Low-carbon economic growth in Chinese cities: a case study in Shenzhen city

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Received: 24 March 2021 / Accepted: 31 October 2022 / Published online: 8 November 2022
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Abstract
Low-carbon economic growth in cities is important for reduction of carbon emissions in China. As the best practice city in China, Shenzhen city has experienced rapid economic growth with low carbon emissions. The study aims to evaluate the performance of Chinese cities on low-carbon economic growth through the case study of Shenzhen city. The study carries out the Tapio decoupling model for analyzing decoupling state, and uses the Kaya–Logarithmic Mean Divisia Index decomposition model to determine the main driving factors of carbon emissions in Shenzhen. Results indicate that Shenzhen has greatly decoupled carbon emissions with economic growth. The analysis of driving factors of carbon emission shows that the declining energy intensity and the upgrading industrial structure effectively hamper the increase of carbon emissions in Shenzhen. The decline in energy intensity in Shenzhen may come from an improvement of production efficiency of the industries. However, the irrational energy consumption structure, fast-growing economic output, and industry scale are hampering the low carbon emissions of Shenzhen. All estimated industries are highly dependent on coal and oil although some industries have slightly increased their proportion of clean energy consumption. Pursuing more clean energy consumption in the industry will be a key development strategy for reducing emissions in the future. Moreover, as Shenzhen is a fast-growing city, the increasing economic output and industry scale are inevitable. Changing people’s way of living could also help in reducing carbon emissions in cities.

Keywords Cities · Decoupling · Energy consumption structure · Low carbon

Introduction
In the United Nations General Assembly 2020, China announced that carbon dioxide emissions will be at a peak by 2030 and carbon neutrality will be reached by 2060. As the world’s largest emitter, China is making an effort on reducing carbon emissions. China has early fulfilled its commitment in Paris Agreement 2005 that by 2020, carbon emissions will be reduced by 40–45% compared with those in 2005. In the future, China will take more measures and make policies on reducing carbon emissions (Mallapaty 2020). As a developing country, China maintains its fast economic growth, with an average growth rate of 8% in the last decade. Even in 2020, in the face of the COVID-19 pandemic, China still had an economic growth rate of 2.3%. Maintaining economic growth while reducing carbon emissions is a key issue for China’s sustainable development that requires much effort.

Cities play an important role in decoupling economic growth with carbon emission because cities in the world make 80% of the total domestic production while generating 70% of the total carbon emission (Wang and Wang 2019). The number and size of Chinese cities are growing rapidly due to fast urbanization. So the future increase of carbon emission in China will primarily come from cities (Feng et al. 2018). Studying cities’ carbon decoupling and driving factors can help to make a suitable and effective plan for carbon emission reduction.

The present study makes an in-depth analysis in Shenzhen city, the best-performing city in low-carbon economic growth in China. Shenzhen city is the frontier of a low-carbon city and a demonstration pilot on ecological cities in China. Research indicates that Shenzhen belongs to the top
lowest-emission-intensity cities in China (Zhou et al. 2018). The city is the third-largest city in China, following Beijing and Shanghai, with a GDP of 0.4 trillion US dollars in 2019 and a population of approximately 13 million. Established in 1980, the city is located beside Hong Kong (Fig. 1) and is China’s first Special Economic Zone. In the last decade, Shenzhen was experiencing fast economic growth with a growth rate of nearly 10%, and its carbon intensity decreased by 11% (Shenzhen Environmental status bulletin, 2019). In 2019, the Chinese central government appointed Shenzhen as the “demonstration pilot area of socialism with Chinese characteristics.” This notion indicates that Shenzhen is supposed to play a principal role in Chinese future reform on emission reduction. The analysis of Shenzhen’s performance on carbon emission could help clarify how to promote low-carbon economic growth in Chinese cities.

The study focuses on the energy-intensive industries in Shenzhen. More than half of energy-related carbon emissions in China is sourced from energy-intensive industries (Lin and Wang 2015). In this study, energy-intensive industries contain the following: (1) petroleum processing, coking, and nuclear fuel industry, (2) raw chemical materials and chemical products manufacturing industry, (3) non-metallic mineral products manufacturing industry, (4) ferrous metal smelting and pressing industry, (5) nonferrous metal smelting and pressing industry, and (6) electric and heat power industry (the statistics bulletin of the national economy and social development in 2010). In the following context, the number of each industry is used to represent the industry directly. The outputs of energy-intensive industries in Shenzhen increased by approximately 158% in the last decade from 103 billion Yuan in 2010 to 264 billion Yuan in 2018 and always accounted for approximately 12% of GDP in Shenzhen (Fig. 2). So reducing the carbon emissions of energy-intensive industries is the key to low-carbon economic development in Shenzhen. Due to data limitation, other industries in Shenzhen are not considered in the study.
The decoupling of states and driving factors of carbon emissions in Shenzhen are analyzed in the study. This article has two parts, namely, the Tapio decoupling model to analyze the decoupling state of Shenzhen and the Kaya–Logarithmic Mean Divisia Index (LMDI) decomposition model to determine the main driving factors of carbon emissions in Shenzhen. The decoupling index presents the relationship between CO₂ emissions and economic development. The Tapio decoupling model is used extensively in literature, which can effectively reduce the deviation of analysis caused by the time scale (Tapio 2005; Feng et al. 2018). The Kaya–LMDI model is a combined method to effectively illustrate the impact factors on carbon emission growth (Ang 2004; Wen and Zhang 2019; Li et al. 2020). It will help in breaking down the drivers, which are observable, controllable, and interpretable.

This article is organized as follows. “Literature review” section makes literature review on carbon decoupling and driving factors for low carbon cities. “Research methods” section presents research methods including the calculation method of carbon emission, the Tapio decoupling model, and the Kaya–LMDI model. Then, “Results on carbon emissions and decoupling states” section presents the results of carbon emission and the decoupling state, and “Drivers of carbon emissions” section analyzes the driving factors on carbon emission growth. Finally, “Conclusions” section concludes the study.

**Literature review**

The low-carbon economic growth in cities could be achieved through, for example, improvement in constructions (Cai et al. 2020), transportation (Azizalrahman and Hasyimi 2018; Tan et al. 2021), technological progress (Cheshmehzangi et al. 2018), financial schemes (Peng and Bai 2021), certain sectors’ development (Pongthanaisawan et al. 2018), and policy instruments (Ma et al. 2021). In this study, the emphasis is to make clear which factors are the main contributor to emission reduction in Shenzhen city.

The driving factors for carbon emission could be GDP growth (Zhang et al. 2019), industrial scale (Zeng et al. 2014), energy consumption structure (Mallapaty 2020), energy intensity (Zheng et al. 2019), industrial structure (Wang et al. 2021) and so on. For example, Zhang et al. (2019) analyzed a heavy manufacturing city in China, Shijiazhuang. They revealed that the gross domestic product (GDP) growth greatly contributes to the emission, whereas the energy intensity improvement in industries benefits emission reduction. Azizalrahman and Hasyimi (2018) established a multi-criteria evaluation model to identify low carbon cities, in which the criteria contain transportation, water management, and land use. Based on the exiting literature, the study analyzes the main driving factors for Shenzhen’s carbon emission through the Kaya–LMDI model.

In literature, less research on carbon decoupling and driving factors is carried out for a city, especially for Chinese cities. The studies mostly are taken for a country (Wang et al. 2018; Wu et al. 2019a, b), for a region (Pongthanaisawan et al. 2018; Wang and Wang 2019), and for certain industries (Song et al. 2019; Wang et al. 2020). Beijing and Shanghai, being Chinese largest cities, have been studied and found that the construction and transportation decouple weakly from economic growth with carbon emissions although the agriculture and industries have strong decoupling (Wang and Wang 2019). As the national pilot low carbon city project in China, Shenzhen is rarely studied (Cheshmehzangi et al. 2018). Shenzhen city is experiencing fast economic growth and emission restriction. The case study of Shenzhen could well guide other cities of developing countries who have...
the same difficulty, and is an important supplement to low carbon city analysis.

**Research methods**

**Calculation of carbon emissions**

The estimation of the carbon emission of energy-intensive industries in Shenzhen is the first step in the analysis. This study uses the method recommended by the IPCC to estimate carbon emissions of energy-intensive industries in Shenzhen. Currently two methods are mainly used for carbon emission measurement, namely, the model estimation method and the material balance algorithm. The former needs to build an estimation model, which is mostly used for carbon emission measurement at the national level. The material balance algorithm is typically used for carbon emissions at the regional and industry levels (Xiao 2013). The material balance algorithm refers to the quantitative analysis of materials used in the production process based on the principle that the input and output in the production process follow the law of conservation of mass (Shao et al. 2010; Wu et al. 2019a, b). The method divides the total carbon emissions into the emissions of fossil fuel combustion and the emissions of electricity consumption in the terminal sector. This study adopts the detailed technical classification and fuel classification-based estimation method provided by the Intergovernmental Panel on Climate Change (IPCC) (Kru- ger et al. 2000). The latest carbon emission coefficients of 9 types of energy (Table 1) are used. Mostly only 3–4 types of energy were taken for carbon emission calculation in the literature (Wang et al. 2018; Zhang et al. 2019). Hence, the study can obtain a more exact and complete result on emission calculation.

### Table 1 Correlation coefficients of various energy sources

| Types of energy   | Carbon oxidation rate | Net calorific value (TJ/10³ t) | Carbon dioxide emissions factor (t CO₂ * TJ⁻¹) | Standard coal factor (kg standard coal/kg) |
|-------------------|-----------------------|---------------------------------|-----------------------------------------------|-------------------------------------------|
| Raw coal          | 0.918                 | 20.91                           | 94.6                                          | 0.7143                                    |
| Crude oil         | 0.979                 | 41.82                           | 73.33                                         | 1.4286                                    |
| Gasoline          | 0.986                 | 43.07                           | 69.30                                         | 1.4714                                    |
| Kerosene          | 0.980                 | 43.07                           | 71.87                                         | 1.4714                                    |
| Diesel oil        | 0.982                 | 42.65                           | 74.07                                         | 1.4571                                    |
| Fuel oil          | 0.985                 | 41.82                           | 77.73                                         | 1.4286                                    |
| Petroleum gas     | 0.989                 | 50.18                           | 63.07                                         | 1.7143                                    |
| Natural gas       | 0.990                 | 38.93                           | 56.10                                         | 1.1000–1.3300                             |
| Electric power    | /                     | /                               | /                                            | 0.1229                                    |

Note: The unit of net calorific value of natural gas is MJ/m³, and the unit of the fold standard coal coefficient is kilogram standard coal/cubic meter. The unit of electric power is 0.1229 kg standard coal/kilowatt-hour. Source of the first three columns: Ma et al. (2021)
Among them, \( C \) represents the carbon dioxide emissions generated by the consumption of electric energy; \( Q \) represents the terminal electricity consumption of the industry; and \( \lambda \) represents the average carbon dioxide emission factor of the regional power grid in that year.

**Tapio decoupling model**

According to the concept of the Tapio decoupling model, the decoupling index can be determined by:

\[
D = \frac{\Delta C^t_{i-1}}{\Delta TOV_{i-1}} - \frac{C^t - C^{t-1}}{C^{t-1}} \left( \frac{TOV^t - TOV^{t-1}}{TOV^{t-1}} \right)
\]

where \( D \) means the decoupling index; \( \Delta C^t_{i-1} \) represents the change of carbon emission; \( \Delta TOV_{i-1} \) indicates the change of energy-intensive industries’ output. Tapio (2005) noted that the decoupling states can be categorized into eight grades listed in Table 2. Strong decoupling is the best state to realize the development of a low-carbon economy, whereas strong negative decoupling indicates the worst relationship between economic development and the environment.

**Kaya–LMDI model on decomposition**

Based on the basic idea of Kaya identity, this study constructs the following extended form:

\[
C = \sum_i \sum_j \frac{l_{ij}}{E_i} \times \frac{E_i}{\text{TOV}_i} \times \frac{\text{TOV}_i}{\text{TOV}} \times P \times \text{ES}_i \times \text{EI}_i \times \text{IS}_i \times Y \times P
\]

\[
P = \sum_i \sum_j \frac{EC_i}{\text{TOV}} \times \text{ES}_i \times \text{EI}_i \times \text{IS}_i \times Y \times P
\]

where \( C \) represents the total carbon dioxide emissions; \( c_{ij} \) represents the carbon dioxide emissions generated by the industry in the \( j \)th energy consumption; \( E_i \) represents the industry’s consumption of the \( j \)th energy; \( E_i \) represents the total energy consumption of the sector; and \( \text{TOV} \) represents the total industrial output value. As a result, the carbon emission in energy-intensive industries can be represented by six factors, \( EC, ES, EI, IS, Y, \) and \( P \) respectively represent carbon emission coefficient, energy consumption structure, energy intensity, industrial structure, economic output, and the number of employees. Thus, the change of carbon emission can be decomposed as follows:

\[
\Delta C = C^t - C^0 = \Delta EC + \Delta ES + \Delta EI + \Delta IS + \Delta Y + \Delta P
\]

As the carbon emission coefficient of different fuels is constant, \( \Delta EC = 0 \) (Fan and Lei 2017). If a zero value exists in the decomposition, then the value will be replaced with 0.00001 to facilitate the calculation (Ang and Pandiyan 1997). According to the Kaya–LMDI decomposition model, the decomposition of each impact factor is determined as follows:

\[
\Delta EC = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{EC_i^t}{EC_j^0} \right)
\]

\[
\Delta ES = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{ES_i^t}{ES_j^0} \right)
\]

\[
\Delta EI = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{EI_i^t}{EI_j^0} \right)
\]

\[
\Delta IS = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{IS_i^t}{IS_j^0} \right)
\]

\[
\Delta Y = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{Y^t}{Y^0} \right)
\]

\[
\Delta P = \sum_i \sum_j L \left( C_i^t, C_j^0 \right) \ln \left( \frac{P^t}{P^0} \right) = \sum_i \sum_j \left( \frac{C_i^t - C_j^0}{\ln C_i^t - \ln C_j^0} \right) \ln \left( \frac{P^t}{P^0} \right)
\]

**Data sources and processing**

The study spans from 2010 to 2019. Most of data is from Shenzhen Statistical Yearbook (2010–2019). According to China’s statistical standards, the sources of energy are raw coal, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, natural gas, and electricity. The carbon dioxide emission factor of each year in the calculation was taken from China Regional Power Grid Base Line Emissions Factor. As the “China Regional Grid Base Line Emissions Factor” calculates the emission factor of 2 years ago, the data used in the calculation adopt the statistical data of the last
2 years. For example, the 2011 regional grid CO₂ emission factor was taken from the 2013 China Regional Grid Base Line Emissions Factor published by the Climate Change Department of the National Development and Reform Commission. In addition, the 2012 regional grid CO₂ emissions factor was taken from the 2014 China Regional Grid Base Line Emissions Factor, and so on. However, the carbon dioxide emission factors of 2015, 2016, 2017, and 2018 are all taken from the 2017 China Regional Grid Base Line Emissions Factor because the factor is only published in the 2017 China Regional Grid Base Line Emissions Factor. The standard coal coefficient was converted from the China Energy Statistics Yearbook 2018, which is shown in Table 1.

Results on carbon emissions and decoupling states

Generally, economic growth is accompanied by carbon emissions in China (Xie et al. 2019). It is shown in Fig. 3 that the carbon emission of Shenzhen increased slowly during 2009–2018, whereas the carbon emission decreased slightly in 2011–2016. It should be noted that the outputs of energy-intensive industries experienced a rapid growth rate each year at an average of 10%.

Table 3 presents three decoupling states in Shenzhen during 2009–2018, namely, strong decoupling, week decoupling, and expansive negative decoupling. The state of 2011–2016 is strong decoupling, which indicates that low carbon emission is accompanied by economic growth. This finding is in accordance with the result illustrated in Fig. 4, that is, a decline of energy intensity in 2011–2016 is seen. Since 2011, all kinds of policies have been implemented in Shenzhen to promote low-carbon economic development, such as “The planning of reducing backward production capacity,” “Improving the energy-intensive industries,” and “Introducing clean energy in production.” The decoupling state reflects that the implementation of these policies is very effective in the city. However, the decoupling state was changed to be expansive negative decoupling during 2015–2017, which means that the decoupling state becomes worse. 2015–2016 is the period of transferring the implementation of the twelfth 5-year plan to the thirteenth 5-year plan in China. Accordingly certain measures were taken for economic and industrial reforms during the period. It leads to the carbon emission
of Shenzhen increased temporally in 2016 (Fig. 3) and decoupling state declined during 2015–2017.

The study compares the decoupling states of Beijing, Shanghai, Zhuhai, and Shenzhen based on the existing study results of Feng et al. (2018) and Wang and Wang (2019). Table 4 indicates that in 2010–2015, Shenzhen and Beijing were at strong decoupling states. However, Shanghai and Zhuhai had changed on the decoupling states. Compared with other cities, Shenzhen performs better on decoupling economic growth with carbon emission.

### Drivers of carbon emissions

According to the Kaya–LMDI decomposition, the carbon emission of energy-intensive industries can be decomposed into five driving factors: energy consumption structure ($\Delta ES$), energy intensity ($\Delta EI$), industrial structure ($\Delta IS$), economic output ($\Delta Y$), and industry scale ($\Delta P$). The last line of Table 5 indicates the accumulated values in 2009–2018. The energy intensity ($\Delta EI$) and industrial structure ($\Delta IS$) can effectively impede the increase of carbon emission, with negative values of $-622.86$ and $-250.14$ million tons, respectively. However, the energy consumption structure ($\Delta ES$), economic output ($\Delta Y$), and industry scale ($\Delta P$) contribute positively to promote carbon emission. The largest contribution of carbon emission is sourced from the economic output of Shenzhen, which is 1127.46 million tons.

#### Energy intensity

The energy intensity ($\Delta EI$) reflects the energy consumption per unit output, which has played an important role in restraining the increase of carbon emissions of energy-intensive industries in Shenzhen. The city has launched energy-saving activities for decades, thereby effectively declining energy intensity. Shenzhen’s energy consumption per GDP was reduced by 19.5% in 2013–2017. The energy intensity of Shenzhen in 2017 was 0.199 tons of standard coal equivalent per 10,000 Yuan, which is almost half of the national average value and close to the levels of developed countries (Shenzhen Statistical Yearbook). Figure 4 indicates that the energy intensity of the industries had a downward trend in 2010–2015, presenting an inverted V-shape in 2016–2018. Strengthening the technological capacity should be the reason for decreasing energy intensity (Zeng et al. 2014). Figure 5 indicates that the productivity of nearly all energy-intensive industries has increased in 2009–2018. Certain
### Table 5 Drivers of carbon dioxide emissions in energy-intensive industries

| Year     | EC     | ES     | EI     | IS     | Y      | P      | C      |
|----------|--------|--------|--------|--------|--------|--------|--------|
| 2009–2010| 29.4   | 25.17  | 293.19 | −75.25 | −87.29 | 291.97 | 477.19 |
| 2010–2011| −1.2   | 3.98   | −187.07| −156.41| 352.47 | −22.96 | −11.19 |
| 2011–2012| 32.34  | −6.83  | −340.67| −43.27 | −305.38| 443.01 | −220.79|
| 2012–2013| −35.68 | 1.12   | −44.25 | −118.49| −128.32| 213.33 | −112.28|
| 2013–2014| −28.98 | −8.98  | −91.66 | 16.17  | 167.11 | −60.75 | −7.09  |
| 2014–2015| −30.3  | −6.15  | −111.61| −37.31 | 98.56  | −90.19 | −176.99|
| 2015–2016| 0      | −22.19 | 58.15  | 2.09   | 206.77 | −188.49| 56.33  |
| 2016–2017| 0      | 158.07 | 850.85 | −81.15 | 326.46 | −97.52 | 1156.70|
| 2017–2018| 0      | 29.01  | −1049.79| 243.48 | 497.07 | 73.21  | −207.02|
| 2009–2018| −34.4  | 173.20 | −622.86| −250.14| 1127.46| 561.61 | 954.84 |

**Fig. 5** Productivity of energy-intensive industries in Shenzhen
industries with low technological and production efficiency have been improved under the inspection and support of the city government.

**Industrial structure**

The industrial structure ($\Delta IS$) is another factor restraining the increase of carbon emissions in energy-intensive industries because it makes negative contributions in the estimated period. The scales of energy-intensive industries have been adjusted and improved significantly in the last decade (Feng et al. 2018). As illustrated in Fig. 6, the ratios of outputs of various energy-intensive industries have been changed in the estimated period. In the energy-intensive industries, the electric and heat power industry (6) account for 50% of the total output, which is the highest ratio. Figure 6 presents four industries, (1), (2), (3), and (5), increasing their output proportions and two industries, (4) and (6), decreasing the output proportions in the estimated period.

Figure 7 illustrates the contributions of carbon emissions of various energy-intensive industries in Shenzhen. The carbon emission mainly comes from the production and supply of electricity and heat industry (6), which accounts for more than 90% of the total emission and the proportion is still increasing. The non-metallic mineral product manufacturing industry (5) is the second-largest contributor of carbon emission, but its contribution proportion decreased fast from 4.872 to 1.5%. Notably, except for the electric and heat power industry (6), the other five industries’ carbon emission contributions were all decreasing gradually in the last 10 years.

Comparing the six energy-intensive industries, the performances of the petroleum processing industry (1), raw chemical materials and products manufacturing industry (2), non-metallic products manufacturing industry (3), and nonferrous metal smelting and pressing industry (5) are better. These industries produce an increasing output while decreasing carbon emission. For the ferrous metal smelting and pressing industry (4), the output and carbon emission declined at the same time. However, regarding the electric and heat power industry (6), the carbon emission keeps rising although the output ratio has been reduced. The foregoing discussion indicates that the industrial structure in Shenzhen distributes relatively reasonably. With regard to the electric and heat power industry (6), which has high and rising carbon emission, the proportion of output is decreased. On the contrary, the proportions of the output of other industries with decreasing ratios on carbon emission are increased.

**Energy consumption structure**

The energy consumption structure ($\Delta ES$) has a positive contribution to emission growth. Figure 8 provides the energy consumption structure of each industry in 2009, 2012, 2015, and 2018. In the pie chart, the gray color means coal; blue means oil; green means gas; and yellow means clean energy, which contains nuclear, water power, and wind power. Through the comparison of the energy consumption distribution in 4 years, we can find that the clean energy consumption ratio increased in industries (1) and (5) during these 4 years, whereas no change in clean energy consumption in other industries exists. Many studies have found that clean energy consumption in China is still currently low (Fan and Lei 2017; Sun et al. 2018).

For industries (1), (2), (3), and (5), the energy consumption structure was changed in the period, but the movement focused on the proportion of coal and oil. For industries (2), (3), and (5), the coal consumption ratio goes up, whereas the
Fig. 7 Contributions of carbon emission of various energy-intensive industries.
oily consumption ratio goes down. For industry (4), the movement focuses on the oil and gas consumption ratios. Notably, in industry (6), coal consumption accounted for more than 50% of the energy consumption in 2009. Moreover, the ratio of coal consumption rose continuously from 2009 to 2018. The proportion of coal consumption in the electric and heat power industry (6) reached 95% in 2018, indicating that the electric industry becomes more highly dependent on coal for production than before.

The change of using coal and oil as the main energy source is quite limited, although the government always emphasized the reform of energy consumption structure in industrial measures and policies. In the case of Shenzhen, 5/6 of industries’ energy consumption still highly relies on coal. Moreover, 1/3 of industries have made progress on increasing the clean energy consumption ratio, and 2/3 of industries have not made any progress. The adjustment of the energy consumption structure is a very complicated issue (Sun et al. 2018).

**Economic output and industry scale**

The rapid economic growth and acceleration of industrialization could lead to an increase in carbon emission (Zeng et al. 2014). Table 5 indicates that the economic output (ΔY) and industry scale (ΔP) are the main drivers of increased carbon emissions in Shenzhen. In this study, the economic output (ΔY) is represented by the output of energy-intensive industries, and the industry scale (ΔP) is represented by the number of employees.

The expansion of the industrial scale could result in a rapid increase in carbon emissions in the energy-intensive industries in China (Du et al. 2018). Although the total population increase rapidly in 2009–2018 (Table 6), the scales of energy-intensive industries increased (Table 7). This indicates that the economic output and industry scale are the main drivers of increased carbon emissions in Shenzhen.

**Table 6** The population growth in Shenzhen city during 2009–2018

| Year | Population (thousand) | Growth rate (%) |
|------|-----------------------|----------------|
| 2009 | 9950.1                | 4.27           |
| 2010 | 10,372.0              | 4.24           |
| 2011 | 11,229.4              | 8.27           |
| 2012 | 11,958.5              | 6.49           |
| 2013 | 12,571.7              | 5.13           |
| 2014 | 13,178.6              | 4.83           |
| 2015 | 14,080.5              | 6.84           |
| 2016 | 14,953.5              | 6.20           |
| 2017 | 15,873.1              | 6.15           |
| 2018 | 16,661.2              | 4.97           |

Source: Shenzhen Statistical Yearbook
**Fig. 9** Employee number of energy-intensive industries

![Employee number of energy-intensive industries](image)

**Fig. 10** Electricity consumption of various sectors in Shenzhen (data is sourced from the interviews)

![Electricity consumption of various sectors in Shenzhen](image)

**Fig. 11** Electricity consumption in the tertiary industry in Shenzhen (data is sourced from the interviews)

![Electricity consumption in the tertiary industry in Shenzhen](image)
industries do not change significantly. Figure 9 indicates that the total employee number increased gradually in 2009–2013 but decreased slightly in 2013–2018. Thus, contributions of industry scale (ΔP) to carbon emission in 2013–2017 are all negative values (Table 5). This result demonstrates that reducing industries’ scales could effectively release the pressure of the rising carbon emission. Moreover, accompanied by the fast economic growth, the industries’ output also increases rapidly (Fig. 2). Thus, the main contributor to carbon emission is the growing economic output.

The output growth of energy-intensive industries mainly comes from the electric and heat power industry (6). Electricity consumption increases because of the city’s expansion. As illustrated in Fig. 10, the electricity consumption in the primary industry nearly remained constant in 2009–2018, and the electricity consumption in all other sectors increased. Notably, only the tertiary industry has an incremental growth in electricity consumption, whereas the secondary industry usage and residential usage have a decreasing growth rate. In the study, the primary industry comprises agriculture, forestry, animal husbandry, and fishery; the secondary industry mainly encompasses coal, natural gas, steel, machines, electricity, and construction; and the tertiary industry mostly includes real estate, wholesale, tourism, transport, information services, and financial intermediation. This result indicates that the tertiary industry has faster growth in electricity consumption. In the tertiary industry, the amounts of electricity consumption of public services and organizations, real estate, and transportation increase more quickly than in other sectors (Fig. 11). These three sectors are linked exactly with the increasing demand caused by Shenzhen’s rapid population growth in 2009–2018. Thus, the change of people’s life mode, such as low emission transportation, could help in declining carbon emissions in cities.

Conclusions

To illustrate the low-carbon economic growth in Chinese cities, this study makes an extensive analysis of the performance of carbon emissions of the energy-intensive industries in Shenzhen city in 2009–2018. The study estimates the decoupling states of carbon emission from economic growth using the Tapio model and examines driving factors of carbon emissions using the Kaya–LMDI model. The results indicate that the carbon emission of the energy-intensive industries in Shenzhen went up slightly. Meanwhile, Shenzhen was experiencing rapid economic growth at approximately 10% during the period. Moreover, the decoupling state estimation indicates that Shenzhen strongly decouples the carbon emission with economic growth in nearly all estimated years. This result illustrates that the fast economic development is accompanied by low carbon emission in Shenzhen. The analysis of driving factors of carbon emission indicates that the decreasing energy intensity and the improving industry structure effectively hinder the increase of carbon emissions. However, the rapid growth of economic output, industrial scale, and irrational energy structure stimulates the carbon emission rise.

Shenzhen represents the leading city on low-carbon economic development in China. Two main aspects are implemented well in Shenzhen. First, the production efficiency of the industry is high because of technological progress in the city. Hence, Shenzhen’s energy intensity performs as well as those in developed countries. Second, the industrial structure is adjusted effectively. The output ratios of the industries with increasing carbon emissions are declined, and vice versa. The case of Shenzhen city illuminates that technological progress and rational industrial structure could largely benefit to emission reduction. The government of Shenzhen has taken various policies to guide the industries to improve efficiency and make adjustment. In many other cities, when pursuing emission reduction, the policy focus is on establishing clean industries while the existing industries are generally neglected. This could not indeed help to reduce the carbon emission in the cities.

The irrational energy consumption structure still hinders Shenzhen’s low carbon emission. Reducing the dependence on coal and increasing clean energy usage are still a major challenge. With the commitment of carbon neutrality before 2060, development and utilization of solar, wind, geothermal, and nuclear energy sources should be emphasized further in the future (Mallapaty 2020). Shenzhen has implemented some policies in order to change the energy consumption structure. Besides getting rid of energy waste industries, importing gas from central Asia, building nuclear power station, and establishing emission exchange market were implemented gradually in Shenzhen city. Meanwhile, promoting low emission in residential areas such as reducing energy consumption in people’s life is planning by the government of Shenzhen. Similarly, other Chinese cities are facing to the same problem of irrational energy consumption structure. Although replacing coal with clean energy sources is greatly admitted by municipal governments, it is nearly implemented in Chinese cities actually. The adjustment of energy consumption structure is a big challenge to Chinese cities.

Author contribution XL contributed to conception and design of the research, writing of the manuscript, and approving the version to be published; ZX contributed to acquisition and analysis of data and drafting the work; ZW (Wang) and ZW (Wei) contributed to critical revision of the manuscript for important intellectual content.
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