dependent. This offsets the performance of carbon taxes. Third, indirect energy-intensive industries such as construction and transport are insensitive to the industrial carbon tax. Finally, comparing the impacts of the four tax rate models, the optimal industrial carbon tax for China is found to be a fixed differentiated tax rate, in which energy-intensive sectors are taxed ¥75/t and low-carbon sectors are taxed ¥50/t.

Keywords Input–output method · Optimal carbon tax · Tax rate model · Industry · China

Introduction
As a responsible country that actively reduces CO2 emissions, the Chinese government promised to reach the peak of CO2 emissions by 2030 and achieve carbon neutrality by 2060 (Li et al. 2021b). The goal of carbon neutrality is not an issue of energy substitution and technological breakthroughs but emits forward new and hard constraints on China’s sustainable development (Chen and Lin 2021; Zhang 2021). To promote the enterprises to manage CO2 emissions and transform to a green production model, China has launched a national carbon emission trading system (namely, ETS) covering all large enterprises in key energy-intensive industries in 2017. However, the high fluctuation of the carbon price in the ETS market causes the expected return on investments in low-carbon technology upgrading to be uncertain, which is unfavorable to carbon neutrality. Given the extremely large amount of carbon emissions accompanied by vast diversity across different regions and industries, the government is considering introducing a differentiated industrial carbon tax on enterprises outside the carbon trading market in the future (National Development and Reform Commission.
Because more than 70% of energy consumption and carbon emissions come from industries in the production field, choosing an appropriate industrial carbon tax rate for China is important for policymakers to reduce carbon emissions from industries (Weng et al. 2021). Furthermore, as China is the largest CO2 emitter in the world, the analysis of the optimal industrial carbon tax for China can provide valuable information for emission abatement across other regions in the world.

Designing an efficient tax rate is a vital task. Regarding the carbon tax rate model, the existing literature mainly proposes two dimensions: uniform (Li et al. 2019; Jia and Lin 2020) vs. differentiated carbon taxes (Tan et al. 2021; Weng et al. 2021) and dynamic (Zhang et al. 2020) vs. fixed carbon taxes (Cao et al. 2019; Chien et al. 2021). The former reflects whether a uniform tax rate is applied to different taxpayers, and the latter reflects whether the tax rate changes over time. Thus, there are four basic carbon tax rate models: the uniform tax rate, the differentiated tax rate, the fixed tax rate, and the dynamic tax rate.

Most of the existing literature explores the environmental policy performance by a fixed uniform carbon tax (Alegoz et al. 2021; Carroll and Stevens 2021). However, the fixed uniform carbon tax neglects the obvious difference between taxpayers and fails to reflect the pollutant-pays principle. That will cause inequalities and offset the policy efficiency of carbon taxes (Wang and Wang 2021). Meanwhile, an efficient carbon tax must consider not only how carbon taxes impact the current economy but also how the size of the tax should be adjusted across time due to external changes from technological improvements, environmental constraints, etc. (Engström and Gars 2015). Therefore, it is necessary to explore the effects of different carbon tax rate models deeply. To comprehensively reflect the mix of the carbon tax rate model, the sub-models include the fixed uniform tax rate, the fixed differentiated tax rate, the dynamic uniform tax rate, and the dynamic differentiated tax rate. Our analysis is based on the sub-model.

The CGE model is the most widely applied method in the existing literature (Tang et al. 2015). However, it can only simulate the impacts of a given tax on the economy and therefore fails to calculate a reasonable tax rate under certain constraints (Jiang and Zhang 2004). Against this background, by adopting a dynamic optimal tax module, we construct a dynamic input–output (namely, I-O) optimization model based on the general equilibrium theory. The model is mainly constructed based on balanced relationships in the I-O table. Meanwhile, to fully describe the interactive relationships among all agents, some modules in the dynamic CGE model are concluded as follows: (1) the module of income and expenditure of agents and (2) the module of savings and investment and (3) the dynamic block. The dynamic I-O optimization model is widely applied to water management (An et al. 2021), carbon tax (Li et al. 2019), pollution management (Song et al. 2019), etc. Therefore, it is suitable for environmental policy analysis.

As to the carbon intensity constraints, China’s carbon peak policy strengthens the controls on total carbon emission and carbon intensity, while China’s carbon neutrality strategy addresses the overall transformation of both production mode and lifestyle (Zhang 2021). Considering the existing industrial structure and technical level, emission reduction is an arduous task, which cannot be accomplished in one stroke (Commentator of Economic Daily 2022). Therefore, in the short term, given the coal-based energy structure, the country is guided to make major technological improvements and energy transition through market tools, such as ETS or carbon tax (Chen and Lin 2021; Song et al. 2021). In the long run, the carbon neutrality strategy should vigorously promote a comprehensive and profound transformation of production mode and lifestyle under ecological civilization (Zhang 2021). That means that China’s sustainable development should change the existing energy-intensive development model to a green one and balance the relationship between development and emission reduction. This paper focuses on the carbon intensity constraints in the short term.

This paper aims to investigate the optimal industrial carbon tax rate for China from 2021 to 2030 under given carbon intensity constraints via a dynamic I-O optimization model. By comparing the effects of the two basic options for setting tax rates, this paper comprehensively explores strategies for designing an appropriate industrial carbon tax rate.

Our contributions are as follows. First, by adopting a dynamic optimal tax module, we construct a dynamic I-O optimization model based on the theory of equilibrium. This model ensures the carbon tax policy analysis considers not only how carbon taxes impact the current economy but also how the size of the tax should be adjusted across time due to external changes. Second, the two dimensions of the tax rate model are comprehensively investigated in one analysis, including whether a uniform tax rate should be applied for different taxpayers and whether the tax rate should change over time. The expansion is helpful to fully understand the effects of different tax rate models. Third, this study extends the policy analysis of the carbon tax to the industry level and explores the impacts of a carbon tax shock on different industries. It provides the necessary information for setting the tax rate within a differentiated industrial carbon tax in the future.

The remainder of this paper is structured as follows. Section 2 presents the literature review. Section 3 describes the methodologies, data sources, and scenarios. Section 4 shows the results and discussion. Section 5 concludes and provides policy implications.
Literature review

According to the basic approach to calculating the optimal carbon tax rate used, the existing literature on the optimal carbon tax can be divided into two categories: the Pigouvian tax approach and the standards and pricing approach. The former approach seeks to calculate a damage function in which the marginal net private profit equals the marginal external cost. In a first-best world, where climate externalities are the only source of inefficiency, equilibrium is achieved by imposing a tax equal to the difference between that profit and cost. This tax rate is the optimal Pigouvian tax (Pigou 1932; Engström and Gars 2015). However, the recycled revenue effect and the tax interaction effect cause the optimal carbon tax to deviate from the Pigouvian tax (Bovenberg and Mooij 1994; Bovenberg and Goulder 1996; Bovenberg and Ploeg 1998). Because of the challenges in the calculation of the cost of environmental damage, the Pigouvian tax is difficult to identify in practice. Against this background, Baumol and Oates (1971) proposed an alternative approach called the standards and pricing approach. This approach involves choosing environmental standards first and using environmental taxes to bring the level of environmental damage down to that accepted in the standards. Under the framework of standards and pricing approach, extensions of this literature have established integrated assessment models by introducing climate-related temperature equations into neoclassical growth models (Nordhaus 2007; Hassler and Krusell 2012; Engström and Gars 2015; Wesseh and Lin 2018). To date, all carbon taxes have been implemented against certain environmental or economic standards rather than based on the Pigouvian tax (Ekins and Barker 2001). This paper adopts this approach.

Regarding the research on the carbon tax rate model for China, scholars have conducted much research, and the main conclusions are as follows. First, a dynamic uniform carbon tax rate is advocated by some researchers (Fan et al. 2016; Zhang et al. 2020). These scholars believe that the optimal carbon tax should increase with the GDP growth rate over time. A mild initial tax rate can offset the negative impacts of a carbon tax on the economy (Liao and Zheng 2016). Second, some scholars believe that a dynamic differentiated carbon tax rate is suitable for addressing the diversity across regions and sectors. Zhang et al. (2019) proposed that the optimal carbon tax model for China is a dynamic differentiated one, following the principle of a low initial rate that gradually increases. Li et al. (2012) noted that a differentiated carbon tax is better than a uniform carbon tax rate for steel because of the lower abatement costs. Third, some scholars have focused on the fixed carbon tax model in different scenarios (Hu et al. 2021; Ma et al. 2021a; Tan et al. 2021; Weng et al. 2021). Because the assumptions and methodology vary significantly, the optimal carbon tax rate is found differentiated accordingly. Generally, most studies agree that a lower carbon tax rate cannot effectively lead to cleaner energy consumption, while a higher carbon tax rate on energy-intensive industries can achieve greater environmental improvements (Lin and Jia 2018).

In general, the existing literature on the optimal carbon tax for China has mainly focused on the uniform carbon tax given certain environmental standards, and few studies have paid attention to the regional differentiated carbon tax. However, the research on industrial carbon taxes is insufficient. Second, few studies have comprehensively investigated the two dimensions of the carbon tax rate in one analysis: uniform carbon tax vs. differentiated carbon taxes and dynamic carbon taxes vs. fixed carbon taxes. Third, compared with the research in the fixed carbon tax, the studies of the dynamic carbon tax are scarce. As a result, the key information for the design of a carbon tax is relatively inadequate.

Methodologies, data, and scenarios

This study adopts the method proposed by Li et al. (2019) and Song et al. (2019). The model is constructed based on balanced relationships in the I-O table, including the horizontal balance and the vertical balance. The interactive relationships among all agents are shown in Fig. 1. All industries are engaged in production, consumers provide the factor inputs and obtain income, the government collects taxes from producers and consumers, and consumers and the government spend their income on consumption and investment. A balance exists between the supply and demand of materials and values. CO₂ emissions are caused by production and consumption activities.

This model includes two parts: objective functions and constraints. There are three objectives: the maximization of GDP, minimization of carbon emissions, and minimization of the carbon tax burden. Given the balanced relationships in the I-O table, the following constraints exist: balance in material flows, balance in value flows, balance between the income and expenditure of institutions, balance between investment and savings, the target reduction in carbon intensity, and requirements for GDP growth, among others.

This paper has extended the reference model as follows: (1) an optimal dynamic tax block is added to explore the optimal carbon tax rate problem subject to a given environmental standard and (2) in the dynamic block, technological improvements and capital flow across industries are consolidated.


\section*{Model construction}

\subsection*{Model assumptions}

The assumptions of this model are as follows: (1) a fixed production structure for industries, which means the direct requirement coefficient is fixed and (2) constant returns to scale, and (3) the carbon cost can be fully transferred to the downstream industries. The terms can be found in Table. 8 in Appendix 1.

\subsection*{Objective function}

1) Maximization of GDP

The economic objective of the government is to maximize economic growth ($GDP_t$) subject to certain economic and environmental constraints. The formula can be written as follows:

$$\text{max } GDP_t = \sum_{j=1}^{n} v_j P_{j,t} X_{j,t}$$  

(1)

where $v_j$ denotes the value-added coefficient of industry $j$, $P_{j,t}$ denotes the price rate of industry $j$, $X_{j,t}$ denotes the output of industry $j$, $t$ represents the year.

2) Minimization of carbon emissions.

To achieve sustainable economic development, the environmental objective of the government is to minimize the total amount of carbon emissions ($TCO_t$) produced for a given level of output. The formula can be written as follows:

$$\min TCO_t = \sum_{i=1}^{n} SCO_{i,t} + \sum_{i=1}^{n} ECO_{i,t}$$  

(2)

where $SCO_{i,t}$ denotes the carbon emissions of industry $i$, $ECO_{i,t}$ denotes the carbon emissions of end-users.

3) Minimization of the carbon tax burden.

According to the principle of profit maximization, the optimal carbon tax rate is defined as the tax rate that makes each industry achieve its emission reduction target with the minimum extra carbon tax cost. The carbon tax burden ($ETB_t$) is defined as the ratio of the total carbon tax ($TCTAX_t$) to GDP, according to the study of Wang and Liu (2005). The formula can be written as follows:

$$\min ETB_t = \frac{TCTAX_t}{GDP_t}$$  

(3)

\subsection*{Constraints}

(1) Balance in material flows.

In line with the horizontal balance in the I-O table, the demand for commodities and services must equal the supply. For industry $i$, total output equals or is greater than the sum of intermediate inputs and final demand.
where $A$ denotes the direct requirement coefficient matrix, $\lambda_i$ denotes the factor-productivity coefficient, $HD_{i,t}$ denotes the household consumption of the $i$-th good, $GD_{i,t}$ denotes the government consumption of the $i$-th good, $INV_{i,t}$ denotes the capital formation for the $i$-th good, $EM_{i,t}$ denotes the exports from the $i$-th good, and $IM_{i,t}$ denotes the imports to the $i$-th good.

(2) Balance in value flows.

In line with the vertical balance in the I-O table, the revenue of each industry must equal its costs. For industry $j$, total output and subsidies from the government ($subsidy_{j,t}$) are equal to the sum of intermediate inputs, labor compensation, fixed asset depreciation, direct taxes, and the carbon tax.

$$P_{j,t} \times X_{j,t} \times (1 + tacu_{j,t}) + subsidy_{j,t} = \sum_{i} a_{ij,t} P_{j,t} \times X_{i,t} \times (1 + tacu_{i,t}) + ratehk_{j,t} P_{j,t} \times (1 + tacu_{j,t}) + depri_{j,t} K_{j,t} P_{j,t} \times (1 + tacu_{j,t}) + ind_{j,t} X_{j,t} \times (1 + tacu_{j,t}) + SCTAX_{j,t}$$

where $tacu_{j,t}$ denotes the carbon tax rate per unit of output in industry $j$, $ratehk_{j,t}$ denotes the income rate for industry $j$, $depr_{j,t}$ denotes the rate of depreciation in industry $j$, $K_{j,t}$ denotes the capital stock of industry $j$, $tind_{j,t}$ denotes the indirect tax rate in industry $j$, and $SCTAX_{j,t}$ denotes the carbon tax of industry $j$.

(3) Balance between the income and expenditure of households and the government.

a. Income and expenditure of households.

Household income is the sum of labor remuneration and the operating surplus from each industry (Eq. 6). Total household income ($YHT_t$) is spent on direct taxes ($GHTAX_t$) (Eq. 7), household savings ($SAVH_t$) (Eq. 8), and household consumption (Eq. 9). The share ($conh_t$) of all goods in household consumption is fixed according to the I-O structure. Total household income equals total household expenditure (Eq. 10).

$$SAVH_t + SAVG_t + depr_{i,t} \times K_{i,t} \times P_{i,t} \times (1 + tacu_{i,t}) = \sum_{i} P_{i,t} \times INV_{i,t} + \sum_{i} P_{i,t} \times (EM_{i,t} - IM_{i,t})$$

$$YHT_t = \sum_{j} ratehk_{j,t} \times X_{j,t} \times P_{j,t} \times (1 + tacu_{j,t})$$

$$GHTAX_t = t_h \times YHT_t$$

$$SAVH_t = s_h \times (1 - t_h) \times YHT_t$$

$$HD_{i,t} \times P_{i,t} = conh_t \times \left(YHT_t - SAVH_t - GHTAX_t\right)$$

$$YHT_t = GHTAX_t + SAVH_t + HD_{i,t} \times P_{i,t}$$

where $t_h$ denotes the direct tax rate and $s_h$ denotes the household savings rate.

b. Income and expenditure of the government.

Government income ($YGT_t$) consists of indirect taxes ($GINDTAX_{j,t}$), direct taxes, and the total carbon tax (Eq. 11). It is spent on government savings ($SAVG_t$) (Eq. 12), emission abatement subsidies (Eq. 13), and government savings (Eq. 14). Total government income must equal total government expenditure (Eq. 15).

$$YGT_t = \sum_{j} GINDTAX_{j,t} + GHTAX_t + TCTAX_t$$

$$SAVG_t = s_g \times YGT_t$$

$$subsidy_{j,t} = SCTAX_{j,t} \times tcsr$$

$$GD_{i,t} \times P_{i,t} = cong_t \times \left(YGT_t - SAVG_t - \sum_{i} subsidy_{i,t}\right)$$

$$YGT_t = \sum_{i} GD_{i,t} \times P_{i,t} + SAVG_t + \sum_{i} subsidy_{i,t}$$

where $s_g$ denotes the government savings rate, $tcsr$ denotes the abatement subsidy rate, and $cong$ denotes the share of the $i$-th good in government expenditure.

(4) Balance between investment and savings.

Total savings is sourced from household savings, government savings, and fixed asset depreciation. The fixed asset depreciation of one industry is linearly related to its capital stock through the rate of depreciation. Total savings is spent on net exports, inventory, and new investments.

(5) Carbon emissions and carbon tax.

a. Carbon emissions.

Carbon emissions, including industrial and household carbon emissions, are caused by fossil fuel consumption (Eq. 17). The industrial carbon emissions coefficient is the rate of industrial carbon emissions per unit of output ($ECI_t$). For details on the calculation process, please refer to the study of Ma et al. (2021b). The industrial carbon emission coefficient is affected by improvements in energy...
efficiency (\(\theta\)). National carbon intensity (\(N_{\text{intensity},i}\)) is the rate of total carbon emissions per unit of GDP (Eq. 18).

\[
TCO_{i,t} = A\lambda_i \times X_{i,t} \times \frac{ECI_i}{1 + \theta} + (HD_i + GD_i) \times \frac{ECI_i}{1 + \theta}
\]

\(N_{\text{intensity},i} = \frac{TCO_{i,t}}{GDP_{i,t}}\)  \(\text{(18)}\)

b. Carbon tax.

According to a study conducted by the Ministry of Finance, the initial taxation stage for the carbon tax in China is proposed to be set at the production level. Then, for industry \(j\), the carbon tax can be written as in Eq. 19.

\[
SCTAX_{j,t} = \begin{cases} 
SCO_{j,t} \times \theta_{i, j} & \text{if } h_i \\
SCO_{j,t} \times l_j & \text{if } l_i
\end{cases}
\]

\(\text{(19)}\)

(6) Carbon intensity.

According to the relevant national policies, the reduction in carbon intensity must meet the set target.

\[
\psi_i \leq \frac{N_{\text{intensity},i,t+1} - N_{\text{intensity},i,t}}{N_{\text{intensity},i,t}} \leq \psi_u
\]

\(\text{(20)}\)

where \(\psi_u\) denotes the upper bound on the national carbon intensity and \(\psi_i\) denotes the lower bound on the national carbon intensity reduction.

(7) Other constraints.

a. Steady growth in imports and exports.

Because the proportion of imports and exports to total output is relatively low, this paper assumes that it is linearly related to total output. The formulas can be written as follows:

\[
EM_{i,t} = EM_{i,t} \times em_i
\]

\(\text{(21)}\)

\[
IM_{i,t} = IM_{i,t} \times im_i
\]

\(\text{(22)}\)

where \(em_i\) denotes the rate of export for the \(i\)-th good and \(im_i\) denotes the rate of import for the \(i\)-th good.

b. Steady growth in GDP.

The yearly GDP growth rate (\(\text{rate}_{\text{gdp}}\)) should be maintained above a certain level.

\[
\frac{GDP_{i,t+1} - GDP_{i,t}}{GDP_{i,t}} \geq \text{rate}_{\text{gdp}}_i
\]

\(\text{(23)}\)

c. Steady growth in output.

The yearly output growth rate should remain within a certain range.

\[
\text{rate}_{x,i} \leq \frac{X_{i,t+1} - X_{i,t}}{X_{i,t}} \leq \text{rate}_{x,u}
\]

\(\text{(24)}\)

where \(\text{rate}_{x,u}\) denotes the upper bound on the output growth rate and \(\text{rate}_{x,i}\) denotes the lower bound on the output growth rate.

d. The range of the acceptable optimal carbon tax.

The yearly optimal dynamic carbon tax rate should remain within a certain acceptable range.

\[
t_i < \text{th}_i, t_i < \tau_u
\]

\(\text{(25)}\)

where \(\tau_u\) is the upper bound on the optimal carbon tax rate and \(\tau_i\) denotes the lower bound on the optimal carbon tax rate.

(8) Dynamic block.

a. Technological improvement.

The technological improvement coefficient must increase at a certain rate (\(\gamma\)).

\[
\lambda_i = \lambda_i \times (1 + \gamma)
\]

\(\text{(26)}\)

b. Capital stock and capital flow.

For industry \(j\), the capital stock is linearly related to its total output through the capital production coefficient (\(h_j\)) (Eq. 27). Net investments and the capital stock in year \(t\) collectively accumulate as the capital stock in year \(t + 1\) (Eq. 28). Capital is assumed to flow from industries with a lower return on capital (ROI) to industries with a higher ROI until the ROI is constant across industries (Eq. 29 and Eq. 30). The amount of new investment in industry \(i\) depends on total new investments and the dynamic share of the investment distribution in that industry (\(\eta_{i,j}\)) (Eq. 31).

\[
X_{j,t} \leq h_jK_{j,t}
\]

\(\text{(27)}\)

\[
K_{j,t+1} = K_{j,t} \times (1 - \text{depr}_j) + \Delta K_{j,t}
\]

\(\text{(28)}\)

\[
\text{ARK}_i = \sum \left[ \left( \frac{K_{i,t}}{\sum_i K_{i,t}} \right) \times R_i \times \text{Kdist}_{i,t} \right]
\]

\(\text{(29)}\)

\[
\eta_{i,j} = \left( \frac{K_{i,t}}{\sum_i K_{i,t}} \right) \times \left[ 1 + \beta_i \times \left( \frac{R_i \times \text{Kdist}_{i,t}}{\text{ARK}_i} - 1 \right) \right]
\]

\(\text{(30)}\)

\[
\Delta K_{i,t} = \eta_{i,j} \times \sum_i P_{i,t} \times \text{INV}_{i,t} / PK_i
\]

\(\text{(31)}\)
where $ARK_i$ denotes the average return on capital, $R_i$ denotes the return on capital factor, $kdist_i$, denotes the coefficient of capital distortion, and $\beta_i$ denotes the capital flow coefficient for industry $i$.

The algorithm for solving the proposed model and sensitivity testing

This paper adopts the NSGA-II to solve this multi-objective optimization model, which is one of the most widely used and most stable evolutionary algorithms. Multi-objective optimization usually results in a Pareto solution set with numerous nondominated solutions instead of only one best solution as in a single-objective optimization problem. Therefore, the multicriteria tournament decision (MTD) method is used to select the most appropriate solution from the numerous Pareto-optimal solutions in the set according to the preferences of the decision-maker. MTD is widely used to ascertain the most appropriate solution from the numerous Pareto-optimal solutions in the set according to the preferences of the decision-maker. MTD is widely used to ascertain the final solution from a Pareto-optimal set for multi-objective decision problems (Parreiras and Vasconcelos 2007; Yu et al. 2015). Further details on the MTD can be found in Appendix 2. Each objective receives equal weight. Sensitivity testing for the proposed model can be found in Appendix 3.

Industry classification and data

Industry classification

The industries are separated into two groups according to the Chinese energy conservation regulations. Eight industries are identified as energy-intensive industries, such as coal-mining and fuel processing products, while the remaining 23 industries are identified as low-carbon industries. The detailed industry classification is shown in Table 9 in Appendix 4.

Data and parameter setting

The data are mainly derived from the Chinese I-O table issued by the National Bureau of Statistics in 2017 (http://www.stats.gov.cn/english/Statisticaldata/AnnualData/). Original energy data are derived from the China Energy Statistical Yearbook of 2018 (National Bureau of Statistics PRC 2018). The following industry-level variables are derived from the corresponding factors in the I-O table divided by the total output of the corresponding industries: the direct requirement coefficient ($a_{ij}$), income rate ($rateh_k$), share in household consumption ($conh_i$), share in government consumption ($cong_i$), indirect tax rate ($ind_t$), value-added coefficient ($v_j$), rate of import ($imi_j$), rate of export ($emi_j$), and inventory rate ($inv_j$). The direct tax rate ($t_h$), household savings rate ($s_h$), and government savings rate ($s_g$) are determined by actual information from the National Bureau of Statistics from 2017.

The rate of fixed-asset depreciation ($depr_i$) is taken from the research of Lou (2015). The industrial carbon emission coefficient ($ECI_i$) is taken from the research of Ma et al. (2021b). The range of industry output changes [$rate_x$, $rate_u$] is set to [0, 20%] on the basis of the research of Yu et al. (2015) and Jiang (2020). The abatement subsidy rate ($tcsr$) is set to 20%, following the research of Tang et al. (2015) and Xiao et al. (2020). Since most scholars suggest a moderate carbon tax at the beginning and few studies propose a carbon tax rate that exceeds ¥200/t (Yi Li et al. 2021a; Ma et al. 2021a; Weng et al. 2021), the range of acceptable optimal carbon tax rates [$r_t$, $r_u$] is set to [$20$t, $200$t], taken from the study of Zhao and Yin (2016).

The coefficients $\phi_y$ and $\phi_\gamma$ are set in line with the 13th Five-Year Plan of China. By 2018, national carbon intensity in China had fallen 45.8% since 2005 (Ministry of Ecological and Environment PRC 2019). To meet the target reduction in carbon intensity, national carbon emissions intensity should further decrease by 19.2–24.2% from its 2005 level. Accordingly, the annual average rate of decrease is set to be within (1.6%, 2.02%).

Scenarios

According to the two dimensions for setting tax rates, the sub-models include the fixed uniform tax rate, the fixed differentiated tax rate, the dynamic uniform tax rate, and the dynamic differentiated tax rate. The scenarios are designed based on the sub-models. For detailed scenario descriptions, please refer to Table 1.

The baseline case without an industrial carbon tax is the BAU scenario. In line with the relevant previous literature, the rate of technological improvement ($\gamma$) is set at 2% (Lu and Chen 2020), and the yearly energy efficiency improvement rate ($\theta$) is set at 1.5% (Wei and Ma 2015; Zhang and Ma 2020). The forecasted GDP growth rate from 2021 to 2030 ($rategdp_t$) is taken from the research of CASS (2020).

Based on related government reports and the previous literature, the fixed uniform carbon tax rates are set to ¥40/t (Li and Yao 2020), ¥50/t (Yi Li et al. 2021a) and ¥60/t (Dong 2020).

The differentiated carbon tax in the European countries that have implemented a carbon tax is usually set to 50% across industries (Su et al. 2009). Therefore, under the fixed differentiated tax rate, we increase the carbon tax rate by 50% for energy-intensive industries. Thus, the tax rates for low-carbon industries are set to ¥40/t, ¥50/t, and ¥60/t, while...
the tax rates for energy-intensive industries are set to ¥60/t, ¥75/t, and ¥90/t.

Results and discussion

The optimal dynamic uniform and differentiated tax

The optimal dynamic uniform and differentiated carbon tax rates under given carbon intensity constraints from scenarios C1 and D1 for 2021–2030 are shown in Fig. 2. From 2021 to 2022, there is no tax because this stage still allows the national carbon intensity reduction target to be met. Starting in 2023, the optimal tax rates in both scenarios increased over time. The optimal dynamic uniform tax rate increases from ¥35.84/t to ¥166.54/t, while the optimal dynamic differentiated tax rate for energy-intensive and low-carbon industries increases from ¥42.21/t and ¥28.14/t, to ¥182.57/t and ¥121.71/t, respectively.

For the dynamic tax rate, the tax implementation date in both scenarios is relatively late, and the initial tax rate level is low, beginning in the range [¥28/t, ¥60/t] in 2023–2024. This leads to weak carbon intensity constraints on industries, which could not effectively guide industries to begin consuming cleaner energies. As a result, carbon emission levels of all industries are high in the initial stage. Beginning in 2026, the dynamic tax rate rises rapidly, even becoming several times higher than the fixed tax rate by 2030. This demonstrates that if the industrial carbon tax is promulgated later together with a lower initial tax rate, although GDP growth can be maintained at a higher level in the beginning, such a tax rate level cannot effectively guide industries to choose cleaner energy consumption patterns. Therefore, to meet the target reduction in carbon intensity in a short time, more of the pressure on industries is transferred to a later stage. All this causes a relatively higher tax rate to become necessary.

The optimal dynamic uniform tax rates are found to be higher than the optimal dynamic differentiated tax rates in most cases from 2021 to 2030. The average carbon tax burdens in the two scenarios are 1.0978% and 0.9102%, respectively (see Table 2 for details). This is due to the differentiated carbon tax model emphasizing that different polluters should pay carbon taxes according to their damages, and high-emission industries should bear additional tax costs. In this way, negative externality spillovers can be prevented, and tax equity can be reflected to some extent. The total tax burden of the differentiated carbon tax model is smaller.

Environmental effects

Carbon emissions

As Fig. 3 shows, total carbon emissions in China continue to rise in all scenarios from 2021 to 2030. The carbon emissions in scenario BAU increase from 9.69 billion tons to 19.96 billion tons, with an average annual growth rate of 7.55%. Given that the industrial carbon tax was introduced, the increase in carbon emissions is effectively slowed down in all scenarios. It is shown that there are lag effects in the industrial carbon tax and

| Scenario | Tax rate (¥/ton) | Changes in carbon intensity | Average carbon tax burden |
|----------|----------------|-----------------------------|----------------------------|
| C1       | 166.54         | 19.20%                      | 1.0978%                    |
| D1       | 189.82, 126.55 | 19.22%                      | 0.9102%                    |
the energy transition cannot complete in a short time. In the long run, the policy impacts of the industrial carbon tax have been gradually enlarged, which leads to carbon emission reductions being more significant. In addition, it is found that the carbon emissions level of the dynamic tax is higher than that of the fixed tax before 2026, which can be explained by the lower tax rate in the beginning.

The carbon emission reductions during 2021–2030 in all scenarios are illustrated in Table 3. From 2021 to 2030, the carbon emissions’ reduction in all scenarios gradually rises over time. The carbon emission reductions in the differentiated tax are larger than that of the uniform tax. That means the more tax is levied on energy-intensive industries, the more carbon emissions reduction there is. This result is in line with the findings of Lin and Jia (2018). Although the tax rates of the dynamic carbon tax are the highest since 2026, the overall carbon emissions are the smallest. This implies that the environmental effect of the dynamic carbon tax is inferior to that of the fixed carbon tax.

Figure 4 illustrates the variation in the industrial carbon emissions reductions in all scenarios compared with the BAU scenario in 2030. In all scenarios, the top three contributors to emissions abatement are electricity production, metal smelting, and chemical industry. Carbon emission reductions are mainly driven by output changes and the carbon emission coefficient.

The top three industries are all basic industrial commodity providers with high energy consumption and have the largest

| Year | A1 | B1 | A2 | B2 | A3 | B3 | C1 | D1 |
|------|----|----|----|----|----|----|----|----|
| 2021 | 0.05 | 0.09 | 0.08 | 0.10 | 0.10 | —— | —— | —— |
| 2022 | 0.15 | 0.18 | 0.18 | 0.20 | 0.18 | 0.21 | —— | —— |
| 2023 | 0.23 | 0.25 | 0.24 | 0.26 | 0.25 | 0.29 | 0.23 | 0.23 |
| 2024 | 0.34 | 0.37 | 0.35 | 0.40 | 0.39 | 0.41 | 0.25 | 0.26 |
| 2025 | 0.41 | 0.45 | 0.43 | 0.46 | 0.45 | 0.48 | 0.35 | 0.35 |
| 2026 | 0.47 | 0.51 | 0.50 | 0.52 | 0.51 | 0.55 | 0.44 | 0.44 |
| 2027 | 0.62 | 0.62 | 0.62 | 0.63 | 0.61 | 0.65 | 0.58 | 0.57 |
| 2028 | 0.72 | 0.75 | 0.73 | 0.75 | 0.75 | 0.77 | 0.72 | 0.71 |
| 2029 | 0.86 | 0.87 | 0.88 | 0.89 | 0.88 | 0.91 | 0.87 | 0.87 |
| 2030 | 0.93 | 0.95 | 0.95 | 0.97 | 0.96 | 0.98 | 0.96 | 0.96 |
| Total | **4.77** | **5.04** | **4.95** | **5.18** | **5.09** | **5.35** | **4.40** | **4.38** |

Fig. 2 The optimal dynamic uniform and differentiated carbon tax rates from 2021 to 2030.
carbon emissions in the baseline year. Therefore, their carbon emission reductions are larger than those of other industries. The shares of coal consumption in the top three sectors reach 60%, 16.96%, and 6.84%, respectively. For such energy-intensive industries, the industrial carbon tax would lead to high carbon tax costs and provoke a decline in supply. Thus, the carbon emission reductions in these three industries are relatively higher than those of the others.

**Carbon intensity**

Carbon intensity in all scenarios in 2030 is shown in Table 4. Although the amount of carbon emissions continues to rise over time, carbon intensity declines. In scenario BAU, carbon intensity falls by 12.27% from 2021 to 2030, decreasing from 1.55 to 1.37 t/¥10,000. When the industrial carbon tax is introduced, the decreases in carbon intensity accelerate. The decreases in scenarios B2, B3, C1, and D1 are the greatest, accounting for 19.25%, 19.35%, 19.20%, and 19.22%, respectively. Each of the above four scenarios meets the minimum target for carbon intensity reductions, while the rest of the scenarios fail to do so. Meanwhile, the decreases in the carbon intensity of the dynamic carbon tax are still not significant. Similar to the effects of carbon emissions, the carbon intensity reductions in the differentiated tax are better than that of the uniform tax.

The variation in the carbon intensity reductions of industries in all scenarios relative to the BAU scenario in 2030 is shown in Fig. 5. In all scenarios, the top three industries with the largest carbon intensity reductions are electricity production, fuel processing, and metal smelting. In scenarios B2, B3, C1, and D1, which meet the carbon intensity reduction target, the top three industries contribute approximately 18%, 17%, and 16%, respectively. However, the decreases in carbon intensity among some of the energy-intensive industries are even smaller than those among some of the low-carbon industries, such as construction and transportation. This is mainly because these two industries can be categorized as indirectly energy-intensive industries, which consume a large amount of energy-intensive intermediate inputs, while their direct energy consumption is smaller. As a result, the direct carbon tax costs are lower, and the direct impacts of the industrial carbon tax are smaller.

| Scenario | Carbon intensity (tons/10 thousand yuan) | Carbon intensity reduction | Reduction target met? |
|----------|------------------------------------------|---------------------------|-----------------------|
| BAU      | 1.3663                                   | 12.27%                    | No                    |
| A1       | 1.3022                                   | 18.73%                    | No                    |
| B1       | 1.2989                                   | 19.02%                    | No                    |
| A2       | 1.3001                                   | 18.91%                    | No                    |
| B2       | 1.2964                                   | 19.25%                    | Yes                   |
| A3       | 1.2978                                   | 19.12%                    | No                    |
| B3       | 1.2953                                   | 19.35%                    | Yes                   |
| C1       | 1.2970                                   | 19.20%                    | Yes                   |
| D1       | 1.2968                                   | 19.22%                    | Yes                   |

Fig. 3  Carbon emissions in all scenarios from 2021 to 2030
**Economic effects**

**GDP growth rate**

The average annual GDP growth rate during 2021–2030 is shown in Table 5. The average annual growth rate of GDP is 5.97% in scenario BAU. All other scenarios cause GDP losses to some extent. In general, the GDP losses from the dynamic tax rates are greater than those from the fixed tax rates, while the GDP losses from the differentiated tax rates are greater than those from the uniform tax rates. Nevertheless, even with the greatest GDP losses in scenario D1, the magnitude of these GDP losses is only −0.67%. Thus, the negative impacts of the industrial carbon tax are relatively mild.

Greater carbon tax rates are found to be associated with more fluctuations in the GDP annual growth rate (see Fig. 6 for details). Among all scenarios, the fluctuations in scenarios C1 and D1 are the largest, at 3.30% and 3.22%, respectively. Because of the late taxation date and the low initial tax rates, the dynamic tax rate exchanges environmental losses for GDP benefits in the early stages, when high levels of emissions are accumulated. To reduce the carbon intensity to the target level in a short period, a high tax rate needs to be imposed on industries. Thus, the high tax rate has large negative impacts on the economy, resulting in the largest fluctuations in GDP growth. In this way, to ensure stable economic growth, the industrial carbon tax should be promulgated with moderate rates and as early as possible, which should encourage all industries to reduce their carbon emissions to an appropriate level.

**Industry output**

As shown in Fig. 7, the variation in industry output in all scenarios relative to the BAU scenario in 2030 varies

| Scenario | Average annual GDP growth rate | Average annual losses in of GDP growth |
|----------|-------------------------------|---------------------------------------|
| BAU      | 5.97%                         | ——                                    |
| A1       | 5.84%                         | −0.13%                                |
| A2       | 5.69%                         | −0.29%                                |
| A3       | 5.50%                         | −0.48%                                |
| B1       | 5.57%                         | −0.40%                                |
| B2       | 5.37%                         | −0.60%                                |
| B3       | 5.31%                         | −0.67%                                |
| C1       | 5.34%                         | −0.63%                                |
| D1       | 5.30%                         | −0.67%                                |

**Fig. 4** The variation in carbon emission reductions of industries in all scenarios compared with the BAU scenario in 2030
significantly. The industries with the largest declines in output are coal mining and electricity production. In scenario C1, the decline in output for coal mining reaches 38.73% in 2030. Obviously, the industrial carbon tax can effectively reduce the coal consumption of industries and guide them to choose cleaner energies. However, except for the above two energy-intensive industries, the declines in output for the remaining energy-intensive industries are not significant. This is due to the large quantity of capital stock distributed across the energy-intensive industries, which is caused by China’s extensive development in the past. The overall share of the capital stock in eight energy-intensive industries in the base year is 39.81%. More specifically, the share of the capital stock in transportation reaches 26.26%, and the coefficient of the capital distortion in the construction industry is 38.29. As a result, investments are path-dependence and still flow into energy-intensive industries, which offset the impacts of the industrial carbon tax to some extent.

In contrast, the decreases in the output of some low-carbon industries exceed decreases in some energy-intensive industries, such as other manufacturing, repair services, and furniture manufacturing. This is mainly because such industries have the lowest share of investment, accounting for 0.05%, 0.02%, and 0.50% in the base year, respectively. Moreover, the capital production coefficients are as high as 3.86, 3.63, and 2.40. Therefore, a small change in investment could lead to a large change in output. Given this fact, more attention needs to be given to the problem of path-dependence in investments when implementing an industrial carbon tax.

**Industry price**

As shown in Fig. 8, the variation in industry prices in all scenarios relative to the BAU scenario in 2030 is significant. In all scenarios, the energy-intensive industries have the greatest price changes. The industry with the largest price change is electricity production, reaching 4.91% in scenario D1. As the third-largest energy provider, electricity production has a wide influence on other industries, so its price change is the largest. Energy-intensive industries, such as fuel processing, metal smelting, and coal mining, provide basic industrial commodities and energy, each of which plays important role in the industrial chain. Thus, their corresponding prices increase significantly.

The price changes in the energy-intensive industries under the dynamic carbon tax are the largest; those under the fixed differentiated carbon tax are next, and those under the fixed uniform carbon tax are the smallest. For example, the price increase for electricity production in scenario D1 is 4.78 times higher than that in scenario A1, 3.82 times higher than that in A2, and 3.17 times higher than that in A3. The reason is that the tax rate in scenario D1 exceeded ¥150/t in 2030, a very large amount. We can conclude that the higher is the carbon tax rate, the higher is the commodity price. This implies that the tax burden of the dynamic carbon tax is the largest.

The prices of the indirect energy-intensive industries are insensitive to the carbon tax. The price changes in construction and transportation average only 0.02% and 0.26%, respectively. In contrast, some low-carbon industries which have close production relationships with energy-intensive industries have large price increases. For example, the price increase of P&G extraction and metal mining reach 0.49% and 0.69%, respectively.

**Comparison of policy benefits and costs between all scenarios**

This paper simulates the environmental and economic effects from 2021 to 2030 of four different tax rate models. In Table 6, a comprehensive policy evaluation table is established that includes the four dimensions of cumulative GDP losses, cumulative carbon tax burden ratio, cumulative carbon emissions reductions, whether the carbon intensity reduction target is met, and whether the carbon neutrality target is met. The fixed differentiated tax rate model results in greater cumulative

| Scenario | Cumulative GDP losses | Cumulative carbon tax burden ratio | Cumulative carbon emissions reduction | Reduction target met? | Carbon neutrality target met? | Total policy benefits |
|----------|-----------------------|----------------------------------|-------------------------------------|-----------------------|-----------------------------|----------------------|
| A1       | −1.2933%              | −0.4864%                         | 3.7939%                            | No                    | No                          | 2.0142%              |
| A2       | −1.9861%              | −0.6071%                         | 4.6445%                            | No                    | No                          | 2.0513%              |
| A3       | −3.5804%              | −0.7275%                         | 5.4849%                            | No                    | No                          | 1.1771%              |
| B1       | −2.7280%              | −0.6470%                         | 6.4238%                            | No                    | Yes                         | 3.0487%              |
| B2       | −4.1752%              | −0.8076%                         | 7.1085%                            | Yes                   | No                          | 2.1256%              |
| B3       | −4.6949%              | −0.9677%                         | 7.7819%                            | Yes                   | No                          | 2.1193%              |
| C1       | −3.3968%              | −1.0978%                         | 5.7054%                            | Yes                   | No                          | 1.2108%              |
| D1       | −3.7027%              | −0.9102%                         | 6.0085%                            | Yes                   | No                          | 1.3956%              |
losses than the other three models. This model places higher tax rates on energy-intensive industries and achieves relatively greater environmental improvements. This reflects the pollutant-pays principle to an extent and effectively encourages energy transitions. Regarding the dynamic tax rate model, scenario C1 results in the highest cumulative carbon tax burdens, reaching up to 1.0978%. Although the late tax implementation date and low initial carbon tax rate prevent more GDP losses, the high level of carbon emissions in the early years results in a higher tax rate in the later years. Furthermore, the higher carbon tax rate needed to reduce carbon intensity to a target level in the short term causes large fluctuations in GDP growth. The policy benefits of scenarios C1 and D1 are only 1.2108% and 1.3956%, respectively. According to the study of Liu and Hu (2022), the carbon sink of China in 2030 will increase to 38.23 billion t, which can absorb and store approximately 47.41–67.67 billion tons of CO₂. Comparing the carbon emissions with carbon sink, all scenarios fail to meet the carbon neutrality target.

Regarding the overall policy benefits, we conclude that the differentiated tax rate model is superior to the uniform tax rate model, and the fixed tax rate model is superior to the dynamic tax rate model. Since carbon emissions are mainly produced by energy-intensive industries, a higher carbon tax rate on those industries can not only achieve greater emission reductions but also provide a large degree of tax fairness. On the other hand, compared with the dynamic tax rate model, the fixed tax rate model has milder negative impacts on the economy and imposes a smaller carbon tax burden. Therefore, the fixed differentiated tax rate model has the advantages of both differentiated tax rates and fixed tax rates, so it is the best tax rate model.

Compared with all the other scenarios, the overall policy benefits of scenario B2, which impose a tax of ¥50/t on low-carbon industries and ¥75/t on energy-intensive industries, are the largest.

**Discussion**

Previous studies have investigated the environmental and economic effects of a carbon tax in China. More detailed
comparisons with other studies are listed in Table 7. We compared the critical indicators of models, including carbon emissions, carbon intensity reduction, and GDP. All three results of this research are smaller than those of Li et al. (2019) because we place limitations on the GDP growth rate according to the study of Lou (2015). The volume of carbon emissions and carbon intensity in 2030 in our research are greater than the studies of Lin and Jia (2018) and Niu et al. (2020). These differences are because that there is no limitation on the labor and capital factors supply, which results in a greater output. This limitation will be improved in future research. Regarding the dynamic optimal carbon tax rate, the carbon tax burdens in scenarios C1 and C2 in 2030 are 1.73% and 1.82%, respectively, which are similar to 2% in the study of Fan et al. (2016).

Conclusions and policy implications

To investigate the optimal industrial carbon tax rate for China, this paper simulates the environmental and economic effects of different scenarios from 2021 to 2030 via an integrated dynamic I-O model. The main conclusions are as follows.

(1) Given the same carbon intensity constraints, the optimal tax rate model is the fixed differentiated tax rate. The fixed differentiated carbon tax can not only lead to greater environmental improvements but also provide a large degree of tax fairness. The largest policy benefits in all scenarios are from scenario B2, 2.1256%, where the tax is set to ¥50/t for low-carbon industries and ¥75/t for energy-intensive industries.

(2) The existing investment structure is path-dependence and offsets the policy effects of a carbon tax to some extent. A large amount of capital stock is distributed across the energy-intensive industries due to China’s energy-intensive development. As a result, investments are path-dependent and still flow to energy-intensive industries, which offset the impacts of the industrial carbon tax.

(3) Indirect energy-intensive industries such as construction and transport are insensitive to the industrial carbon tax. Such industries consume a large amount of energy-intensive intermediate inputs, while their level of direct energy consumption is low. As a result, the output and price changes in indirectly energy-intensive industries are not significant.

Based on the above results and discussions, we present the following policy suggestions for setting the industrial carbon tax rate:

(1) As a supporting environmental tool of Chinese ETS, the fixed differentiated carbon tax is proposed to be introduced at a moderate rate step by step. The high
fluctuation of the carbon price in the ETS market causes the expected return on investments in low-carbon technology upgrading to be uncertain, which is unfavorable to carbon neutrality. In contrast, the fixed differentiated carbon tax is beneficial to a low overall carbon tax burden and the stability of economic growth. Furthermore, it can reflect the pollution-pays principle to the greatest extent. It is suggested that the fixed differentiated carbon tax should be promulgated from loose to tight and adjusted according to the policy performance by stages. Some energy-intensive industries, such as electricity production and metal smelting, can be selected as test pilots for the fixed carbon tax. Based on experimental experiences, the fixed differentiated carbon tax can be promoted to the whole country.

More attention should be paid to improving the existing investment structure to a cleaner one. More capital should be guided to the equipment investments on the key infrastructure of emerging information industries, such as cloud computing, big data, mobile internet, and artificial intelligence. This will improve the production efficiency and product quality of the existing production system. Meanwhile, to attract more long-term capital to enter into the high-tech industries, the tolerance of investment failures in high technology in financial institutions should be improved.

For indirect energy-intensive industries, technology standards other than carbon taxes should be adopted for regulation. For construction, to reduce energy inputs from the source, high durable and green materials are first to be used to prolong the service life of buildings. In addition, whole life-cycle management is suggested to cover the stages of planning, design, production, and operation of buildings, which can reduce the waste in reworking. For transport, it is suggested to speed up changes in transportation models, from the highway to railway and from the highway to water in medium- and long-distance transportation; on the other hand, the application of new energy should be accelerated.

The limitations of this article are as follows: (1) Because there are no constraints on the labor and capital factors, the short-term shock of Covid-19 on the labor supply and household consumption cannot be captured. (2) The heterogeneity of key industries with priority development in future national strategy is not concluded. All the above limitations will be improved in future research.
Fig. 8 The variation in industry prices in all scenarios relative to the BAU scenario in 2030
The multicriteria tournament decision method

The MTD is a widely used decision method that provides a ranking of all alternatives in a Pareto-optimal set by a tournament function, according to the preferences of the decision-makers (Parreiras and Vasconcelos 2007; Yu et al. 2015). The detailed process is as follows.

First, for a given objective in the model, the number of times that alternative \( a \) wins the tournament against each other solution \( b \) from the Pareto-optimal set \( U \) can be described as follows:

\[
t_s(a, b) = \begin{cases} 1, & \text{if } fit_s(b) - fit_s(a) > 0 \\ 0, & \text{if } fit_s(b) - fit_s(a) \leq 0 \end{cases}
\]

where objective \( s \) is a tournament. \( fit_s(a) \) represents the value of the objective function when alternative \( a \) is chosen. \( fit_s(b) \) represents the value of the objective function when alternative \( b \) is chosen.

Second, the tournament function \( T_s(a, U) \) provides the ratio of the number of times that alternative \( a \) wins the tournament against other solutions in the Pareto-optimal set \( U \).

The formula can be written as follows:

**Table 8 Terms:**

| Variable | Definition | Variable | Definition |
|----------|------------|----------|------------|
| \( GDP_t \) | Gross domestic product | \( K_{j,t} \) | Capital stock of industry \( j \) |
| \( SO_{i,t} \) | Carbon emissions of industry \( i \) | \( \Delta K_{j,t} \) | Capital stock formation in industry \( j \) |
| \( ECO_t \) | Carbon emissions of end-users | \( ARK_{t} \) | Average return on capital |
| \( TCO_t \) | Total carbon emissions | \( R_{t} \) | Return on capital factor |
| \( TCTAX_t \) | Total carbon tax | \( N_{intensity,t} \) | National carbon intensity |
| \( ETB_t \) | Carbon tax burden ratio | \( a_{ij} \) | Direct requirement coefficient |
| \( X_{j,t} \) | Output of industry \( j \) | \( \lambda_{j} \) | Factor-productivity coefficient |
| \( P_{j,t} \) | Price rate of industry \( j \) | \( \gamma \) | Technology improvement rate |
| \( HD_{i,t} \) | Household consumption of the \( i \)-th good | \( A \) | Direct requirement coefficient matrix |
| \( GD_{i,t} \) | Government consumption of the \( i \)-th good | \( kdist_{i,t} \) | Coefficient of capital distortion |
| \( EM_{i,t} \) | Exports from the \( i \)-th good | \( cong_{i,t} \) | Share of the \( i \)-th good in government expenditure |
| \( IM_{i,t} \) | Imports to the \( i \)-th good | \( \eta_{i,t} \) | New capital formation coefficient for industry \( i \) |
| \( INV_{i,t} \) | Capital formation for the \( i \)-th good | \( \beta_{i} \) | Capital flow coefficient for industry \( i \) |
| \( YHT_{t} \) | Total household income | \( h_{j} \) | Capital production coefficient for industry \( j \) |
| \( SAVH_{t} \) | Household savings | \( tacu_{j} \) | Carbon tax rate per unit of output in industry \( j \) |
| \( YGT_{t} \) | Total government income | \( t_{h} \) | Carbon tax rate for energy-intensive industries |
| \( subsidy_{j,t} \) | Abatement subsidy to industry \( i \) | \( t_{l} \) | Carbon tax rate for low-carbon industries |
| \( SAVG_{t} \) | Government savings | \( ECI_{i} \) | Carbon emission coefficient for industry \( i \) |
| \( GHTAX_{t} \) | Direct tax | \( \theta \) | Energy efficiency improvement rate |
| \( GINDTAX_{j,t} \) | Indirect tax on industry \( j \) | \( inv_{j} \) | Expenditure share of the \( i \)-th good in total investment |
| \( TSAV_{t} \) | Total savings | \( \varphi_{u} \) | Upper bound on the national carbon intensity reduction rate |
| \( TINV_{t} \) | Total investment | \( \varphi_{l} \) | Lower bound on the national carbon intensity reduction rate |
| \( PK_{t} \) | Price of capital factor | \( emi_{i} \) | Rate of export for \( i \)-th good |
| \( v_{j} \) | Value-added coefficient of industry \( j \) | \( imi_{i} \) | Rate of import for \( i \)-th good |
| \( rateh_{j} \) | Income rate for industry \( j \) | \( rategdp_{t} \) | Annual GDP growth rate |
| \( conh_{j} \) | Share of the \( i \)-th good in household expenditure | \( rates_{u} \) | Upper bound on the output growth rate |
| \( s_{t} \) | Government savings rate | \( rates_{l} \) | Lower bound on the output growth rate |
| \( tcsr \) | Abatement subsidy rate | \( i \) | Industry |
| \( depr_{j} \) | Rate of depreciation in industry \( j \) | \( h \) | Energy-intensive industries |
| \( s_{h} \) | Household savings rate | \( l \) | Low-carbon industries |
| \( t_{h} \) | Direct tax rate | \( t \) | Time |
| \( tind_{j} \) | Indirect tax rate in industry \( j \) | \( t_{u} \) | Upper bound on the optimal carbon tax rate |
| \( SCTAX_{j,t} \) | Carbon tax of industry \( j \) | \( t_{l} \) | Lower bound on the optimal carbon tax rate |
where $U$ represents the entire Pareto-optimal set.

Finally, to aggregate the scores into a global ranking function, all criteria and their weights are considered. The aggregation function can be evaluated using the following formula:

$$R(a) = \left( \prod_{s=1}^{o} T_s(a, U)^{w_s} \right)^{1/o}$$

where $R(a)$ denotes the total score for alternative $a$ in all tournaments. $w_s$ denotes the weight of objective $s$, with $w_s > 0$, and $\sum_{s=1}^{o} w_s = 1$. $o$ denotes the total number of objectives.

### Appendix 3

Sensitivity testing is necessary, as some key parameters in the model may significantly affect the robustness of the simulations. A sensitivity analysis is performed to determine how different values of certain key independent variables affect the simulation results. This model represents the multi-objective optimization problem of setting the industrial carbon tax rate subject to certain carbon intensity reduction constraints. Thus, the carbon intensity reduction constraints and the weights on the objectives are the key parameters of the model. Since most of the other parameters adopted in the model have already been tested in the existing literature, only the carbon intensity reduction constraints and objective weights are tested in this paper.

Given that the simulation results mainly focus on the environmental and economic effects of the industrial carbon tax, the key indicators are CO$_2$ emissions reduction, carbon intensity reduction, and the GDP growth rate. Based on the above, the sensitivity analysis investigates the effect of the carbon intensity reduction constraints and the objective weights on the above three key indicators.

Following the study of Hosoe et al. (2010), the following testing standards for the sensitivity analysis are proposed:

1. A variable attribute is considered to be stable if the sensitivity analysis results are stable, that is, if there is no change from a positive to negative coefficient.
2. There should be no significant change in the order of importance within the same group of variables.

The changes in the key indicators when the carbon intensity reduction constraints change by $+0.1\%$ or $-0.1\%$ are shown in Fig. 9. The changes in the key indicators when the objective weights change by $+10\%$ or $-10\%$ are shown in Fig. 10. None of the key indicators in either test changed from positive to negative and all showed strong stability. We can conclude that the key parameters pass the sensitivity testing and that the settings for these key parameters are reasonable.

![Fig. 9](image-url) The changes in the key indicators from the simulation due to different carbon intensity constraints

![Fig. 10](image-url) The changes in the key indicators from the simulation due to different weights on the objectives
Appendix 4

Table 9 Industry classification, industry codes

| Industry classification | Industry code | Industry | Industry classification | Industry code | Industry |
|-------------------------|---------------|---------|-------------------------|---------------|---------|
| Energy-intensive industries | S2 | Coal mining | Low-carbon industries | S10 | Education-related products |
|                         | S11 | Fuel processing |                           | S15 | Metal products |
|                         | S12 | Chemical industry |                         | S16 | General machinery |
|                         | S13 | Nonmetallic products |                     | S17 | Special machinery |
|                         | S14 | Metal smelting |                         | S18 | Transport equipment |
|                         | S25 | Electricity production |                         | S19 | Electrical equipment |
|                         | S28 | Construction |                         | S20 | Other electronic equipment |
|                         | S30 | Transport |                         | S21 | Instrumentation |
| low-carbon industries   | S1 | Agriculture |                         | S22 | Other manufacturing |
|                         | S3 | P&G extraction |                         | S23 | Recycling |
|                         | S4 | Metal mining |                         | S24 | Repair services |
|                         | S5 | Nonmetal mining |                     | S26 | Gas production |
|                         | S6 | Food |                         | S27 | Water production |
|                         | S7 | Textile |                         | S29 | Wholesale trade |
|                         | S8 | Leather manufacturing |                       | S31 | Services |
|                         | S9 | Furniture manufacturing |               |      |         |

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