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Peaking Carbon Emissions in a Megacity through Economic Restructuring: A Case Study of Shenzhen, China

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Abstract: With the growing cost of carbon emissions reduction, the application of industrial restructuring to suppress carbon emissions is becoming more attractive. By constructing an input-output optimization model, this study explored how industrial restructuring helps megacities synergistically achieve carbon peak and high-quality development. The results showed that through contributing 164.4% of the reduction in emissions from 2020 to 2025, industrial structure optimization significantly inhibited the growth of carbon emissions; From 2020 to 2025, the manufacturing structure continued to be high-end, which resulted in a reduction in industrial carbon emissions by 10.3%; through vigorous development of the low-carbon service industry, the carbon emission of the service industry would continue to slow down at an average annual rate of 2.4%. Industrial premiumization and the low-carbonization of the modern service sector are the key driving forces for Shenzhen to achieve low-carbon transformation. The results also showed that the power and retail sectors are the most important for emissions reduction. This study can provide a roadmap for megacities on how to explore potential emission reduction via optimizing their economic structure to help them achieve their carbon emissions peak.

Keywords: I-O optimization model; industrial restructuring; emission reduction potential

Citation: Yang, Y.; He, F.; Ji, J.; Liu, X. Peaking Carbon Emissions in a Megacity through Economic Restructuring: A Case Study of Shenzhen, China. *Energies* **2022**, *15*, 6932. https://doi.org/10.3390/en15196932

Academic Editor: Wen-Hsien Tsai

Received: 9 August 2022
Accepted: 16 September 2022
Published: 22 September 2022

1. Introduction

Cities are widely believed to be the world's biggest energy consumers and carbon dioxide emitters and are the main targets for achieving carbon peaking and neutrality in the world [1,2]. In China, more than 60% of the population lives in urban areas, and that figure is expected to climb to 70% by 2030 [3]. Further, as cities consume 80% of the Chinese energy and generate approximately 85% of emissions they play an increasingly important role in addressing the challenges of climate change [4]. Technological revolution and structural adjustment are the two main means of inhibiting the increase in emissions [5,6]. Technological progress has been the main driving force behind the decline in carbon emissions in China over the past 20 years [7–9]. With the increasing marginal cost of technology emission reduction [10,11], the cost, speed, and effect of emission reduction should be considered for the construction of low-carbon cities. Relying on technological progress alone to reduce emissions makes it difficult for megacities to reach their carbon peaking and carbon neutrality goals. Thus, from the perspective of industrial restructuring, research on carbon emissions reduction is essential. Research on the impact of economic restructuring on carbon peak mostly remains at the national and regional levels, while such research at the city level is relatively scarce. Su et al. (2021) took social welfare maximization as the objective function, optimized the parameters of technological progress, and implemented the I-O comprehensive optimization model to explore the socio-economic impact of industrial structure adjustment [12]. The study found that the emission reduction effect of structural change is better than that of technological progress. Liu et al. (2020) found that structural adjustment improves the utilization efficiency of water and energy by planning and adjusting the economic structure within the industrial sector. This study attempted to find the potential path of industrial structure optimization and adjustment under the constraint of water-energy, taking Hebei province as the case study [13]. In their study of the differences in economic growth, energy consumption, and carbon emissions following the optimization of cross-regional and single-regional industrial structures, Zhu et al. (2021) demonstrated that provinces can optimize the industrial structure through industrial transfer, realizing the rational layout of the industry and achieving the planning goals of emission, economy, and energy [14]. At the city level, Su et al. (2020) estimated the energy-related emission reduction potential for 2030 for four different types of urban agglomerations (including energy production, light, and heavy manufacturing, and high-tech development) through improved scenario design, and the results showed that the optimization of economic structures can promote energy-related emissions to peak before 2030 [15].

To quantify the impact of industrial restructuring on peak carbon emissions, different approaches have been applied, including I-O optimization and scenario analysis models. Taking total social welfare maximization as the objective function, Mi et al. (2017) proposed a comprehensive optimization model based on the IO model, which aimed to evaluate the effect of China's industrial restructuring and determine how energy intensity reduction can simultaneously achieve economic growth and emission reduction targets [16]. Through constructing a dynamic IO optimization model with the economy, carbon emissions, and employment as the multi-objectives, Yu et al. (2018) indicated that China can make energy-related emissions peak in 2022–2025 by adjusting the industrial structure of energy-intensive and heavy chemical industries [17]. Analyzing the impact of different driving factors on CO_2 emissions in China from 2000 to 2016, Zhang et al. (2019) proposed a combination of the logarithmic mean divisor index (LMDI) method and scenario analysis to explore the impact of industrial structure changes on China's carbon intensity reduction potential under different scenarios [18]. The results indicated that, from 2020 to 2030, the influence of industrial structure optimization on CO_2 emission changes from the promotion of emissions to their suppression and the inhibition effects are increasing over time. Under the scenario of rapid economic growth, industrial structure optimization showed the greatest potential for emission reduction, indicating that the 65% emission reduction target would be fully achieved by 2030. The input-output optimization analysis can more accurately predict the impact of changes and interactions between various industries on carbon emissions peaking, while the combination of LMDI and scenario analysis can evaluate the impact of changes in industrial structure factors on carbon emissions under different scenarios. Based on the input-output optimization model, this study qualitatively and quantitatively analyzes the impact of industrial structure on carbon peak targets and evaluates the emission reduction potential of industrial restructuring, which can provide a detailed roadmap for megacities structure adjustment.

Due to the incompleteness of the input-output data, most existing studies focus on analyzing the impact of industrial structure adjustment on carbon emissions at the national, provincial, or key industries level [19,20]. By constructing an I-O optimization model and combining scenario analysis, this study was extended to the analysis of industries (including 12 sectors) at the city level; the impact of changes in an industry's structure and its associated emission reduction potential were quantitatively evaluated, addressing the gaps in the existing research. Meanwhile, according to the economic structure characteristics of megacities, the constraints in the input-output optimization model at the regional level are supplemented and modified. For example, in the constraints of industrial structure, our research accurately screened out industries that are encouraged and limited from developing. Regarding employment constraints, this paper considered the employment opportunities provided by the unit added value may change with the development of low-carbon technologies, which was different from the existing research. Finally, this study provides a roadmap for exploring how megacities can synergistically achieve carbon peak goals and high-quality development through economic restructuring.

2. Methods

This section explains the main differences in the methods used in this study from those of previous national- and provincial- level studies [Mi et al. (2017) and Su et al. (2020)], highlighting the improvements and contributions of this paper to the city-level input-output table and constraints of the optimization model. In terms of the city-level input-output model (Section 2.1), the final demand section of the urban input-output table is composed of final consumption, capital formation, net export, out-of-province net transfers out in domestic, and out-of-city net transfers out in province. Compared with a regional input-output table (Region refers to nation and province in this study), the variables 'out-of-province net transfers out in domestic' and 'out-of-city net transfers out in province' are unique to the urban level input-output table. Hence, applying the I-O optimization model at the city level could provide an important and analyzable perspective. As shown in Table 1 and Equation 1, the following two variables are added: the out-of-province net transfers in domestic and out-of-city net transfers out in province. Regarding the optimization model, parameters such as energy consumption per unit of value added (b_{ikt}), carbon emissions per unit of value added (d_{ikt}) and employment opportunities attained by per unit of value added (m_{it}) in the energy consumption (Section 2.2.1), carbon emissions (Section 2.2.2), and employment constraints (Section 2.2.3) need to be optimized for the case of Shenzhen city. In addition, further equations to encourage or restrict sectors in the model are added in the industrial structure adjustment constraints (Section 2.2.3). Full details of the input-output model and socio-economic constraints of the optimization model are as follows:

Table 1. Simplified version of I-O table.

		Final Demand (y_{it})					
	Intermediate Matrix	**Consum-Ption**	**Capital Formation**	**Net Export**	**OP-OD**	**OC-OP**	**Total Output**
Intermediate Matrix	z_{it}	s_{it}	f_{it}	o_{it}	pd_{it}	cp_{it}	x_i
Value Added	v_i						
Total Input	x_j						

2.1. Input-Output Model

To ensure the balance of the social and economic system, the input-output analysis takes the establishment of a series of linear equations as the constraint condition of model optimization. The city-level input-output table is different from the national and provincial input-output tables. To distinguish them, the simplified version of the urban input-output table is shown in Table 1:

In Table 1, the final demand can be expressed as:

$$y_{it} = s_{it} + f_{it} + o_{it} + pd_{it} + cp_{it} \quad (1)$$

where y_{it}, s_{it}, f_{it}, o_{it}, pd_{it}, and cp_{it} are n-dimensional column vectors, which represent final demand, consumption, capital formation, net export, out-of-province net transfers out in domestic (OP-OD), and out-of-city net transfers out in province (OC-OP), respectively. Among them, pd_{it} and cp_{it} are unique at the city level, which is different from the research of Mi et al. (2017) and Su et al. (2020).

$$z_{ij} = a_{ij} \cdot x_j \quad (2)$$

z_{ij} is an n-dimensional matrix, indicating the consumption of products from sector j to sector i; a_{ij} represents the direct consumption coefficient; v_j is an n-dimensional column vector and represents the added value of the sector j; x_i represents total output; and x_j represents total input.

The adjustment of the industrial structure needs to meet the balance of the economic system, that is, the input-output balance constraint, which is expressed as follows:

$$X = (I - A)^{-1} Y \tag{3}$$

$$X = (I - A_c)^{-1} V \tag{4}$$

where X is the total output of sector i, I is the identity matrix A is the direct consumption coefficient matrix composed of a_{ij}; Y is the final demand; A_c is the diagonal matrix, which represents the direct distribution coefficient matrix, and the value of the diagonal matrix is each column direction in A.

This study assumed that the direct consumption coefficient of Shenzhen in 2030 is the same as that in 2019, the technical coefficient matrix (the I-O structure) would not change in a short time.

2.2. Optimization Model

Based on Section 2.1, this section details the construction of an input-output optimization model. Seven constraints were introduced to the model to enhance the realism of results, mainly including economic level, energy consumption, carbon emission, employment level, industrial structure adjustment, consumption level, and non-negative constraints. The details of the constraints of the model are as follows:

2.2.1. Economic Development Constraints

Under the background of the impact of the epidemic and the increasing economic uncertainties in the world, the adjustment of the urban economic structure must be based on the stable operation of the macro-economy, so it is necessary to ensure a certain GDP growth rate.

$$GDP_t = \sum_{i=1}^{n} v_{it} \tag{5}$$

$$(1 + \alpha_t) \leq \frac{GDP_t}{GDP_{t-1}} \tag{6}$$

where GDP_t represents the total added value of the economy in the year t; v_{it} represents the added value of the sector i in the year t; and α_t represents the GDP growth rate in the year t, which is a given exogenous parameter.

2.2.2. Energy Constraints

Economic development cannot be separated from the support of energy. However, for most fields, the energy supply is limited. In order to control energy consumption and intensity, the annual growth of energy consumption needs to be limited. The total energy consumption can be expressed as:

$$E_t = \sum_{i=1}^{n} \sum_{k=1}^{m} b_{ikt} \cdot v_{it} + \sum_{k=1}^{m} eh_{kt}^{p} \cdot pop_t \tag{7}$$

$$E_t \leq (1 + \beta_t) E_{t-1} \tag{8}$$

$$\frac{E_t}{G_t} \leq (1 - \gamma_t) \frac{E_{t-1}}{G_{t-1}} \tag{9}$$

where b_{ikt} represents the energy consumption per unit of added value in sector i during the year t for fuel type k; v_{it} is the added value of sector i in year t; eh_{kt}^{p} represents the energy consumption per capita of the residents during year t for fuel type k; pop_t represents the resident population of the city in year t; $\sum_{k=1}^{m} eh_{kt}^{p} \cdot pop_t$ represents the total amount of m kinds of energy consumed by residents in period t; β_t represents the growth rate of energy consumption; and γ_t represents the rate of decline in energy intensity.

2.2.3. Carbon Emission Constraints

For Shenzhen, controlling the growth rate of CO_2 is a prerequisite that can help it simultaneously achieve carbon peak targets and high-quality development:

$$C_t = \sum_{i=1}^{n}\sum_{k=1}^{m} d_{ikt} \cdot b_{ikt} \cdot v_{it} + \sum_{k=1}^{m} ch_{kt}^{p} \cdot pop_t \tag{10}$$

$$C_t \leq (1+\varepsilon_t)C_{t-1} \tag{11}$$

$$\varepsilon_t \leq 0, t > \bar{t} \tag{12}$$

where d_{ikt} is the carbon emissions per unit of added value in sector i during the year t for fuel type k; ch_{kt}^{p} represents direct household carbon emissions generated by energy activities in year t; ε_t represents the growth rate of carbon emissions in year t; and $\bar{t}$ indicates the peak time.

2.2.4. Employment Constraints

When labor productivity increases, the employment proportion of the labor force in the manufacturing industry decreases correspondingly [21]. With the increase in the proportion of advanced manufacturing industries, the employment opportunities driven by the unit value added of the manufacturing industry in Shenzhen decreased in 2015, 2017, and 2019, which are 5.41, 4.66, and 4.41 jobs per million yuan, respectively. Those figures indicate that the employment opportunities brought by the unit manufacturing value added will decrease with the adjustment of its internal structure. Therefore, we assumed that the employment provided by the unit manufacturing value added changes over time:

$$M_t = \sum_{i=1}^{n} m_{it} \cdot v_{it} \tag{13}$$

$$\frac{M_t}{M_{t-1}} \geq (1+\frac{pop_t}{pop_{t-1}}) \tag{14}$$

where M_t represents the total employment opportunities in year t; m_{it} refers to the employment opportunities attained by unit added value in sector i in period t; and pop_t refers to the resident population in period t.

2.2.5. Industrial Structure Adjustment Constraints

The studies by Mi et al. (2017) and Su et al. (2020) did not indicate the development of which sectors need to be encouraged or restricted. Considering the different resource endowments of each city, screening the encouraged and restricted sectors of the city is necessary to realize precise industrial restructuring.

Chang et al. (2015) introduced the industrial linkage method to screen encouraged and restricted industries. However, this approach was based on historical data and only focused on past industrial development, excluding the future trend analysis of strategic emerging industries [22].

This problem was solved in three steps: Firstly, Screening encouraged industries according to government planning. Secondly, referring to the research by Chang et al. (2015), we introduced the industrial linkage coefficient and eliminated the restricted industries.

Finally, referring to the methods of Mi et al. (2017) and Su et al. (2021), the upper and lower limits of structural changes were set for unrestricted industries.

According to the planning document of Shenzhen Municipal Government, this study set sector l as an encouraged industry, as shown by Equation (15):

$$\frac{v_{lt-1}}{G_{t-1}} \leq \frac{v_{lt}}{G_t} \leq \frac{(1+q_t)v_{lt-1}}{G_{t-1}}(l = 1,2,\ldots,L) \tag{15}$$

According to the analysis of industrial linkage, this study set sector j as a limited sector, which satisfies Equations (16)–(18):

$$\frac{(1+\rho_t)v_{jt-1}}{G_{t-1}} \leq \frac{v_{jt}}{G_t} \leq \frac{v_{jt-1}}{G_{t-1}}(j = 1,2,\ldots,J) \tag{16}$$

$$\frac{v_{it}}{G_t} \geq (1+\eta_t)\frac{v_{it-1}}{G_{t-1}}(i = 1,2,\ldots,n, i \neq l, j) \tag{17}$$

$$\frac{v_{it}}{G_t} \leq (1+\mu_t)\frac{v_{it-1}}{G_{t-1}}(i = 1,2,\ldots,n, i \neq l, j) \tag{18}$$

where v_{lt} is the added value of sector l in year t; G_t represents the added value in year t; q_t represents the upper limit of the structural adjustment of encouraged sectors, and ρ_t represents the lower limit of the structural adjustment of limited sectors; η_t, μ_t represent the given exogenous parameters.

2.2.6. Consumption Constraints

Promoting the upgrading of residents' consumption is the most important goal of urban economic restructuring. Strengthening residents' consumption will help protect the economy from the impact of fluctuations in external demand.

Following the research of Mi et al. (2021) and Su et al. (2017), we assumed that the proportion of consumption, capital formation, and net exports in final demand in period t is the same as that in the year 2019. At the same time, consumption needs to meet:

$$\theta_1 \leq \frac{\sum_{i=1}^{n} s_{it}}{G_t} \leq \theta_2 \tag{19}$$

where s_{it} refers to the consumption of sector i in year t; $S_t = \sum_{i=1}^{n} s_{it}$ represents the total consumption in year t; and θ_1 and θ_2 are the given exogenous parameters.

2.2.7. Nonnegative Constraints

Supposing that the value added and a total output of sector i in year t are not less than 0:

$$v_{it} \geq 0 \tag{20}$$

$$X_t \geq 0 \tag{21}$$

2.2.8. Objective Function

Industrial structure optimization is a problem of sustainable development, the core of which is to coordinate the relationship between economic interests and ecological environment protection [23]. Even when the primary influence of industrial structure optimization is the economy, carbon emissions, energy consumption, or employment, its most important purpose is to realize the maximum whole social welfare [24].

To distinguish it from the multi-objective input-output optimization model [25], this study used the optimal economic growth theory for reference, and only took the maximization of the welfare of the whole society as the objective function [26], with the equation as follows:

$$W = \sum_{t=1}^{T} H_t log(\frac{c_t}{H_t}) \frac{1}{(1+\rho)^{t-1}} \quad (22)$$

where W represents the total social welfare level; H_t represents the resident population in year t; c_t represents the consumption in year t; ρ represents the pure rate of time preference.

3. Study Area and Data

3.1. Study Area

As a special economic zone in China, Shenzhen is located in the Pearl River Delta on the southeastern coast of China and is regarded as China's 'Silicon Valley'. As the first Chinese megacity among C40 Cities Climate Leadership Group members, Shenzhen has been leading in economic growth and environmental improvement. In the process of Shenzhen's rapid social and economic development, its carbon emissions per capita have always been at a low level [27].

By 2021, with a resident population of 17.6 million and an urbanization rate of 100%, it became China's economic center city and one of the mega-cities with the best economic benefits. According to the China Net Zero Carbon City Development Report (2022) [28], Shenzhen leads China in the net zero carbon index, which shows that Shenzhen has actively become a low-carbon pioneer city with the theme of innovation leading the sustainable development of megacities, and has made great efforts in protecting the ecological environment, promoting green and low-carbon development, and enhancing the balanced development between the environment, economy, and society in recent years.

3.2. City Input-Output Tables

Shenzhen has not published its I-O table. Applying a non-survey method by Zheng et al. (2021) [29], we have harnessed the relevant economic data, treating the Guangdong provincial IO tables as a benchmark to expand, estimate, and compile the I-O table of Shenzhen. The data were obtained from the Guangdong IO table, and the city and Guangdong statistical yearbooks [30]. When estimating the inflow and outflow of each region in the province, it was assumed that the trade pattern of the inflow and outflow of each region in the province is equal and that that outside the province is also applied to the trade pattern of each region in the province. The column coefficient decomposition method was used to decompose the inflow and outflow data of each region, and then the decomposed results were adjusted and modified by RAS (also known as a "biproportional" matrix balancing technique; the R is referred to as a diagonal matrix of elements modifying rows, the A as the coefficient matrix being modified, and the S as a diagonal matrix of column modifiers.) [31] until the equal requirements of inflow and outflow between regions in the province were met.

We used the Guangdong province IO table in 2017 to prepare the Shenzhen IO Table 2017 and updated it to obtain the IO tables in 2015 and 2019. Further, according to the method by Liu and Peng (2010) [32], we deflated the updated price city I-O tables. The price indices used in the deflation process came from the Shenzhen Statistical Yearbook [33]. The final step was to aggregate sector classifications in various data into 12 sectors shown in Table 2 based on the characteristics of the industrial structure of Shenzhen.

3.3. Energy Data

According to the energy consumption structure of Shenzhen, we utilized the terminal energy consumption data to represent that of various sub-sectors and aggregate different types of energy into five fuel types (including coal, oil, gas, external power supply, and primary electricity, in a unit of tons of coal equivalent). The data on energy consumption in Shenzhen came from the Shenzhen Statistical Yearbook [33] and other public data. In detail, the industrial energy data came from the data released by the Shenzhen Bureau of Statistics.

Applying the proportional conversion method referred to that used by Shan et al. (2017) [34], we constructed the provincial-city index based on the Guangdong Statistical Yearbook [30] to obtain the energy data of other sectors. In addition, the sectoral classification of energy data needed to be consistent with the sectoral classification of urban IO tables.

Table 2. Sector Information.

	Sectors
s1	Agriculture, forestry, hunting, and fishery
s2	Mining industry
s3	Other manufacturing industries
s4	General equipment manufacturing
s5	Special equipment manufacturing
s6	Electrical machinery and equipment manufacturing
s7	Communication, computer, and other electronic equipment manufacturing
s8	Electricity, gas, and water supply
s9	Construction
s10	Transportation, warehousing, and postal
s11	Wholesale and retail accommodation and catering
s12	Other services

3.4. City Carbon Dioxide Emissions

We calculated urban carbon emissions from energy activities according to the "top-down" reference approach proposed by Liu et al. (2018) [35,36]. Because the data of the Scope 3 emissions were not available, we only calculated the carbon emissions of Shenzhen in Scope 1 and 2.

As for emission factors, sector-specific factors in Shenzhen were obtained from guidelines for the compilation of provincial greenhouse gas inventories [37] and guidelines for the compilation of greenhouse gas inventory in cities and counties (districts) of Guangdong Province [38]. More than 60% of Shenzhen's power consumption comes from external power supplied by the southern power grid. As the emission factor of the Southern Power Grid varies with the proportion of installed capacity of non-fossil energy, this study predicted the factor from 2019 to 2030 based on the social responsibility report of Southern Power Grid 2020 [39]. Moreover, adjustments were made based on industrial structure characteristics, so that the sectoral classification of the adjusted urban carbon emissions inventory was consistent with that of the city IO table.

4. Scenario Analysis

4.1. Scenario Definition

In this study, a scenario analysis was conducted to measure the impact of industrial structure adjustment on carbon emissions and evaluate the emission reduction potential of industrial structure optimization. For convenient analysis, we took 2019 and 2030 as the reference and target years, respectively. Specific scenario design details are as follows:

(1) Business as usual scenario (BAU). This study set Shenzhen's GDP growth rate from 2019 to 2030 to decrease by 0.1% per year based on Shenzhen's GDP growth rate of 6.9% in 2019. From 2019 to 2030, Shenzhen's industrial structure remained unchanged, that is, it kept the same structure as that in 2019. From 2019 to 2030, based on the growth rate of energy consumption of 3.8% in 2019, this paper set the growth rate of energy consumption to decrease by 0.1% every year. Meanwhile, based on the growth rate of carbon emissions of 2.8% in 2019, the growth rate of carbon emissions was set to decrease by 0.4% per year, and decrease by 0.3% per year after it was less than 0 between 2019 and 2030. The details of Shenzhen's economic growth rate and other parameter settings are shown in Appendix A, Table A1. (2) Structure optimization scenario (OPT). Compared with the BAU scenario, the only difference is that to better evaluate the emission reduction potential generated by the optimization of industrial structure, we adjusted the industrial structure of Shenzhen in the model, such as screening industries that are encouraged and limited to

develop and setting growth restrictions on all industries. Finally, the details of industrial restructuring are shown in Section 4.2.

Finally, three main research stages were included in this study: 2019–2020, 2021–2025, and 2026–2030; the difference in carbon emissions between BAU and OPT is defined as the emission reduction potential of industrial restructuring.

4.2. Sectors Screening

By introducing the industrial linkage approach, Chang et al. (2015) screened encouraged and limited sectors based on historical and existing data. However, the above method can analyze the development of industries in the past and cannot predict the development trend of emerging industries.

To fill the gap, this study first screened out the encouraged sectors based on government planning and other public documents; then, referring to the research by Chang et al. (2015) [22], we introduced the industrial linkage coefficient and eliminated the sectors closely related to residents' lives to determine the restricted sectors. Finally, for encouraged industries, the upper limit of structural adjustment is assumed to be 4% in 2019 and will increase linearly by 0.2% per year, the lower limit is 0; for limited industries, the lower limit of structural adjustment is assumed to be −4% and will decrease linearly by 0.2% per year, the upper limit is 0; for other industries, the lower limit of structural adjustment is assumed to be −4.7% in 2019 and will decrease linearly by 0.2% per year, the upper limit of structural adjustment is assumed to be 4.7% in 2019 and will increase linearly by 0.2% per year (Figure A1). The details of the parameter settings are shown in Appendix A, Table A1. According to the 14th Five-Year Plan of Scientific and Technological Innovation in Shenzhen [40], the sectors encouraged by Shenzhen were selected, which included: high-end manufacturing equipment (S4–S6), new generation electronic information (S7), and modern service (S12). As shown in Figure A2, the restricted sectors in which both the influence coefficient and the sensitivity coefficient are less than 1 are Agriculture, Forestry, Hunting and Fishery (S1), Mining (S2), Electricity, Gas, and Water Supply (S8), Transportation, Warehousing and Postal (S10), and Wholesale and Retail Accommodation and Catering (S11); among these, S8, 10, and 11 are all public basic industries related to people's livelihoods, so they were excluded from the restricted development sectors. In Other Manufacturing (S3), the papermaking and metal manufacturing industries belong to high energy consumption, heavy pollution, and high emissions, which account for a relatively high proportion of S3, and their development should be restricted. Meanwhile, to rectify the disorderly expansion of the construction industry (S9) to suppress the demand for high energy-consuming raw materials, its rapid development should be limited. Finally, we determined four industries that need to be restricted (S1–3, S9) and five industries that need to be encouraged (S4–7, S12).

5. Results and Discussion

5.1. Pathway to Peak CO_2 Emissions

The results show that Shenzhen has formed a characteristic industrial structure and mode of economic development, which is dominated by the tertiary industry and driven by advanced manufacturing and modern service industries (Figure 1). Shenzhen's GDP is predicted to grow at an average annual rate of 6.5% between 2019 and 2030 and become the third city in China to exceed CNY 4 trillion ($500 billion at 2019 price levels) in 2026. During the study period, the secondary industry will grow at an average annual rate of 5.2%, the added value will reach CNY 1.9 trillion, and its proportion in GDP will drop from 41.4 to 36.3%, of which the proportion of high-end manufacturing will increase sharply by nearly 7%. Meanwhile, the tertiary industry will grow at an average annual rate of 7.33%, and its added value will increase by 1.2 times to CNY 3.4 trillion, rising from 58.5% in 2019 to 63.7% in 2030.

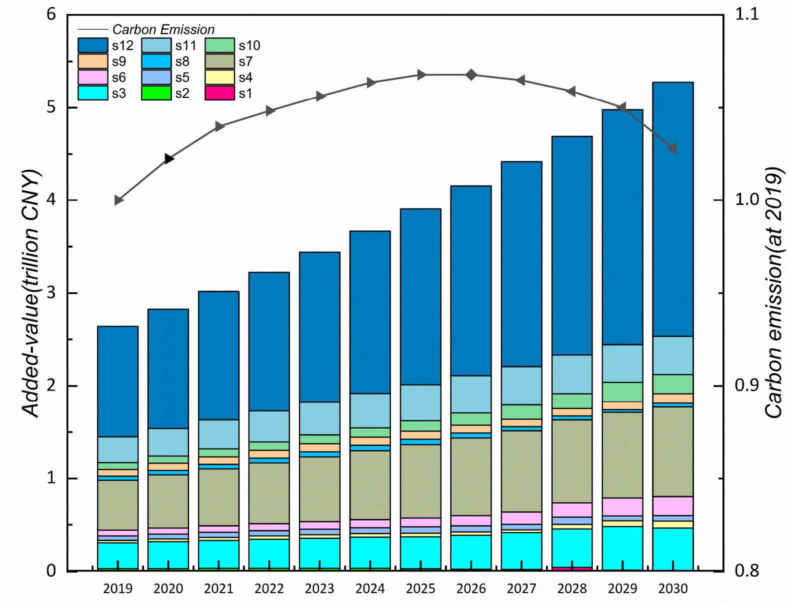

Figure 1. The carbon peak path of economic structure adjustment in Shenzhen from 2019 to 2030. The *X*-axis represents the added value of industries (in units of CNY 1 trillion); the *Y*-axis represents the relative value of carbon emissions with 2019 as the base year; the direction of the solid triangle highlights the trend of emissions growth, and the inverted diamond indicates that carbon emissions have reached the peak level.

In 2026, the CO_2 peak level will increase by 6.8% and the average annual growth rate of CO_2 will drop to 0.9%. Carbon emissions will decline rapidly after a period of peak "plateau", and the cumulative emissions will reach 934.2 Mt CO_2 by 2030. From 2019 to 2030, Shenzhen's land space and environmental resources will gradually become saturated, the population growth trend will continue to slow down, and the direct household carbon emission increment will show an accelerated downward trend, with an average annual growth rate of only 1.8%, increasing from 13.2 to 15.7%. The carbon intensity of Shenzhen will drop by 48.8%, from 0.28 tons/ten thousand yuan to 0.20 tons/ten thousand yuan in 2025 and 0.14 tons/ten thousand yuan in 2030, which can meet the emission reduction targets of Guangdong Province.

5.2. Industrial Restructuring Helps to Achieve a Carbon Peak

Shenzhen's economic restructuring is mainly a process of "Substituting high-carbon and low-value-added industries for low-carbon and high-value-added industries", as shown in Figure 2. With the upgrading of industrial structure, carbon emissions can reach the peak level in 2025, with the peak level increasing by 5.4%. The GDP of the primary industry decreased by CNY 220 billion, and the structural proportion decreased by 0.1 percentage points; With the adjustment of industrial structure, the carbon emission of the primary industry showed an accelerated downward trend, and the carbon emission intensity decreased by 21.7%; the influence of industrial structure on carbon peak goals gradually increased. Dominating by strategic emerging industries, the accelerated development of the advanced manufacturing industry helped the GDP of the secondary industry increase by CNY 41.61 billion, and the structural proportion decreased by 2.8 percentage points. Among them, other manufacturing industries with high emissions and low added value have the largest structural decline, and their structural proportion has decreased by 1.6 percentage points. From 2019 to 2025, the carbon emission of the secondary industry increased by 1.0 Mt, and the carbon emission intensity decreased from 0.34 in 2019 to 0.24 in 2025, with a decrease of 29.6%. Shenzhen has made great efforts to develop its distinctive low-carbon service industry, the added value of the tertiary industry has increased rapidly, by CNY 85.24 billion, and its structure ratio has increased by 3.3%. Meanwhile, the growth rate of carbon emissions in the tertiary industry has been slowing down, and the carbon emission intensity has decreased by 18.4%. In particularly, the carbon emission intensity of the modern service industry with "low emissions and high added value" has dropped the fastest among all industries, reaching 31.2%.

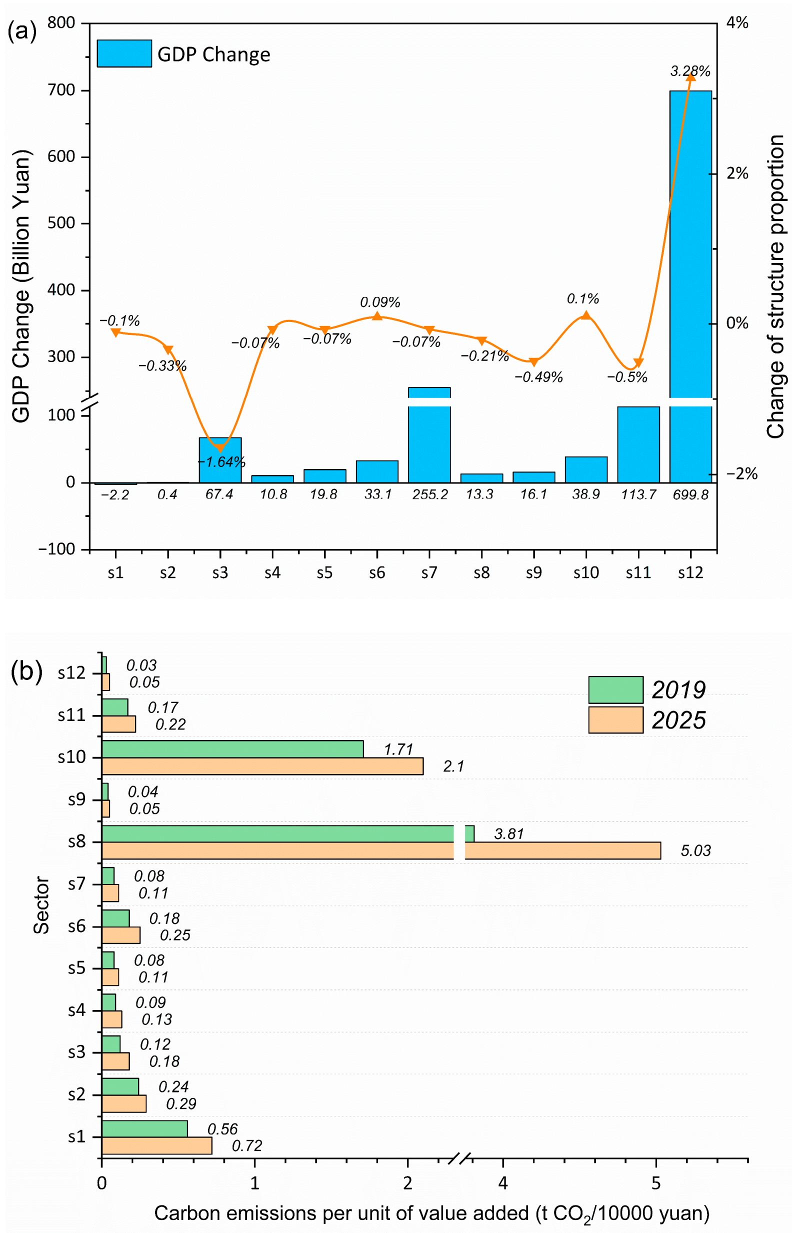

Figure 2. (**a**) Shenzhen's actual values of activity (GDP) and structure change (sectoral value added in GDP), and (**b**) carbon intensity (carbon emissions per unit of value added) for each sector in 2019−2025 (Based on 2019).

Shenzhen will accelerate the structural adjustment of the industrial sector and phase out the disqualified production capacity of other manufacturing (S3) (including low added value, high energy consumption, and high emissions sub-sectors), and the structural proportion of S3 will decline by 1.6%, with a cumulative increase of −0.6 Mt CO_2. Advanced manufacturing (S4–7) sectors are the leading sectors in Shenzhen. By 2025, the added value will increase by 47.4%, accounting for a significant increase in the proportion of the manufacturing industry, with a cumulative contribution of 0.2 Mt CO_2. The unprecedented development of new energy projects, such as roof photovoltaic, gas, nuclear power, and hydrogen energy, will increase the demand for power generation equipment and products, which will increase the added value of electrical machinery (S6) by 54.0%, contributing to the increment of 0.1 Mt CO_2. As the growth trend of S6 emissions is "U"-shaped, its carbon emissions have the potential for further growth from 2025–2030. By 2025, the added value of electronic communication (S7) will increase by 47.5%. However, due to the high degree of electrification and the application of energy-saving technology, the growth rate of power demand will slow down, and the emission factor of the China Southern Power Grid will decline rapidly, resulting in a reduction in the growth rate of emissions, with an average annual growth rate of only 0.2%.

Notably, the Electric power (S8) and Transportation industries (S10) have the highest carbon emissions and the largest carbon intensity, making them the two most critical sectors for achieving a carbon peak. The share of value added in these two sectors remained virtually unchanged between 2019 and 2021, contributing 85.5% of the incremental emissions (2.1 Mt CO_2). From the 14th FYP (referring specifically to the 14th five-year plan of the national economy), with the upgrading of industrial structure, the structural proportion of Electricity (S8) will change by −0.2%, which will exert a significant "forced" effect on the optimization of energy structure. The relevant policies of the 14th FYP will promote the coal-fired power generation in Mawan Power Plant to upcycle, as well as the unprecedented development of nuclear and gas power. The local power supply structure will be cleaner and low-carbon, and the carbon emissions of the power industry will also decrease at an accelerated trend, decreasing by 1.1 Mt CO_2. By phasing out high energy-consuming vehicles, vigorously promoting new energy vehicles, promoting the construction of low-carbon logistics systems [30], intelligent transportation information systems, unprecedentedly developing the modern logistics industry [41], and other structural adjustment measures, the carbon emission increment of the Transportation sector (S10) will drop rapidly, and the carbon emission increment will decrease by 72.0% by 2024. However, due to the improvement in household income and living standards, Shenzhen's number of private cars will continue to increase sharply. From 2024 to 2025, carbon emissions from the transport sector will increase by 1.4 Mt, but the emission reduction in the power sector will offset the increase. During the 14th FYP period, the added value of other service industries (S12) will increase by more than 8% annually, while its carbon emissions will grow smoothly. By developing industries such as characteristic low-carbon tourism and exhibition services, other service (S12) will become the leading industry to realize the peak goal (See Figure A3). To summarize, the substitution of low-carbon and high-value-added industries for high-carbon and low-value-added industries has played a key role in the decrease in carbon emissions per unit GDP in Shenzhen. See LMDI analysis (Section 5.3) for detailed quantitative analysis.

Following the approach by Su et al. (2021), the logarithmic mean divisor index (LMDI) was used to test the main driving factors of CO_2 emissions in Shenzhen from 2020 to 2030. To briefly explain the role of industrial structure adjustment, from the perspective of the five decomposition factors in the figure, this paper only analyzes the carbon emissions from 2020 to 2025 and from 2025 to 2030. According to the results of the LMDI analysis, the economic structure adjustment effect contributed 164.4% of emission reductions between 2020–2025 and 33.4% between 2025–2030. As seen in Figure 3a, the restructuring effect on the emission reduction of the secondary industry has been gradually enhanced, which will lead to a remarkable reduction in carbon emissions in both periods. As shown in Figure 3b, from 2025 to 2030, the industrial structure adjustment alone will have little impact on the tertiary industry. As seen in Figure 3c, with the demand for transportation services increasing, the activity effect will significantly promote the growth of carbon emissions in the tertiary industry, but the improvement of energy efficiency in the tertiary industry caused by the upgrading of industrial structure will inhibit the greater growth of emissions. Finally, industrial transformation and upgrading have a significant inhibitory effect on the growth of urban carbon emissions.

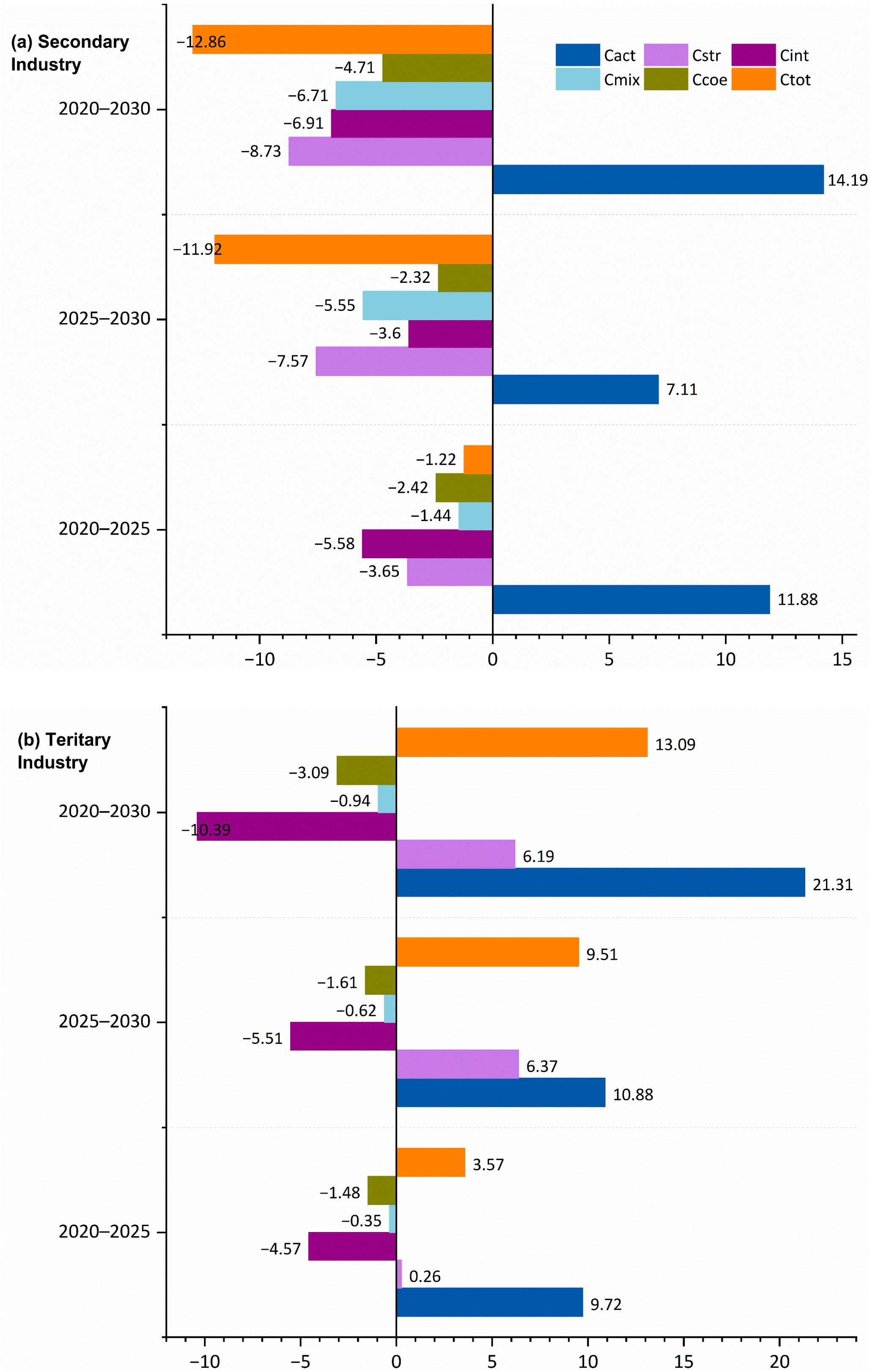

Figure 3. *Cont.*

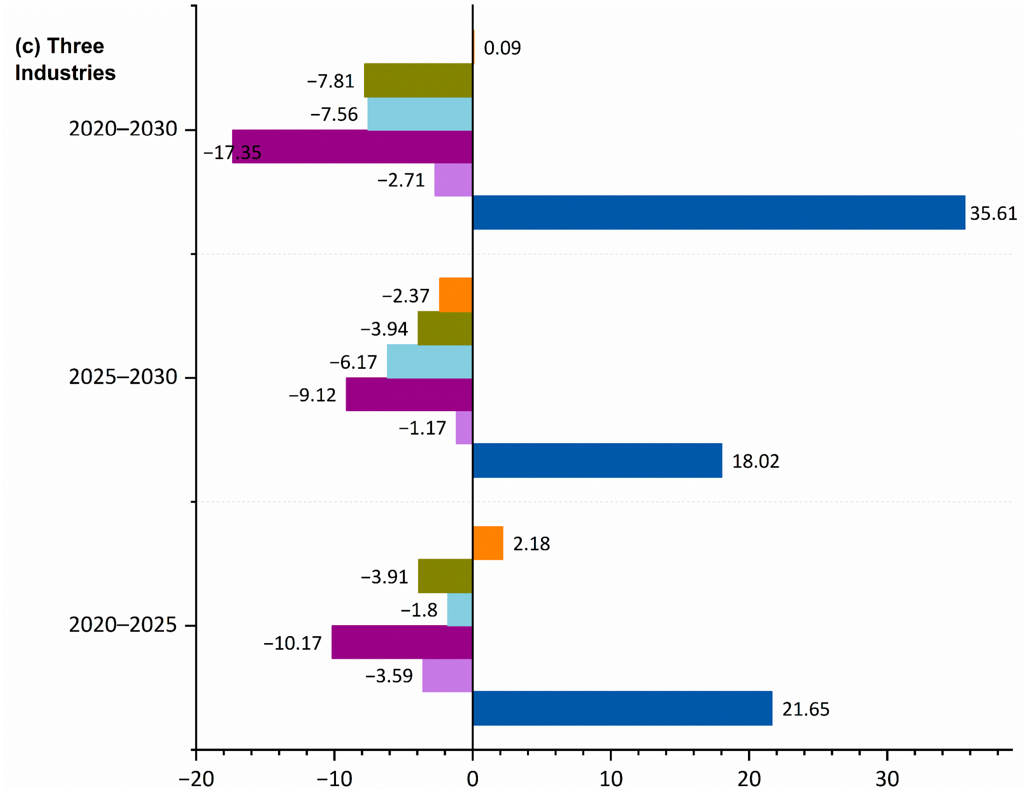

Figure 3. LMDI results in Shenzhen's CO_2 emission from 2020 to 2030 (in the unit of $MtCO_2$). (**a**) LMDI results of secondary industry; (**b**) LMDI results of tertiary industry; (**c**) LMDI results of three industries.

5.3. Industrial Restructuring Balances Carbon Peak and Economic Growth

Under the BAU scenario, carbon emissions will increase with economic growth, and conflicts exist between economic development and carbon peak goals. Without adjusting the industrial structure, environmental protection is sacrificed to promote economic growth to some extent. Compared with the BAU scenario, the added value in the OPT scenario grows faster, with the difference reaching CNY 59.1 billion, and the emission level is much lower than that in the BAU scenario.

The secondary and tertiary industrial structure will be remarkably adjusted from 2019 to 2030. The secondary industry is developing toward high-end, low-carbon, and clean, with the proportion of structure falling from 41.4 to 36.3%, and the share of emissions from 57.6 to 35.8%. The decline in the proportion of emissions is 4.3 times that of the proportion of structure. In the tertiary industry, the modern service industry is characterized by low emissions and high value added. Between 2019 and 2030, the proportion of such industry in total added value will rise from 45.2 to 52.0%, an increase of 6.8%, but the proportion of emissions will only rise from 8.6 to 9.8%, an increase of 1.3%, and the increase in structure is 5.3 times that of emissions.

Thus, the optimization of industrial structure promotes economic growth, provides the feasibility for reducing carbon emissions, and can cooperate to achieve low-carbon transformation and high-quality development. The industrial restructuring will not only maintain a high level of economic growth but also promote the continuous narrowing of the growth rate of emissions, which will successfully resolve the conflicts between carbon peak and economic growth.

5.4. Potential Carbon Emission Reduction of Industrial Restructuring

The emission reduction potential of structural adjustment increases marginally over time, as shown in Figure 4. The potential in the first stage is 0.1 Mt CO_2, in the second stage increases to 2.4 Mt CO_2, and in the third stage reaches 5.6 Mt CO_2. Between 2025 and 2030, the total emission reduction potential will reach 31.5 Mt, accounting for 79.6% of the total emission reduction potential between 2019 and 2030, which shows that the adjustment of the industrial structure still has important implications for the realization of carbon neutrality after helping Shenzhen achieve carbon peak. From 2019 to 2030, the industries with emission reduction potential exceeding 5.0 Mt CO_2 are Electricity (S8), Wholesale and Retail, Accommodation and Catering (S11), Other Manufacturing (S3), and Mining (S2). Among them, the mining industry is energy-intensive. With the continuous upgrading of the industry, the emission reduction potential before reaching the peak level can reach 0.9 Mt CO_2. Then, the emission reduction potential of industrial restructuring will increase fourfold. Industries with low added value and high energy consumption account for a relatively high proportion in Other Manufacturing (S3). By phasing out these industries, the emission reduction potential will reach 2.4 Mt CO_2. From 2025 to 2030, by continuously reducing the proportion of low and medium value-added manufacturing industries, the potential of 3.3 Mt CO_2 emission reduction can be further achieved, which can not only ensure high-quality growth but also achieve the goal of green and low-carbon transformation of society.

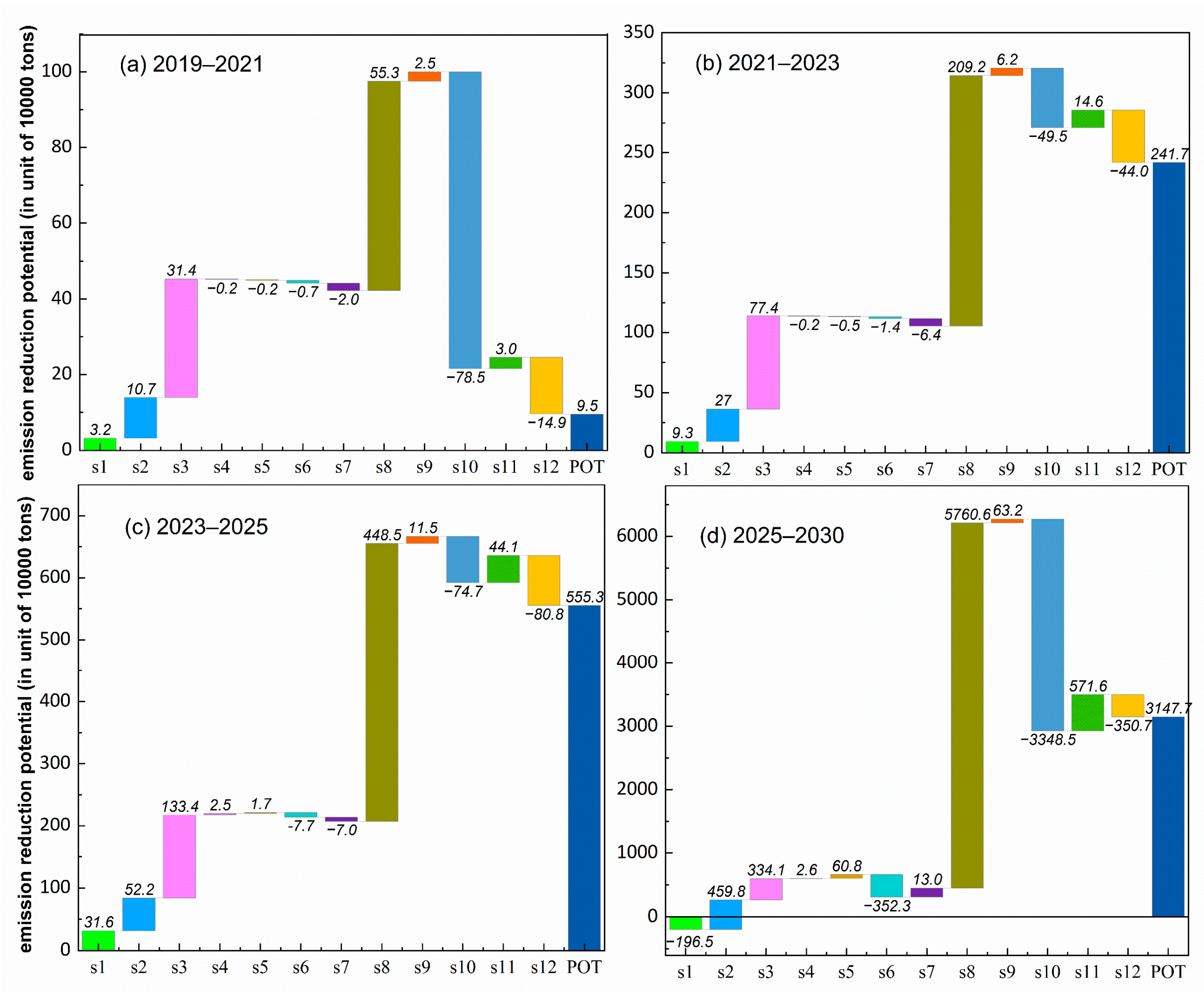

Figure 4. Shenzhen's emission reduction potential for industrial restructuring between 2019 and 2030. A minus sign represents that industrial restructuring could lead to an increase in carbon emissions.

Electricity (S8) has the greatest carbon emission reduction potential, with an average annual emission reduction of 5.9 Mt CO_2. The underlying causes may be that with the advanced manufacturing industry, the development and application of energy-saving technologies and the implementation of strict green building energy conservation and environmental protection standards in the construction industry will greatly reduce power demand. In addition, in the urban power supply structure, local coal-fired power will gradually withdraw, the proportion of clean power (including gas and external power supplies) will rise dramatically, and the power industry will attain a substantial amount of carbon emission reduction potential. From 2020 to 2025, the emission reduction potential of Wholesale, Retail, Accommodation and Catering (S11) will be 0.6 Mt CO_2, while in 2025–2030, the emission reduction potential will increase nine-fold, reaching 5.7 Mt CO_2, which may be due to the surge in green and low-carbon consumption demand from 2025 to 2030.

The optimization of the industrial structure will have a measurable suppression effect on carbon emissions. Electricity (S8), Wholesale and Retail, Accommodation and Catering (S11) will contribute 83.5% of the emission reduction potential, making them the two sectors that are benefitting the most from structural adjustment. Meanwhile, the emission reduction potential of Mining (S2), Special equipment manufacturing (S5), Communication electronics (S7), and Electricity (S8) in 2025–2030 is far greater than that in 2020–2025, which indicates that these sectors are the key driving forces for carbon emission reduction in 2025–2030. By optimizing the structure of these sectors, considerable potential can be attained.

Based on the results of model optimization, this section further analyzes which industries can tap the emission reduction potential. Figure 5 shows the industrial structure change and its carbon emission reduction potential in Shenzhen from 2019 to 2030. From the perspective of industrial structure adjustment, the adjustment of industrial structure mainly showed that the proportion of other manufacturing industries decreased, and the proportion of modern service industries increased in 2019–2025, while the proportion of accommodation and catering in the service industry decreased, and the modern service industry increased further in 2026–2030.

From 2019 to 2021, the proportion of power industry (S8) structure decreased by 0.02%, and its emission reduction potential was 0.55 Mt CO_2, while the proportion of transportation industry (S10) structure increased by 0.06%, and its emission reduction potential was -0.79 Mt CO_2. During this period, the power industry had the greatest emission reduction potential, while the transportation industry could achieve the greatest emission reduction through structural optimization. In 2021–2023 and 2023–2025, electric power decreased by 0.19%, and the emission reduction potential could reach 6.58 Mt CO_2; The modern service industry has increased by 2.55%, and its emission reduction potential is -1.25 Mt CO_2. In these two periods, the power industry has the largest emission reduction potential, while the modern service industry has the largest emission reduction space. From 2026 to 2030, the electric power decreased by 0.76%, and the emission reduction potential reached 57.61 Mt CO_2, while the transportation industry and the electrical machinery and equipment manufacturing industry (s6) increased by 1.05% and 1.53%, respectively, and the emission reduction potentials were -33.49 Mt CO_2 and -3.53 Mt CO_2, respectively. At this stage, the structural optimization of the transportation industry and the electrical machinery and equipment manufacturing industry can be maximized.

To summarize, from 2019 to 2030, the electric power industry and the transportation industry are the two most important and core sectors. Shenzhen can realize its emission reduction potential through the electric power industry, transportation industry, and communication and electronics industry (after realizing the carbon peak goals) through industrial structure adjustment. As shown in Figure 3, after 2023, with the development of digital agricultural services, the emission reduction potential of the agriculture industry has been released, and it has become one of the important sectors for emission reduction.

Overall, we can concentrate on exploring the emission reduction potential of the electric power, transportation, communications, and electronics industries through industrial structure adjustment between 2019 and 2023. After 2023, with the rapid development of digital agricultural services, carbon emission reduction potential will be released making it one of the important sectors of emission reduction.

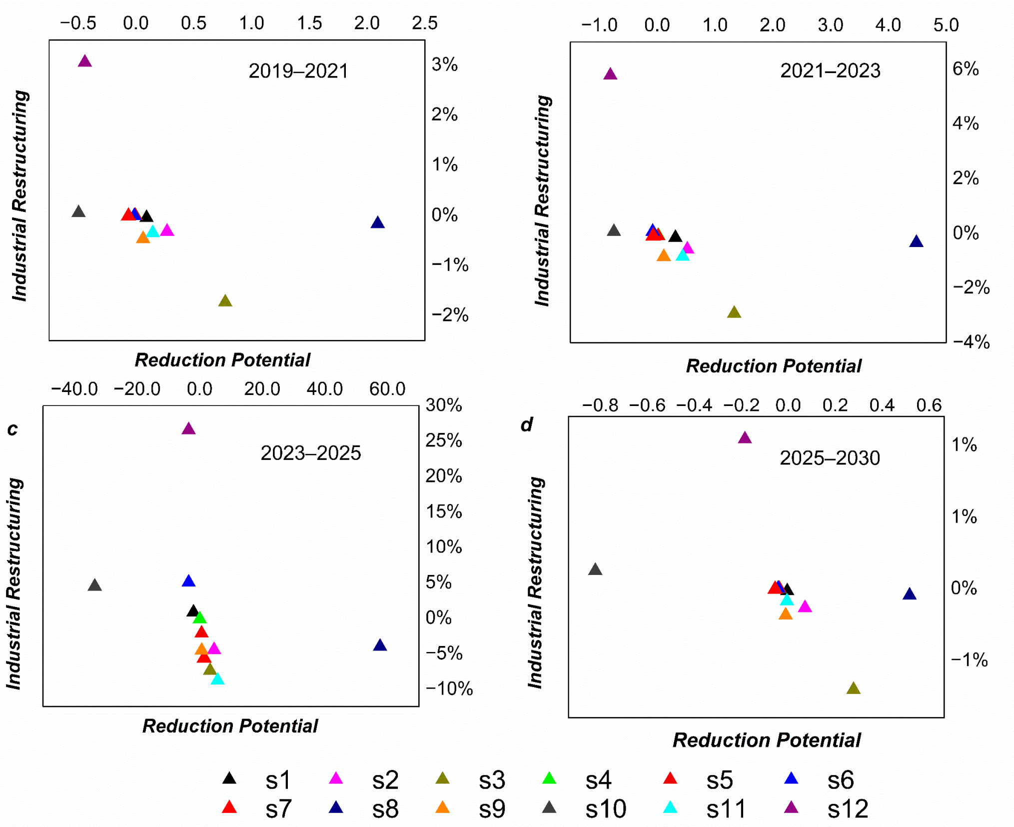

Figure 5. Industrial structure change of S1-S12 sectors and their carbon emission reduction potential in Shenzhen from 2019 to 2030.

5.5. Validation of the Industrial Restructuring Reliability

When applying the I-O optimization model at the city level, setting different economic parameters may lead to unreliable analysis results in terms of GDP, economic structure, energy consumption, carbon emission intensity, etc. Generally, qualitative and quantitative methods can be used to validate the reliability of the model operation results. To enhance the reliability of industrial restructuring analysis results, this study explained the reliability of the application of the input-output optimization model at the city level from two perspectives. The first is comparing the model results with government planning. In terms of GDP, Shenzhen's 14th five-year plan clearly stated that the GDP growth rate would reach 6% and the total added value would exceed CNY 4 trillion by 2025; Our model results showed that the GDP growth rate of Shenzhen would reach 6.5% by 2025 (without considering the impact of the COVID-19), and the difference between them was 2.3%, which met the government planning. In terms of economic structure, Shenzhen strives to develop advanced manufacturing, especially strategic emerging industries; the model results show that the proportion of advanced manufacturing would rapidly increase from 61.6% in 2019 to 65.8% in 2025 and 68.4% in 2030. The rapid development of strategic emerging industries is in line with Shenzhen's development plan; meanwhile, according to the 14th Five-Year Plan of Shenzhen's service industry development [42], the added value of the service industry will exceed CNY 2.5 trillion in 2025, of which the added value of the modern service industry will account for 77%; the model results showed that the added value of the service industry would be CNY 2.4 trillion in 2025, and the added value of the modern service industry would account for 79.0%, which is in line with the government's planning goal. In terms of energy consumption, the energy growth rate in the 13th Five-Year Plan period was as high as 3.8%, while our model results showed that the energy growth rate was only 2.7% in the 14th Five-Year Plan period and 1.7% in the 15th Five-Year Plan period; the significant drop in energy consumption met the requirements of Shenzhen's energy development plan. In terms of carbon emission intensity, China's emission reduction target during the 14th Five-Year Plan period is to reduce carbon emission intensity by 18%, while the model results showed that Shenzhen's carbon emission intensity decreased by 20.6% during the 14th Five-Year Plan period, and Shenzhen completed the emission reduction target.

By comparing the model results with similar megacities, it can be seen that among the global megacities, Shenzhen's economic development level is similar to that of Singapore. The model results showed that the per capita GDP of Shenzhen from 2020 to 2030 is $23,274–38,250 (based on 2019), and the service industry accounts for 58.8–63.7% of GDP; From 1999 to 2009, Singapore's per capita GDP was $21796–38927, with the service industry accounting for 62.1–68.0% of GDP, hence the structure of Shenzhen's economic development is reasonable (63.7% < 68.0%). Among China's megacities, Hong Kong's per capita GDP was $24,655–38,403 from 2002 to 2013. As an economy dominated by the financial industry, Hong Kong's service industry accounted for 85.6–91.1%. The model results showed that, as a postindustrial city, the economic structure of Shenzhen would be reasonable (63.7% < 85.6%).

6. Conclusions

Through applying the I-O optimization model, we have explored how megacities can achieve peak carbon emissions and high-quality development in synergy through economic restructuring, and qualitatively and quantitatively estimated its emission reduction potential. The upgrading of the industrial structure can help Shenzhen achieve its carbon peak. The advanced manufacturing industry with high added value, low carbon, and clean in the secondary industry is growing steadily, and the economic development model of the tertiary industry is maintaining high growth, high efficiency, and low emission, which makes Shenzhen maintain an average annual growth rate of 6.5%, while the carbon emissions can quickly reach the peak level. Among them, industrial restructuring will force the upgrading of energy structure, reduce energy intensity, and improve energy efficiency. Electricity (S8) will become the most critical sector in reducing emissions by gradually phasing out local coal-fired units, increasing the power generation time of gas-fired power plants, and building new gas-fired units. Overall, to thoroughly develop the emission reduction potential of industrial structure adjustment, it is necessary to rectify and eliminate the disqualified production capacity with high energy consumption and high pollution in traditional manufacturing industries, deploy seven strategic emerging industries (including new generation information technology industry, digital economy industry, high-end equipment manufacturing industry, green low-carbon industry, marine economy industry, new material industry, and biomedical industry), facilitate the rapid transformation of the power industry structure, and dramatically develop low-carbon service industries.

The structural emission reduction potential shows a marginal increasing trend, with four industries, Electricity (S8), Wholesale and Retail, Accommodation and Catering (S11), Mining (S2), and Other manufacturing (S3) accounting for 96.74% of the total emission reduction potential. At the same time, as the industry with the largest and fastest carbon emission growth, the transportation industry has substantial potential for emission reduction. Its emission reduction potential can be developed through restructuring and technical innovation, such as speeding up the replacement of oil for trucks with gas, eliminating small-scale and low-end freight logistics, developing low-carbon logistics systems, restraining the growth of total demand in the transportation sector, adjusting the fuel structure for private vehicles, increasing investment in public transportation, and encouraging green commutes.

This study assumes that the technical coefficient matrix will remain unchanged in the short term; it can be revised and updated through the RAS method in the future. Additionally, China recently proposed the construction of the "dual circulation" high-quality development paradigm based on domestic demand, which will have an impact on the final consumption ratio of Shenzhen, and then affect the model results. Moreover, due to the diversity and complexity of carbon dioxide emission sources, it is insufficient to rely on restructuring alone to reduce emissions; in the long run, relevant policy strategies for structural adjustments of energy, consumption, and exports are worthy of further study. Finally, the socio-economic impact of different peak years can be further analyzed to provide policymakers with research programs on different peak paths.

Author Contributions: Conceptualization, J.J.; data curation, Y.Y. and F.H.; formal analysis, Y.Y.; funding acquisition, J.J.; investigation, Y.Y. and F.H.; methodology, Y.Y.; project administration, F.H.; resources, J.J. and X.L.; software, F.H. and X.L.; supervision, J.J.; validation, F.H. and J.J.; visualization, Y.Y.; writing—original draft, Y.Y.; writing—review & editing, Y.Y., F.H., J.J. and X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the Starting Research Fund from Harbin Institute of Technology, Shenzhen (No. GD45001017).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1. Industrial Linkage Analysis

Due to the complexity of the economic system and the correlation between industries, to realize the green and low-carbon transformation, the industrial structure adjustment needs to consider the inhibitory effect of industrial linkage and needs to identify the restricted and encouraged industries to make precise adjustments to various industries. Based on the urban input-output table, this study screened restricted and encouraged industries by calculating the influence coefficient and sensitivity coefficient of each industry.

Appendix A.1.1. Influence Coefficient

Rasmussen et al. (1956) proposed the influence coefficient (also known as backward linkage coefficient) based on the Leontief inverse matrix, which measures the pulling ability of a department on the economy and indicates the influence of products that increase per unit output value of a certain industry on the production demand of other industries [43]. If the value is greater than 1, it indicates that the influence of the development of the industry on other industries exceeds the average level of the economic system. The calculation formula is as follows:

$$BL_j = \frac{\frac{1}{n}\sum_{i=1}^{n} b_{ij}}{\frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij}} \quad (j = 1, 2, \ldots, n) \tag{A1}$$

where BL_j represents the influence coefficient of sector j, b_{ij} is an element in Leontief inverse matrix $\left(B = (I - A)^{-1}\right)$. The larger the influence coefficient, the greater the pulling effect of this industry on other industries.

Appendix A.1.2. Sensitivity Coefficient

Jones et al. (1976) proposed the induction coefficient (forward linkage coefficient) based on the Ghosh inverse matrix to measure the driving ability of a certain department to the economy, indicating the demand induction degree of a certain industry when each industry increases products per unit output value [44]. If the value is greater than 1, it indicates that the demand sensing ability of the industry to the development of other industries exceeds the average level of the economic system. The calculation formula is as follows:

$$FL_i = \frac{\frac{1}{n}\sum_{j=1}^{n} g_{ij}}{\frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}} \quad (i = 1, 2, \ldots, n) \tag{A2}$$

where FL_i represents the sensitivity coefficient of industry i, and g_{ij} is an element in Ghosh inverse matrix ($G = (1 - H)^{-1}$)). The larger the sensitivity coefficient, the greater the promotion effect of this industry on other industries.

Appendix A.2. Logarithmic Mean Divisor Index Analysis

In this study, logarithmic mean divisor index (LMDI) approach was used to test the main driving factors of CO_2 emissions in Shenzhen from 2020 to 2030. Changes in carbon emissions can be decomposed into the sum of five influencing factors: economic activity, industrial structure, energy intensity, energy structure and CO_2 emission factor:

$$\Delta C = \Delta C_{act} + \Delta C_{str} + \Delta C_{int} + \Delta C_{mix} + \Delta C_{ef} \tag{A3}$$

where δc represents total changes in carbon emissions; ΔC_{act} represents industrial activity level; ΔC_{int} represents energy intensity; ΔC_{mix} indicates energy mix structure; ΔC_{ef} represents CO_2 emission factor.

The industrial structure effect can be expressed as follows:

$$\Delta C_{str} = \sum_{ij} \frac{c_{ij}^{t} - c_{ij}^{t0}}{lnc_{ij}^{t} - lnc_{ij}^{0}} ln \frac{str_i^t}{str_i^0} \tag{A4}$$

Appendix A.3. Data Setting

Appendix A.3.1. Sectoral Classification

In 2019, the primary industry in Shenzhen accounted for a relatively low proportion. The primary industry was merged into agriculture, forestry, animal husbandry, and fishery (S1) (agriculture for short). In the secondary industry, coal, oil and gas, metal, non-metallic, and other mining products account for less than 1% of the total structure, and they are merged into the mining industry (S2).

Among the secondary industries, general equipment manufacturing (S4), special equipment manufacturing (S5), electrical machinery and equipment manufacturing (S6), communication equipment, computer, and other electronic equipment manufacturing (S7) (Abbreviated as Communication electronics) account for nearly 70% of the manufacturing industry and are closely related to eight strategic emerging industries. In the secondary industry—besides Mining (S2), Other manufacturing (S3), Advanced manufacturing (S4–7), and Construction (S9)—Electricity, Heat, Water, and Gas production and supply industries were merged into Electricity, Heat, Gas, and Water supply (S8) (Abbreviated as Electricity) to highlight the characteristics of Shenzhen's industrial structure,.

The tertiary industry can be divided into Transport, Postal and Warehousing (S10) (Abbreviated as Transportation), wholesale and retail, accommodation and catering (S11), Other services (S12). Detailed sectoral classification information can be found in Table 2.

Appendix A.3.2. Exogenous Parameter Setting

Table A1 shows the setting of a series of parameters in the model.

Table A1. The settings of exogenous parameters in the model.

Para-Meter	Parameter Definition	Data Sources	Parameter Setting
α_t	Average annual growth rate of GDP	Shenzhen 14th Five-Year Plan [41], Reasonable assumption	GDP growth rate was 6.9% in 2019 and actual growth rate was 6.7% in 2021. Shenzhen plans to reach CNY 4 trillion at the end of the 14th Five-Year Plan. Based on this, it is reasonably assumed that the added value will linearly decrease by 0.1% every year.
b_{ikt}	Energy structure	Guangdong 14th Five-Year Energy Plan [45], reasonable assumption	—
β_t	Energy consumption growth rate	Mi et al. (2017) and Su et al. (2020) studies	It was 3.8% in 2019, and it is assumed that it will decrease linearly by 0.1% every year thereafter.
γ_t	Energy intensity decline rate	Shenzhen 14th Five-Year Plan, reasonable assumption	It was 2.8% in 2019, and it is assumed that it will decrease linearly by 0.1% every year thereafter.
d_{ikt}	Emission factor	Existing data, China Southern Power Grid Report [39]	–
ε_t	Carbon emission growth rate	Historical data	It was 2.8% in 2019, and it is assumed that it will decrease linearly by 0.1% every year thereafter and reach zero in 2026.
ϵ_t	Carbon intensity decline rate	Shenzhen 14th Five-Year Plan, reasonable assumption	The carbon emission intensity reduction target in the 14th FYP is 18%, and it is assumed that in the 15th FYP it is also 18%.
m_{it}	Employment opportunities brought about by unit added value in sector *i* in period *t*	Historical data	During 2015–2019, the employment opportunities provided by a unit of manufacturing added value were 4.98% annually. It is assumed that it will decrease linearly by 0.2% annually during 2019–2030, assuming that the added value employment of other industries remains unchanged.
pop_t	Average annual growth rate of the resident population	Shenzhen 14th Five-Year Plan	—
q_t	Structural adjustment cap for encouraged industries	Mi et al. (2017) and Su et al. (2020) studies, reasonable assumption	The upper limit of structural adjustment is assumed to be 4% in 2019 and will increase linearly by 0.2% per year.
ρ_t	Structure adjustment floor for limited industries	Mi et al. (2017) and Su et al. (2020) studies	The upper limit of structural adjustment is assumed to be −4% in 2019 and will decrease linearly by 0.2% per year.
μ_t	Structural adjustment cap for other industries	Mi et al. (2017) and Su et al. (2020) studies, reasonable assumption	The average growth rate of industrial structure adjustment in 2015–2019 was 4.7% and is assumed that it will increase linearly by 0.2% every year thereafter.
η_t	Structural adjustment floor for other industries	Mi et al. (2017) and Su et al. (2020) studies, reasonable assumption	The average growth rate of industrial structure adjustment in 2015–2019 was −4.7% and is assumed that it will decrease linearly by 0.2% every year thereafter.
θ_1	Lower limit of consumption in GDP	Historical data	Between 2015 and 2019, the minimum consumption proportion was 35%.
θ_2	Upper limit of consumption in GDP	Historical data	Between 2015 and 2019, the maximum consumption proportion was 45%.

Appendix A.4. Additional Results

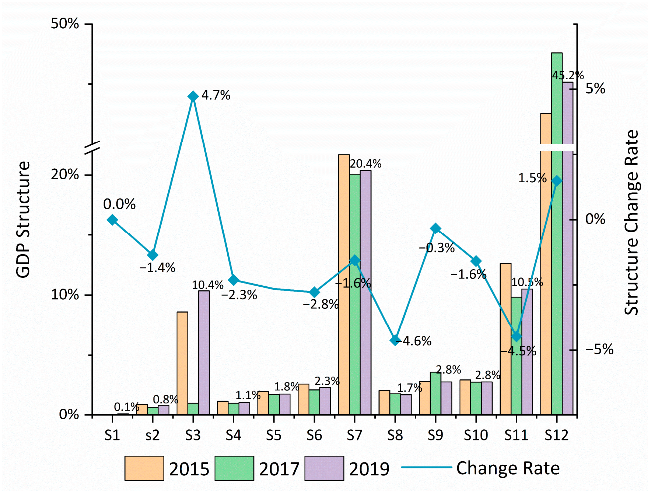

Figure A1. The proportion of industrial structure of 12 sectors in Shenzhen and their average change rate from 2015 to 2019; The line represents the average change rate of industrial structure from 2015 to 2019, the highest value is 4.7%, and the lowest is −4.5%; The structure proportion of 12 industries in 2019 is marked.

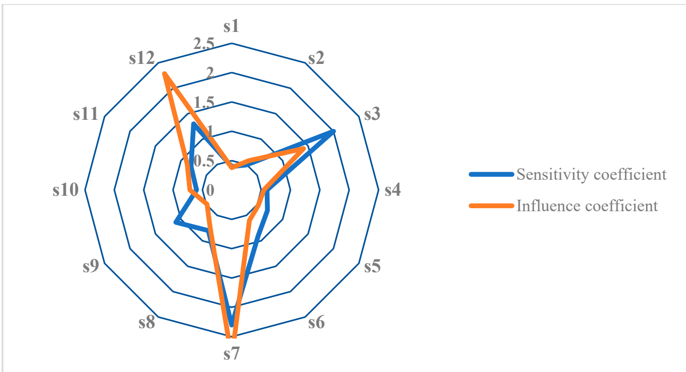

Figure A2. Industrial linkage coefficient(including sensitivity and influence coefficients) of Shenzhen in 2019.

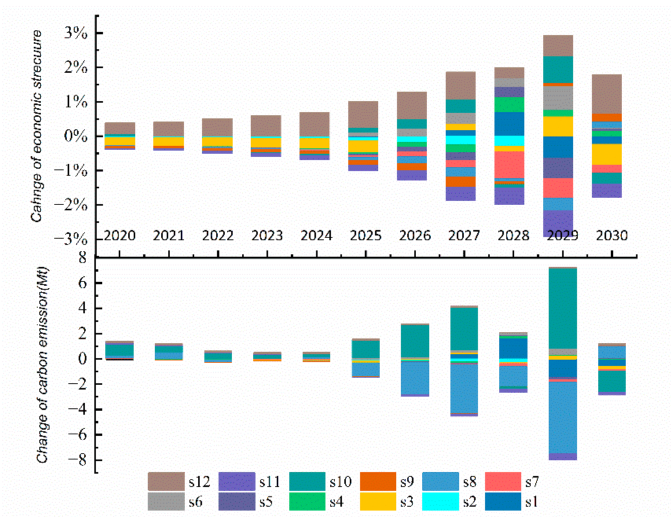

Figure A3. The structural change of the industrial added value and carbon emissions.

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