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RESEARCH ARTICLE

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Cutting CO_2 emissions through demand side regulation: Implications from multi-regional input–output linear programming model

Abstract This study combines multi-regional input–output (MRIO) model with linear programming (LP) model to explore economic structure adjustment strategies for the reduction of carbon dioxide (CO_2) emissions. A particular feature of this study is the identification of the optimal regulation sequence of final products in various regions to reduce CO_2 emissions with the minimum loss in gross domestic product (GDP). By using China's MRIO tables 2017 with 28 regions and 42 economic sectors, results show that reduction in final demand leads to simultaneous reductions in GDP and CO_2 emissions. Nevertheless, certain demand side regulation strategy can be adopted to lower CO_2 emissions at the smallest loss of economic growth. Several key final products, such as metallurgy, nonmetal, metal, and chemical products, should first be regulated to reduce CO_2 emissions at the minimum loss in GDP. Most of these key products concentrate in the coastal developed regions in China. The proposed MRIO–LP model considers the inter-relationship among various sectors and regions, and can aid policy makers in designing effective policy for industrial structure adjustment at the regional level to achieve the national environmental and economic targets.

Keywords CO_2 emissions, demand side regulation, multi-regional input–output model, linear programming model

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1 Introduction

China is currently the world's largest carbon dioxide (CO_2) emitter, accounting for 28% of the total global emissions in 2020 (IEA, 2021). In 2015, the Chinese government submitted the Intended Nationally Determined Contributions target to peak the absolute CO_2 emissions by 2030 and reduce the CO_2 emissions intensity by 60%–65% from that in 2005 (UNFCCC, 2015). In 2020, China's President further announced a more ambitious target to achieve carbon neutrality in 2060. One of the possible key reasons for China's high CO_2 emissions is its irrational industrial structure. Over the past decades, Chinese local governments actively promoted the investment of heavy-industry and carbon-intensive production (e.g., iron, steel, and cement) in pursuit of high economic growth (Green and Stern, 2017). As a consequence, the industrial structure in China has transformed from a less carbon-intensive to a carbon-intensive one (Yu et al., 2018a). In 2020, the industrial sector contributed to 43% of the country's gross domestic product (GDP) and accounted for 65% of the total CO_2 emissions. By comparison, the service sector contributes to 50% of the GDP but only 18% of CO_2 emissions (IEA, 2021; NBSC, 2021). This GDP proportion of the service sector is much lower than that not only in economies of developed countries but also in other developing countries (Xu et al., 2014). Under this background, properly shifting China's industrial structure from emission-intensive industries to less-emission-intensive ones is an important strategy to achieve emissions targets.

Industrial structure adjustment can be achieved in two different ways. The first can be called supply side regulation, which transforms the industrial structure by regulating economic suppliers. For example, the Chinese government has shut down many energy-intensive enterprises during the 11th and 12th Five-Year-Plan (FYP) to reduce energy consumption and CO_2 emissions. The cap-and-trade system has been extensively introduced in the European Union (EU) by allocating permits or allowances to discharge a specific quantity of CO_2 emissions in the supply industries. However, supply side regulation may quickly cut down CO_2 emissions but not mitigate its ultimate source. The reason is that the products from regulated production industries may not be consumed by themselves, but by the other industries or even other regions because of the inter-dependency in the supply chain system. By regulating the producers, the production activities can transfer elsewhere, which can still lead to substantial amount of CO_2 emissions. In addition to the supply side regulation, the other means for industrial output reallocation is the demand side regulation. This approach allocates the environmental responsibility to final consumers instead of producers. Accordingly, consumers are regulated for industrial output reallocation, through policy measures such as collecting taxes on domestic products and controlling government purchases. The regulation of final product can reduce CO_2 emissions, which may be induced by material inputs from each stage in the production of the entire supply chain. Taking the construction sector as an example, CO_2 emissions are induced not only from the sector itself but by its upstream sectors as well, such as iron and steel, cement, and other raw materials (Wang et al., 2015; Kumanayake and Luo, 2018). As a result, by regulating the final products of the construction sector, the CO_2 emissions occurring in the entire supply chain of construction sector can be reduced, and thus demand side regulation addresses the issue from its roots.

The input–output (IO) model is an effective tool to analyze the inter-relationships among various economic sectors. Given the linear relationships in the IO table, the model has been extensively combined with linear programming (LP) to identify strategies for production output reallocation in an economy. The inter/intra-relations imposed on the IO model allows for the design of a production possibility economic frontier. LP models can be used to determine the activity levels to optimize a given objective function, while satisfying the production relations embodied in the IO model (Henriques and Antunes, 2012). The combination of IO and LP can be termed as input–output linear programming (IO–LP) model, and has been widely used in the literature. For example, Cho (1999) used IO–LP model to explore a compromise composition of sectoral outputs to optimize economic growth, environmental pollution, and energy consumption in Chungbuk, South Korea. Hsu and Chou (2000) and Chen (2001) both used IO–LP models to analyze the optimal industrial structure for GDP maximization and CO_2 emissions minimization in Taiwan. Hristu-Varsakelis et al. (2010) explored the output allocation strategy in Greece to optimize economic growth and reduce greenhouse gas (GHG) emissions using an IO–LP model. Fan et al. (2010) utilized an IO–LP model to investigate the industrial shift strategies for GDP maximization and CO_2 emissions minimization in China. San Cristóbal (2012) combined the IO model with a goal programming model to study the effects of reduction in CO_2 emissions and energy requirements on output and labor in different industries in Greece. Cortés-Borda et al. (2015) used the IO–LP model to identify key industries that must be regulated to optimize the economic output and CO_2 emissions for EU-25. Mi et al. (2015) utilized IO–LP model to analyze the potential effects of industrial structure shift on energy consumption and CO_2 emissions in Beijing. Chang (2015) combined a linkage analysis with IO–LP model to identify the key sectors for CO_2 mitigation. Mi et al. (2017) used the model to explore the optimal industrial structure to peak CO_2 emissions in 2026. To reduce energy consumption and related emissions, Xu et al. (2017) employed IO–LP model to explore the optimal strategies through a shift in industrial structure in Wuhu, while Yu et al. (2018a; 2018b) investigated industrial restructuring strategies for energy saving and emissions reduction.

While IO–LP models have been widely used to explore industrial restructuring strategies and reduce energy consumption and CO_2 emissions, most studies focused on the industrial restructuring strategies in one area and ignored regional differences and relationships. Given that different regions closely rely on each other in economic activities through interregional trading, the reallocation of production output in one region can affect not only its own economy and environment but also those of other regions that supply goods and services. Therefore, to achieve the economic and environmental targets in the entire system, the inter-relationship among different individual regions in the system must be considered. A few scholars, such as Sun et al. (2016), Fe et al. (2017), Geschke et al. (2019), and Wang et al. (2020a), used the multi-regional input–output linear programming (MRIO–LP) model to identify the optimal industrial restructuring strategies for CO_2 emissions reduction, but did not investigate the optimal regulation sequence of final products of various sectors in different regions at a minimum decrease in GDP. As a matter of fact, the analysis of such optimal sequence is important such that policymakers may expect to know the critical hotspots across economic sectors for emissions mitigation and thereby undertake proper actions.

These research gaps are addressed in this study by using the MRIO–LP model to identify strategies to reduce economy-wide CO_2 emissions through demand side regulation. A case study of China is performed based on the recently released MRIO table in 2017. Two research questions are addressed: What are the respective impacts of the demand side regulation on CO_2 emissions and economic growth? Which products in which regions should be first regulated to reduce CO_2 emissions at the minimum decrease in GDP? The contributions of this study are summarized as follows. First, the LP model is combined with MRIO to identify the optimal demand side regulation strategies for CO_2 emissions in China using the latest released MRIO table in 2017. Compared with single-regional IO–LP model, MRIO–LP considers the inter-relationship of various regions in the supply chain system. Second, compared with the existing MRIO–LP studies that were based on MRIO table in 2012, the current study is based on MRIO table in 2017, and can therefore reflect the most recent situation in China. Third, we prove the existence of a unique optimal sequence of final products regulation for reducing CO_2 emissions at the minimum loss in GDP.

The rest of this paper is organized as follows. Section 2 details the methodology, including the MRIO–LP model and approach to obtain the optimal regulation sequence of final products. Section 3 performs the proposed model for a case study of China. Finally, Section 4 concludes the study and provides several possible extensions.

2 Methodology

In this section, we first introduce the MRIO–LP model, which can be used to identify which group of final products need regulations to optimize the GDP and reduce CO_2 emissions. Then, we prove the existence of a unique optimal regulation sequence for reduction in CO_2 emissions at the minimum loss in GDP, and the approach to obtain such regulation sequence.

2.1 Multi-regional input–output linear programming model

The objectives of the model are to maximize the GDP and minimize CO_2 emissions, which are two important indicators in most of countries. The model is solved by choosing different levels of final demand to generate insights into how demand changes affect the overall economic and environmental performance. The objective functions can be expressed as follows.

$$\max_{Y} GDP, \tag{1.1}$$

$$\min_{Y} CO_2, \tag{1.2}$$

where GDP is the total GDP in the economy, CO_2 is the total CO_2 emissions from fossil fuel combustion in the economy, and $\boldsymbol{Y}$ is the vector of multi-regional domestic final demand.

The constraints of the model are elaborated as follows.

(1) MRIO balance: According to the Leontief production assumption (Leontief, 1936) for domestic products, the sum of intermediate and final demands must equal to the total output in an economy. Note that the IO model adopts the non-competitive import assumption[1)]. Assuming that in n regions, each has m economic sectors in an economic system, then the MRIO balance constraint can be expressed as follows:

$$\sum_{j}^{m}\sum_{r'}^{n} a_{ij}^{rr'}x_j^{r'} + y_i^r = x_i^r,\ \forall i = 1,\ ...,\ m, \text{ and } r = 1,\ ...,\ n, \tag{1.3}$$

where $x_i^{r'}$ and x_i^r are the outputs of sector i in regions r' and r, respectively; $a_{ij}^{rr'}$ is the technical coefficient, referring to the intermediate input from sector i in region r to produce one unit of output of sector j in region r'; and y_i^r is the final demand of domestic product of sector i in region r. The technical coefficient can be estimated as $a_{ij}^{rr'} = z_{ij}^{rr'} \big/ x_j^{r'}$ ($\forall i,\ j = 1,\ ...,\ m$, and $r,\ r' = 1,\ ...,\ n$), in which $z_{ij}^{rr'}$ is the intermediate input from sector i in region r to sector j in region r'. For the ease of formulation, let $\boldsymbol{A}_{rr'} = \begin{bmatrix} a_{11}^{rr'} & \cdots & a_{1m}^{rr'} \\ \vdots & \ddots & \vdots \\ a_{m1}^{rr'} & \cdots & a_{mm}^{rr'} \end{bmatrix}$ (technical coefficient matrix of economic flow between regions r and r') and $\boldsymbol{A} = \begin{bmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ A_{n1} & \cdots & A_{nn} \end{bmatrix}$ (technical coefficient matrix of multi-region). Let $\boldsymbol{X}_r = \begin{bmatrix} x_1^r \\ \vdots \\ x_m^r \end{bmatrix}$ and $\boldsymbol{X} = \begin{bmatrix} \boldsymbol{X}_1 \\ \vdots \\ \boldsymbol{X}_n \end{bmatrix}$, where $\boldsymbol{X}$ is the vector of output. Let $\boldsymbol{Y}_r = \begin{bmatrix} y_1^r \\ \vdots \\ y_m^r \end{bmatrix}$ and $\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{Y}_1 \\ \vdots \\ \boldsymbol{Y}_n \end{bmatrix}$. Then, constraint (1.3) can be written into its matrix form as $\boldsymbol{AX} + \boldsymbol{Y} = \boldsymbol{X}$.

(2) Estimation of GDP: Constraint (1.4) states that the total GDP of the economy can be estimated by the

[1)] According to Su and Ang (2013), two import assumptions are widely used in IO analysis, i.e., the non-competitive and competitive import assumptions. The former treats the imported products as different from the domestic ones, while the latter treats the imported products to be the same as those produced domestically. The current study adopts the non-competitive assumption.

production approach, as follows:

$$GDP = \boldsymbol{V}^{\mathrm{T}}\boldsymbol{X}, \tag{1.4}$$

where $\boldsymbol{V}$ is the vector of the value-added coefficients of various sectors.

(3) Estimation of CO_2 emissions: Constraint (1.5) states that the total CO_2 emissions in the economy consists of two parts, from production and from households (Medjdoub & Chalal, 2017); the former can be estimated based on production output and CO_2 emissions intensity while the latter can be estimated based on household expenditure and CO_2 emissions intensity. Constraint (1.6) claims that household expenditure comes from private income, which can be considered as linearly related to total output through income rate.

$$CO_2 = \boldsymbol{f}^{\mathrm{T}}\boldsymbol{X} + f_h h, \tag{1.5}$$

$$h = \beta \boldsymbol{R}^{\mathrm{T}}\boldsymbol{X}, \tag{1.6}$$

where h is the total household expenditure, which is linearly dependent on private income; $\boldsymbol{f}$ is the vector of CO_2 emission intensity of production sectors; f_h is the scalar of CO_2 emission intensity of household sectors; $\boldsymbol{R}$ is the vector of private income rate of total output; and β is the proportion of household expenditure in total private income.

(4) Final demand constraints: The domestic final demand is treated as main decision variables in the model. Clearly, the domestic final demand cannot be arbitrarily changed. Hence, upper and lower bounds are given to the domestic final demand in constraint (1.7) as follows:

$$\underline{\boldsymbol{Y}} \leqslant \boldsymbol{Y} \leqslant \overline{\boldsymbol{Y}}, \tag{1.7}$$

where $\overline{\boldsymbol{Y}}$ and $\underline{\boldsymbol{Y}}$ are the upper and lower bounds of domestic final demand, respectively.

Given that the model is LP with two distinct objectives, the epsilon constraint method can be utilized as solution by transferring the CO_2 emission objective to an auxiliary constraint with an adjustable upper bound. By doing so, the bi-criteria LP model can be transformed as a series of single-objective LP models with different upper bounds on the CO_2 emissions constraint, and can easily be solved to obtain a set of Pareto non-dominated solutions[1)].

2.2 Optimal sequence of demand regulation

The Pareto non-dominated solutions can indicate which group of domestic final products must be regulated to optimize *GDP* and CO_2 emissions reduction, but cannot provide suggestions on which products must first be regulated. To answer this question, we move a step further to explore the optimal sequence of demand regulation of domestic products in different regions to reduce CO_2 emissions at the minimum loss in *GDP*. The sequence can be generated on the basis of the following proposition.

Proposition 1: Given the following model,

$$\max_{Y} GDP = \boldsymbol{V}^{\mathrm{T}}\boldsymbol{X}$$

$$\text{s.t.} \quad \boldsymbol{A}\boldsymbol{X} + \boldsymbol{Y} = \boldsymbol{X},$$

$$h = \beta \boldsymbol{R}^{\mathrm{T}}\boldsymbol{X},$$

$$CO_2 = \boldsymbol{f}^{\mathrm{T}}\boldsymbol{X} + f_h h \leqslant \alpha,$$

$$\underline{\boldsymbol{Y}} \leqslant \boldsymbol{Y} \leqslant \overline{\boldsymbol{Y}}, \tag{2}$$

where $\boldsymbol{X}$, $\boldsymbol{Y} \in \boldsymbol{R}^{n\times 1}$ and $\boldsymbol{A} \in \boldsymbol{R}^{n\times n}$. Define $\boldsymbol{W}^{\mathrm{T}} = \boldsymbol{V}^{\mathrm{T}}(\boldsymbol{I}-\boldsymbol{A})^{-1}$, $\boldsymbol{G}^{\mathrm{T}} = (\boldsymbol{f}^{\mathrm{T}} + f_h\beta\boldsymbol{R}^{\mathrm{T}})(\boldsymbol{I}-\boldsymbol{A})^{-1}$, w_i and g_i are the elements in $\boldsymbol{W}$ and $\boldsymbol{G}$, respectively, and $c_i = w_i/g_i$.

When lowering down the value of α, the optimal solution $\boldsymbol{Y}^*$ changes as follows: One element y^* in $\boldsymbol{Y}^*$ with $c_i \leqslant c_j$ $(\forall j)$ would first decline, until it reaches its lower bound $\underline{y_i}$ along with the decrease in α. Then, the other elements in $\boldsymbol{Y}^*$ decrease one by one following the same rule.

Proof: We can prove Proposition 1 by looking at the ratio of change in *GDP* and change in CO_2 emissions with reduction in final demand y_i.

Firstly, we can express CO_2 emissions in model (2) as follows:

$$CO_2 = \boldsymbol{f}^{\mathrm{T}}\boldsymbol{X} + f_h h = \boldsymbol{f}^{\mathrm{T}}\boldsymbol{X} + f_h\beta\boldsymbol{R}^{\mathrm{T}}\boldsymbol{X} = (\boldsymbol{f}^{\mathrm{T}} + f_h\beta\boldsymbol{R}^{\mathrm{T}})\boldsymbol{X}. \tag{3}$$

Given that $\boldsymbol{A}\boldsymbol{X} + \boldsymbol{Y} = \boldsymbol{X}$, $\boldsymbol{X} = (\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{Y}$. Hence, we can rewrite CO_2 emissions as a variable in respect to $\boldsymbol{Y}$:

$$CO_2 = (\boldsymbol{f}^{\mathrm{T}} + f_h\beta\boldsymbol{R}^{\mathrm{T}})(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{Y}. \tag{4}$$

Similarly, we can express *GDP* as a variable respect to $\boldsymbol{Y}$:

$$GDP = \boldsymbol{V}^{\mathrm{T}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{Y}. \tag{5}$$

Let $\boldsymbol{W}^{\mathrm{T}} = \boldsymbol{V}^{\mathrm{T}}(\boldsymbol{I}-\boldsymbol{A})^{-1}$ and $\boldsymbol{G}^{\mathrm{T}} = (\boldsymbol{f}^{\mathrm{T}} + f_h\beta\boldsymbol{R}^{\mathrm{T}})(\boldsymbol{I}-\boldsymbol{A})^{-1}$. Then we can rewrite *GDP* and CO_2 emissions as follows:

$$GDP = \boldsymbol{W}^{\mathrm{T}}\boldsymbol{Y} = \sum_i^N w_i y_i, \tag{6}$$

$$CO_2 = \boldsymbol{G}^{\mathrm{T}}\boldsymbol{Y} = \sum_i^N g_i y_i. \tag{7}$$

According to Eqs. (6) and (7), with the reduction in y_i by Δy_i, *GDP* and CO_2 emissions simultaneously decrease by $w_i\Delta y_i$ and $g_i\Delta y_i$, respectively. The ratio between the decrease in *GDP* and that in CO_2 emissions is

[1)] Pareto non-dominated solutions mean the solutions for which no other feasible solution exists improving the value of a given objective function without worsening the value of, at least, other objective function.

$(w_i \Delta y_i)/(g_i \Delta y_i) = w_i/g_i = c_i$, which indicates that the ratio remains constant with the reduction of final demand y_i and does not depend on the reduction value Δy_i. That is, with reduction in final demand y_i, the marginal decrease in *GDP* for CO_2 emissions reduction is always constant. As such, given $c_i \leqslant c_j$, reducing y_i is always the best choice to reduce CO_2 emissions at the minimum decrease in *GDP*.

From Proposition 1, a certain regulation sequence of various products can be identified to reduce CO_2 emissions at the minimum loss in *GDP*. The sequence can be generated by comparing the values of c_i of various domestic products. Here, c_i can also be interpreted as the Unit Emissions Mitigation Cost (UEMC), representing the *GDP* lost for one unit of CO_2 emissions reduction by restricting the final product in sector *i*. Clearly, the product with smaller UEMC must first be restricted to reduce CO_2 emissions at a smaller decrease in *GDP*.

3 Case study of China

In this section, the proposed model is applied to a case in China. First, the data used in the case study are described, and then the trade-offs between GDP and CO_2 emissions with demand side regulation are assessed through a Pareto frontier analysis. Finally, the optimal regulation sequence of final products in various regions is analyzed.

3.1 Data

In this study, the monetary MRIO table in China in 2017 was utilized, as compiled by NBSC (2021). Tables 1 and 2 include 28 regions, each with 42 economic sectors. The 28 regions were aggregated into 8 regions as provided in Table 1. Each region includes 42 economic sectors as listed in Table 2. The energy consumption data of various fuels used by 28 regions in China can be collected from the *Chinese Provincial Statistics Yearbook for various provinces* (NBSC, 2018). This study considers 19 types of fuel, including raw coal, cleaned coal, washed coal, coke, coke oven gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, refinery gas, other petroleum products, natural gas, liquefied natural gas, heat, and electricity. For each region, the CO_2 emissions from energy consumption in each sector can be calculated based on the approach suggested by *Intergovernmental Panel on Climate Change 2007 guidelines*. The emissions coefficients of each energy type are derived from Liu et al. (2015). The upper bound of final demand is chosen as the final demand in 2017, whereas the lower bound of final demand is chosen as 90% of the final demand in 2017. Thus, the MRIO–LP model contains 483 variables and 724 constraints, which was solved with CPLEX package in Python environment.

Table 1 Eight geographical regions in China

Regions	Provinces/Cities included
Northeast	Heilongjiang, Jilin, Liaoning
Jing–Jin	Beijing, Tianjin
North Coast	Hebei, Shandong
Central Coast	Jiangsu, Zhejiang, Shanghai
South Coast	Fujian, Guangdong, Hainan
Central	Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi
Northwest	Inner Mongolia, Shaanxi, Ningxia, Gansu
Southwest	Sichuan, Chongqing, Yunnan, Guizhou, Guangxi

3.2 Trade-offs between GDP and CO_2 emissions

Table 3 presents 10 Pareto non-dominated solutions that are generated by solving a series of MRIO–LP models with different upper CO_2 emissions targets in Eq. (2). Figure 1 illustrates the GDP and CO_2 emissions corresponding to these 10 solutions.

As can be seen, the Pareto optimal frontier of GDP and CO_2 emissions is a concave curve, indicating that the reduction in final demand simultaneously leads to reductions in GDP and CO_2 emissions. Point 1 denotes the solution with no effects on GDP and CO_2 emissions, and then the negative effects on both increase as we move from point 1 to point 10. At point 10, the GDP and CO_2 emissions can be reduced by 7.7% and 9.0%, respectively, with a restricted regulation of final demand. The results show that a greater reduction in CO_2 emissions through the regulation of final demand is always accompanied with a greater loss in GDP. Each point of the curve corresponds to a certain industrial structure adjustment strategy. According to Proposition 1, all the sectors can be classified into three groups: Those with a demand hitting their lower bound, those with a demand hitting their upper bound, and only one sector with a demand between its lower and upper bounds. Hence, an important outcome of the optimization is the number of sectors with a final demand that is modified to reach a given environmental target. Table 3 shows that the number of sectors that should be regulated increases as we move from maximum GDP (demands of all products hitting the upper bound) to the minimum CO_2 emissions (demands of all products hitting the lower bound).

Although GDP and CO_2 emissions simultaneously decrease when moving from point 2 to point 10, the ratios between their reductions vary in different points. This ratio can be interpreted as the cost for one unit reduction in CO_2 emissions. As seen in Table 3, the cost per unit CO_2 emissions reduction ranges from 2528 yuan/ton in point 2 to 4842 yuan/ton in point 10. Clearly, the solution with smaller mitigation cost can be considered as a more cost-effective strategy for CO_2 emissions reduction. In Table 3, point 2 has the smallest mitigation cost (point 1 is not considered due to no action being taken yet). As we

Table 2 42 economic sectors in China

Code	Sector	Code	Sector
S01	Agriculture	S22	Other manufacturing
S02	Coal mining	S23	Repair service of metal products, machinery and equipment
S03	Petroleum and gas	S24	Electricity and hot water production and supply
S04	Metal mining	S25	Gas production and supply
S05	Nonmetal mining	S26	Water production and supply
S06	Food processing and tobaccos	S27	Construction
S07	Textile	S28	Wholesale and retailing
S08	Clothing, leather, fur, etc.	S29	Transport and storage
S09	Wood processing and furnishing	S30	Hotel and restaurant
S10	Paper making, printing, stationery, etc.	S31	Information transmission, software and information technology services
S11	Petroleum refining, coking, etc.	S32	Finance
S12	Chemical industry	S33	Real estate
S13	Nonmetal mineral products	S34	Leasing and commercial services
S14	Metallurgy	S35	Scientific research
S15	Metal products	S36	Technical service
S16	General machinery	S37	Water conservancy, environment and public facilities management
S17	Specialist machinery	S38	Resident services, repairs and other services
S18	Transport equipment	S39	Education
S19	Electrical equipment	S40	Health and social work
S20	Electronic equipment	S41	Culture, sports and entertainment
S21	Instrument and meter	S42	Public administration, social security and social organizations

Table 3 10 Pareto optimal solutions generated by the MRIO–LP model

Pareto solution	1	2	3	4	5	6	7	8	9	10
CO_2 emissions reduction (%)	0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0
GDP reduction (%)	0	0.4	1.0	1.7	2.3	3.1	3.9	4.7	5.9	7.7
Ratio (yuan/ton CO_2)	–	2528	2922	3133	3324	3517	3661	3830	4163	4842
Number of regulated sectors	0	32	48	53	83	87	103	136	186	224

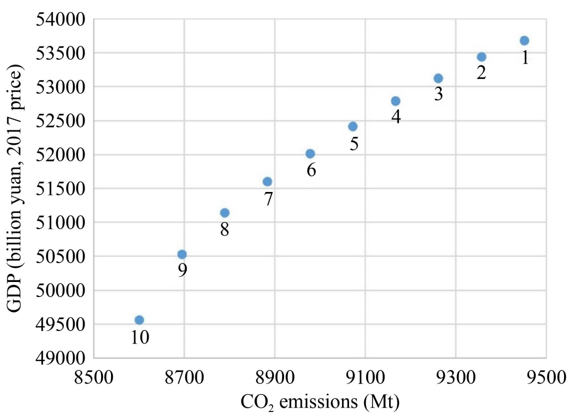

Fig. 1 Optimal Pareto frontier of GDP and CO_2 emissions in China.

move from point 2, the mitigation cost steadily increases until it becomes almost twice as much in point 10. The result implies that, as we move from point 2 to point 10, a greater decrease in GDP is required to achieve the same amount of reduction in CO_2 emissions through the regulation of final demand. From this perspective, the solution of point 2 can be considered as the most cost-effective strategy for CO_2 emissions mitigation among the 10 optimal solutions. With the reduction in CO_2 emissions, any additional unit reduction through demand side regulation becomes less and less cost-effective.

3.3 Optimal sequence of demand regulation

In addition to the identification of optimal non-dominated solutions, we further investigate the regulation sequence of various products to mitigate CO_2 emissions at the minimum decrease in GDP. As indicated by Proposition 1, when we lower the CO_2 emissions target, the final demand of one product with the smallest UEMC first declines until the lower bound is reached. The algorithm proceeds in the same manner for the rest of sectors. Thus, the proposition indicates that a certain regulation sequence can continuously reduce CO_2 emissions at the minimum loss in GDP. Below, we discuss the sequence of the top 32 final products that must first be regulated in China. Table 4 lists the sequence.

From the sectoral perspective, among all the final products, those in metallurgy should first be regulated to reduce the CO_2 emissions in China at the minimum decrease in GDP. The high rank of metallurgy products can be attributed to its high CO_2 emissions footprints across the entire economic system. The emissions may not only come from the metallurgy production sector itself, but also from others that supply it with goods and services. As a result, by regulating the final demand of metallurgy products (including exports), the CO_2 emissions from the entire supply chain can decrease. This finding is consistent with the results of several other studies. Wang et al. (2020b) identified the metallurgy sector has strong connections or interactions with other sectors. Li et al. (2020) also highlighted the critical role of the metal smelting and processing sector in the emissions and resulting value additions. Following the metallurgy products, the other key products that require regulations include nonmetal mineral products, instrumentation, metal products, and chemical industry. Figure 2 shows the effects on GDP and CO_2 emissions in various economic sectors from the regulation of the key 32 products. As can be seen, the sectors with the largest effects are not necessarily those in which the final products are regulated. For example, when regulating the final demand of some sectors, the GDP and CO_2 emissions of some other unregulated sectors are greatly reduced, such as coal mining, petroleum and gas, and petroleum refining, coking sectors. The reason is that those sectors supply a large amount of intermediate goods and services to the regulated sectors. Hence, the regulation of key products of specific sectors significantly affects the production of other sectors in the supply chain system. From this perspective, the proposed model can uncover the complex relationships among sectors and identify the specific products that must first be regulated to reduce the CO_2 emissions at the minimum economic cost.

Table 4 Optimal regulation sequence of top 32 final products in China

Optimal sequence	Products	Regions	UEMC (yuan/ton)
1	Metallurgy	Jing–Jin	1839
2	Metallurgy	South Coast	2156
3	Metallurgy	Central Coast	2465
4	Metallurgy	Northeast	2581
5	Metallurgy	North Coast	2585
6	Metallurgy	Central	2737
7	Metallurgy	Southwest	2916
8	Metallurgy	Northwest	2951
9	Instrumentation	North Coast	3197
10	Instrumentation	Northwest	3230
11	Nonmetal mineral products	Jing–Jin	3331
12	Nonmetal mineral products	North Coast	3387
13	Nonmetal mineral products	South Coast	3497
14	Instrumentation	South Coast	3508
15	Nonmetal mineral products	Northeast	3519
16	Nonmetal mineral products	Central Coast	3597
17	Instrumentation	Central Coast	3697
18	Metal products	Jing–Jin	3733
19	Nonmetal mineral products	Central	3843
20	Instrumentation	Jing–Jin	3874
21	Nonmetal mineral products	Southwest	4028
22	Instrumentation	Southwest	4036
23	Instrumentation	Central	4039
24	Instrumentation	Northeast	4107
25	Chemical industry	North Coast	4542
26	Repair service of metal products, machinery and equipment	South Coast	4549
27	Nonmetal mineral products	Northwest	4641
28	Metal products	Northeast	4740
29	Metal products	South Coast	4756
30	Metal products	North Coast	4771
31	Chemical industry	South Coast	4776
32	Repair service of metal products, machinery and equipment	Southwest	4822

From the regional perspective, Table 4 shows that the key products that first require regulation mostly concentrate in the eastern and coastal more-developed regions in China, including Jing–Jin, South Coast, North Coast, and Central Coast. By contrast, the number of key products in the central and western less-developed regions are relatively small. This finding is controversial given the current situation that the central and western regions in China are actually regions with high CO_2 emissions (Li et al., 2017; Wang and Feng, 2017). The possible reason is that a large number of products consumed in the coastal regions are, in fact, supplied by the central and western regions. In other words, the less-developed regions discharge carbon emissions in their local production to meet the final demand in the more-developed regions in China (Meng et al., 2013; Zhang and Lahr, 2014). As a consequence, the regulation of final products in the coastal regions may reduce not only their own CO_2 emissions, but also those in the central and western regions. As an example, the Jing–Jin region has a number of products that are ranked as the first ones to be regulated, namely, metallurgy, nonmetal mineral products,

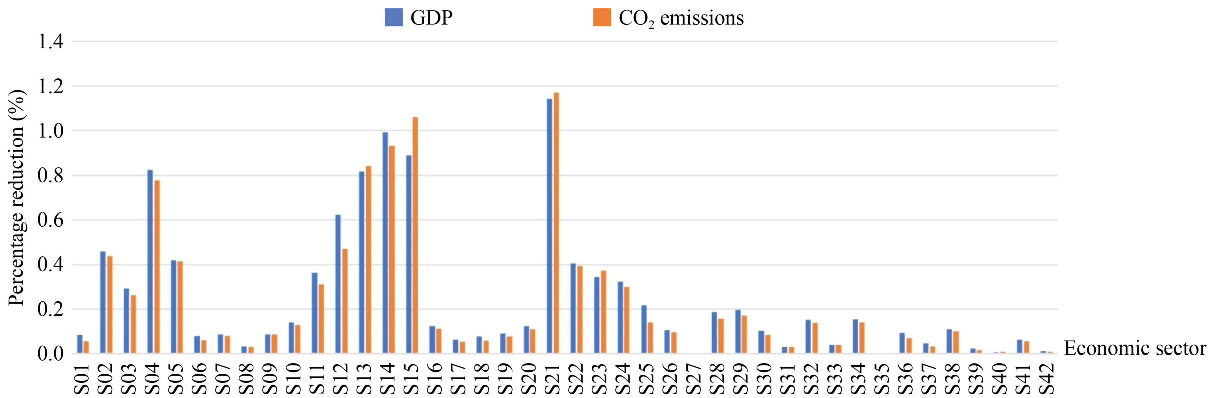

Fig. 2 Percentage reduction in GDP and CO_2 emissions in various sectors by regulating the key 32 products in China.

metal products, and instrumentation (see Table 4). These key products consumed in Jing–Jin region may be supplied not only by local enterprises, but also by other regions. Figure 3 depicts the effects on GDP and CO_2 emissions in various regions by regulating the key 32 products. As can be seen, the effect in Jing–Jin region is not that significant even though several of its products are regulated (see Table 4). By contrast, the GDP and CO_2 emissions are greatly reduced in the North Coast and South Coast regions, in which only a small number of products are regulated. From this point of view, the proposed model can recognize the complex relationship among regions and identify the specific regions that should first be controlled from the demand side to decrease the CO_2 emissions at the smallest loss in GDP.

3.4 Discussion

The above analysis implies that identifying the optimal industrial structure adjustment strategy is not straightforward, but requires careful consideration of the complex interdependent relationship of various sectors and regions in the system. At times, the best strategy to reduce CO_2 emissions may not be to directly regulate most polluting

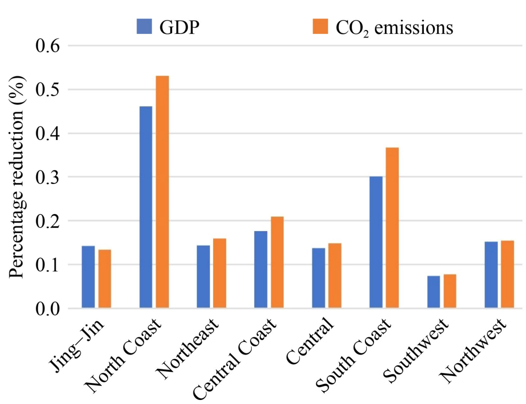

Fig. 3 Percentage reduction in GDP and CO_2 emissions in various regions by regulating the key 32 products in China.

sectors from the supply side, but to regulate those from the demand side that induce a large amount of CO_2 emissions in other sectors. For example, this study finds that the final products that must first be regulated mainly concentrate in coastal and eastern regions in China. However, most of the high emissions-intensive sectors in terms of production are concentrated in western regions. The reason is that most of the final products with high CO_2 emissions are consumed by the coastal and eastern regions and are imported from western regions. One uncertainty of the current model can come from the setting of lower and upper bounds of final demand of different products. Notably, the lower and upper bounds of final demand are chosen quite arbitrarily (from 90% to 100% of 2017 final demand), which can affect the potential and accuracy of CO_2 emissions reduction from demand side regulation. However, setting lower and upper bounds does not affect the optimal regulation sequence of different products, which is the most important outcome in this study.

The results of this optimization model provide valuable policy implications, which can be used in different ways. The most straightforward one is to levy taxes on the final consumption of certain products to reduce their final demand, and therefore the associated CO_2 emissions in the entire supply chain system. However, reducing the final demand can in turn reduce the economic flows and consequently the country's total GDP, which may have negative effects on the employment rate and as such be considered as an unpopular policy measure. Therefore, a more appealing option to decrease the CO_2 emissions (with minimum changes in the economy) is to enhance research on low-carbon technologies that can eventually improve the environmental efficiency of target industries. The environmental savings gained in one industry may eventually propagate to other industries through trade, and therefore enhancing the sustainability level of entire economic system. Compared with the supply side regulation, the demand side regulation has its own advantages in curbing CO_2 emissions in considering the lifecycle emissions of a final product and can cut CO_2 emissions at the source. The fair allocation of environmental responsibility can prevent regions from transferring their high emissions production to those with softer emissions regulations.

4 Conclusions and future extensions

This study combines MRIO and LP models to explore cost-effective strategies to reduce economy-wide CO_2 emissions at the minimum decrease in GDP through demand side regulation, in particular, the optimal regulation sequence of final products is identified. This analysis is necessary as it pinpoints the key sectors with a better potential for reducing CO_2 emissions. The results in this case study of China show that products in metallurgy, nonmetal mineral products, instrumentation, metal products, and chemical industry rank at the top of those that must first be regulated to reduce CO_2 emissions at the smallest sacrifice of economic growth. Most of these key products are consumed by the coastal developed regions, including Jing–Jin, South Coast, North Coast, and Central Coast in China. Moreover, the results also show that the regulation of final demand of certain products may not only affect the GDP and CO_2 emissions in that particular sector and region, but also pose significant effects in the other sectors and regions with close input–output inter-relationship with the regulated sector.

This study can be possibly extended toward following directions. First, the current study only considers two objectives, namely, CO_2 emissions and GDP. However, other objectives are also quite important to social economic system, such as employment rate, energy consumption, water consumption, and air pollutants. Therefore, the current study can be extended to identify the optimal industrial structure adjustment strategy with the consideration of more social–economic objectives. Second, the current study only examines the industrial structure adjustment strategy for CO_2 emissions reduction. However, other effective strategies can be adopted to reduce CO_2 emissions, such as the shift from fossil-fuel based to renewable generation (Kang et al., 2020), transport electrification (Kang et al., 2021), and improvement of energy efficiency. Therefore, another meaningful extension of this study is to integrate the above-mentioned strategies into the IO–LP model to identify the optimal long-term decarbonization pathway in the future. Finally, the current study is based on the MRIO table that assumes a constant allocation proportion of import and export to various regions in production. As such, the optimization model cannot choose the optimal trading strategies and options in different regions. Hence, another possible extension of the current study is to replace the MRIO table by multiple single-regional IO tables. By doing so, in addition to production output and final demand, the trading allocation proportion of important commodities (e.g., electricity and natural gas) can be also endogenized and optimized among different regions.

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