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Study on Contribution of Carbon Emission Intensity Based on Oaxaca-blinder Decomposition Method by Big Data Evaluation in Different Economic Level Cities of Shandong Province

Chongmei Wang[1,*], Chonghong Wang[2]

[1]*School of Management, Shandong Technology and Business University, Yantai, 264005, China*
[2]*Yantai Institute of Technology, Yantai, 264005, China*
[*]*Corresponding author*

Abstract: *We studied the difference in carbon emission intensity by the Oaxaca blinder decomposition method with the panel data of 17 prefecture level cities in Shandong Province from 2007 to 2016. Per capita GDP, industrial structure, urbanization level, and energy consumption intensity are important factors affecting carbon emission intensity. The increase in urbanization rate and energy consumption intensity leads to an increase in carbon emission intensity. The reduction of the proportion of secondary industry in low-level cities is conducive to the reduction of carbon emission intensity. At the same time, we selected factors from the economic, energy, and social indicators in the low-level city rating system to reveal the contribution of different factors to the difference in carbon emission intensity. This is helpful to narrow the gap among the cities, accelerate the transformation from low-carbon cities to non-carbon cities, and realize the economic development of low-level cities.*

Keywords: *low-carbon pilot cities, carbon emission intensity, the big data*

1. Introduction

To actively respond to climate change, in August 2010, the National Development and Reform Commission formally launched national low carbon. In 2003, the British government first mentioned the word 'low carbon economy' in the "energy white paper". According to the connotation and characteristics of low-carbon cities, Lu et al. identified 19 factors affecting the development of low-carbon cities in China, which were divided into five levels, including government awareness, urbanization level, economic development level, energy utilization efficiency, and land use level [1]. Four cities in Shandong province, including Jinan, Qingdao, Yantai, and Weifang, have been listed as low-carbon pilot cities in 2018. The development of low-carbon cities requires economic development as the basis, reducing energy consumption, carbon emission, and carbon emission intensity as the core, and ultimately achieving decoupling of economic growth from energy consumption and inclusive growth of green and sustainable economic development. Based on the surface data model, Chen and Xu explored the impact of different factors on China's carbon emissions from dimensions such as population, wealth, technology level, openness, financial development level, and innovation ability [2]. Qi et al. studied the impact of industrial structure, urbanization level, foreign trade, and technological progress on carbon emission and carbon intensity in economic growth by using interprovincial panel data and lag stage instrumental variables from different economic growth models [3]. From a static perspective, Zhuang pointed out the characteristics that low-carbon cities should have, namely, higher carbon productivity, lower carbon consumption level, and cleaner energy structure [4].

We combine the evaluation indexes of low-carbon cities and the influencing factors of carbon emission to explore the differences in the influencing factors [5]. The establishment of a low-carbon city index system provides a basis for the selection of influencing factors. By taking 17 prefecture-level cities in Shandong province as the research objectives, we select indicators from aspects of economic development capacity, energy consumption level, and social carrying capacity and analyze the difference in carbon emission intensity between low-carbon cities and others. We track the use of the panel data of low carbon cities and make an empirical analysis of low carbon cities respectively to reveale the economic development, energy consumption, the level of urbanization, and industrial structure effect on the carbon intensity of difference. Then, by using the Oaxaca-Blinder decomposition technique, we

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analyze the contribution rate in low-carbon and non-low-carbon cites from two aspects— the characteristic effect and coefficient effect on the research of the big data.

2. Research methods and big data description

2.1. Research methods

The regression model of carbon emission intensity of the low-carbon and non-low-carbon cities is expressed as

$$TE_{it} = \beta_0 + \beta_1 LnY_{\text{it}} + \beta_2 Si_{it} + \beta_3 UR_{it} + \beta_4 E_{it} + \varepsilon_i \tag{1}$$

OLS regression was carried out using the above model, and the regression coefficient of low-carbon cities was obtained as

$$\hat{\beta}^E = (\beta_0^E, \beta_1^E, \beta_2^E, \beta_3^E, \beta_4^E)^T \tag{2}$$

And regression coefficient of non-low-carbon cities as

$$\hat{\beta}^0 = (\beta_0^0, \beta_1^0, \beta_2^0, \beta_3^0, \beta_4^0)^T \tag{3}$$

OLS regression meets the requirements of $E(\varepsilon_i)$ =0 and the Oaxaca-Blinder decomposition method. The characteristic effect and coefficient effect of each explanatory variable can be calculated by O-B decomposition. The characteristic effect of constant term is0, and the coefficient effect is as Eq. (4).

$$(\beta_0^E + \beta_1^E \overline{Y}^0 + \beta_2^E \overline{E}^0 + \beta_3^E \overline{SI}^0 + \beta_4^E \overline{Ur}^0) - (\beta_0^0 + \beta_1^E \overline{Y}^0 + \beta_2^E \overline{E}^0 + \beta_3^E \overline{SI}^0 + \beta_4^E \overline{Ur}^0) \tag{4}$$

From the above methods, the characteristic effect and coefficient effect of energy consumption intensity, industrial structure, and urbanization level can be obtained.

2.2. Data source and index selection

The data used in this paper include panel data of 5 low-carbon cities including Jinan, Qingdao, Yantai, Weihai, Weifang, and 12 other non-low-carbon cities from 2007 to 2016 when the 11th and 12th five-year plans were executed. The data were obtained from the Shandong Statistical Yearbook, China Energy Statistical Yearbook, and statistical yearbooks of the corresponding years of prefecture-level cities.

Referring to "the Provincial Greenhouse Gas Inventory Compilation Guidelines (trial) ", the analysis of carbon emissions in 2007–2016 in Shandong province, carbon emission sources were divided into carbon energy industry, industry and construction industry, agriculture, transportation, living and services by using the department energy consumption data from Shandong Statistical Yearbook and China Energy Statistical Yearbook. The calculation for carbon emission in the province is as follows.

$$C = \sum_{i=1}^{6} \sum_{j=1}^{18} E_j \times F_{ij} \tag{5}$$

where E_j represents emission factors of various energy sources, including raw coal, briquette, coke, crude oil, and other 18 types of energy, and F_{ij} represents the energy consumption of the carbon emission of different sectors.

Due to the limitation of the data in the statistical yearbook, the carbon emission of each prefecture-level city in Shandong province was obtained according to the annual energy consumption of each city multiplied by the energy carbon emission intensity. Among them, the energy consumption of each city is based on GDP consumption of ten thousand yuan, energy carbon emission intensity = CO_2 emission of Shandong province/energy consumption of the whole province.

Currently, economic development, urbanization, population growth, energy intensity, technological

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progress, energy structure, industrial structure, import and export trade, and other aspects are mainly taken as the influencing factors of carbon emission [6]. We explore the differences between low-carbon and non-low-carbon cities of emissions influencing factors. With the low-carbon city's limit (number with panel data of the variables should be less than the number of selected low carbon cities) in Shandong province and the influence of the index system of low-carbon city development, we used carbon intensity as an explained variable, the level of economic development in the economic growth mode, energy intensity, industrial structure and urbanization rate as the influence factors of carbon emissions.

The index of energy consumption per unit of GDP (E) belongs to the category of low carbon productivity and economic transformation. With the improvement of energy efficiency, carbon emission decreases or the growth rate slows down, promoting the development of low-carbon cities. For the level of economic development (Y), we used GDP per capita to represent the economic development level of each city. According to the environmental Kuznetz Curve, carbon emission intensity increases in the early stage of economic development with the increase in per capita GDP [6]. Similarly, in the low-carbon city development index system, per capita GDP belongs to the economic level.

3. Current situation of carbon emission in Shandong province

Figure 1 shows the intensity of carbon emission of each city in Shandong province from 2007 to 2016. The carbon emission intensity of low-carbon cities was significantly lower than that of non-low-carbon cities. The carbon emission intensity of Laiwu, Rizhao, Zibo, Liaocheng, and other non-low-carbon cities is much higher than that of low-carbon cities. The carbon emission intensity of each city in Shandong province has been reduced year by year, meeting the requirements of "low carbon emission" and "high carbon productivity" to achieve green, sustainable and inclusive economic growth and continuous improvement of low-carbon living standards. In terms of carbon emission, the carbon emission of each city in low-carbon cities is more than that of non-low-carbon cities, which is related to the high level of economic development of low-carbon cities. Jinan, Qingdao, Yantai, and Weifang have achieved "high carbon productivity" with economic growth.

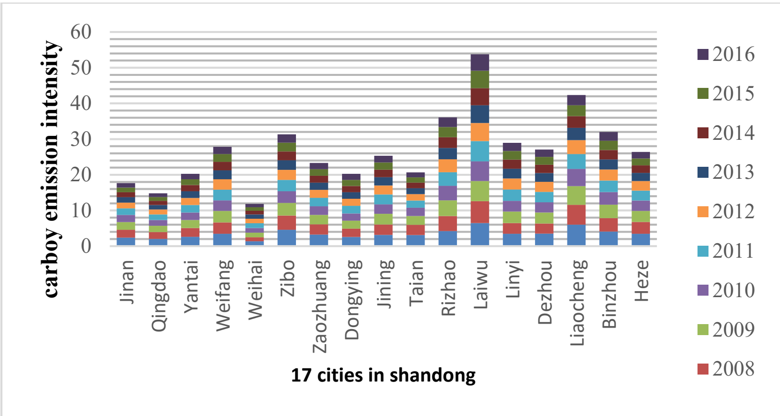

Figure 1: Carbon emission intensity of each city from 2007 to 2016.

4. Empirical research

According to the idea of Oaxaca-Olinder decomposition technology, the selected samples need to be divided into two groups: low-carbon cities and non-low-carbon cities. As shown in Table 1, (1) there are significant differences between low-carbon and non-low-carbon cities in terms of per capita GDP, energy consumption per unit GDP, urbanization level, and other indicators. The per capita GDP and urbanization rate of low-carbon cities are significantly higher than those of non-low-carbon cities, and the index differences between similar cities are relatively small. (2) As for the explained variables, the carbon emission intensity of low-carbon cities is significantly lower than that of non-low-carbon cities, and the intensity of the latter is 1.63 times higher than that of the former in 2007−2016, the carbon intensity of low-carbon city per ten thousand GDP declined from 2.34 (t BiaoMei / $ten thousand) to 1.32 (t BiaoMei/ten thousand yuan). The low-carbon city's carbon intensity is significantly reduced, and the BiaoMei energy consumption of the low-carbon city in 2016 was 2.32t, 1.8 times decreased compared with 2007. Zhou and Zhuang mentioned the requirements of prompting low-carbon city development and improving the urban system carbon productivity [7]. The characteristics of carbon emission intensity

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and influencing factors conform to the application form of the O-B decomposition method.

Table 1: Descriptive statistical analysis of variables in Shandong province.

Vatible	means(LC)	standard deviation	means(NLC)	standard deviation
CO2	1.85	0.64	3.02	1.12
Y	6.74	2.24	4.83	3.10
E	0.8	0.18	1.33	0.69
SI	42.75%	8.23	44.96%	12.88
UR	60.16%	6.24	49.62%	8.77

Data source: Shandong statistical yearbook

4.1. Unit root test and co-integration test of the big data

In order to avoid false regression, the unit root test and co-integration test are needed for panel data. Levin, Lin, Chu test, Breitung test, Fisher-ADF test, and Fisher-PP test were used in this study for homogeneity test and heterogeneity test. Table 2 shows that the results of the tests are significant except for the relatively large probability of the individual test results.

Table 2: Unit root test results of panel data of low-carbon cities and non-low-carbon cities.

Vatible	LLC text	Breitung text	Fisher-ADF text	Fisher-pp text	Conclusion
CO2	(0.000)/(0.000)	(0.913)/(0.002)	(0.000)/(0.001)	(0.000)/(0.000)	stable
Y	（0.000)/(0.000)	(0.494)/(0.773)	(0.002)/(0.376)	(0.507)/(0.000)	stable
E	(0.046)/(0.000)	(0.251)/(0.141)	(0.058)/(0.013)	(0.000)/(0.000)	stable
SI	(0.004)/(0.000)	(0.741)/(0.950)	(0.072)/(0.050)	(0.009)/(0.000)	stable
UR	(0.000)/(0.000)	(1.000)/(1.000)	(0.000)/(0.067)	(0.072)/(0.548)	stable

(low-carbon city)/(non-low-carbon city)

Statistical value	low-carbon cities	non-low-carbon cities
Panel-v	0.9605	0.9981
Panel-rho	0.9664	0.9900
Panel-PP	0.0000	0.0000
Panel-ADF	0.0121	0.0093
Group-rho	0.9971	0.9996
Group-PP	0.0000	0.0000
Group-ADF	0.0738	0.0001

Note: the data in the table are the adjoint probability of co-integration test

The adjoint probability of the horizontal unit root test and co-integration test is calculated for single integration of the same order of variables to verify a long-term stable relationship between variables. Kao test, Pedroni test, and Fisher test were used to verify the co-integration. Table 3 shows that the low-carbon city with PP statistics and ADF statistics shows the opposite trend to the original assumption. There is a long-term co-integration relationship between various factors and other statistics to accept the null hypothesis. The low-carbon and non-low-carbon cities had a long-term co-integration relationship. Co-integration test results of panel data of low-carbon cities and non-low-carbon cities.

Table 3: Regression results of individual fixed effect model.

Vatible	ALL	low-carbon cities	non-low-carbon cities
C	5.616***	1.60***	5.765***
	(13.47)	(1.88)	(12.21)
Y	-0.071***	-0.05***	-0.155***
	(-3.50)	(-2.04)	(-3.96)
E	0.754***	2.59***	0.717***
	(-8.67)	(8.04)	(5.24)
SI	0.002***	0.005***	-0.015***
	(6.21)	(4.47)	-0.015***
UR	-0.067	-0.06***	0.046***
	(0.35)	(-4.61)	(-3.86)

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4.2. Influencing factors of carbon emission intensity

The random effect model is selected for the panel date of low-carbon and non-low-carbon cities, and the Hausman test is carried out. The test results show that the adjoint probability of the Hausman test results s is less than 0.01. That is, the null hypothesis is rejected, and the individual fixed effect model needs to be selected for the carbon emission intensity test of low-carbon cities and non-low-carbon cities.

4.3. Influencing factors of carbon emission intensity

Table 4 shows that the economic development, energy consumption intensity, industrial structure, and urbanization level have important influences on the carbon emission intensity. Low-carbon cities have the same influence as non-low-carbon cities in terms of per capita GDP, energy intensity, and urbanization level. With the increase in per capita GDP, low-carbon and non-low-carbon cities reduce carbon dioxide emissions, and the level of economic development has a more significant impact on non-low-carbon cities. Based on the empirical analysis of average carbon emission intensity and per capita GDP of non-low-carbon cities, it is found that there is an inverted U-shaped relationship between economic development level and carbon emission intensity of non-low-carbon cities. The inflection points are calculated as 4.62 ten thousand yuan/person and 7.39 ten thousand yuan/person. The per capita GDP of most non-low-carbon cities is less than 4.62, so it is at the leftmost end of the inverted 'U' curve. According to the statistical results, the coefficient of energy consumption intensity of low-carbon cities is much higher than that of non-low-carbon cities. The energy consumption per unit of GDP of low-carbon cities is reduced by one unit, and the carbon emission intensity is reduced by 2.586 units, while that of non-low-carbon cities is only reduced by 0.716 units. The energy intensity coefficient of all cities is close to that of non-low-carbon cities, which is related to the significant proportion of non-low-carbon cities in Shandong province. To reduce carbon emissions per unit of GDP has been listed in 2020 by the Chinese government action to reduce emissions commitments and the 12th five-year plan, China is in the intermediate stage of industrialization with the second industry dominant in the gross national product (GNP).

4.4. Contribution of various influencing factors to the difference in carbon emission intensity

Table 4: Characteristic effect, coefficient effect and proportion of each factor.

Varible	Characteristic effect	proportion%	coefficient effect	proportion%
C	0	0	-4.163	368.43
Y	-0.09168	8.14	0.51681	45.74
E	-1.37058	121.30	2.48577	-220.00
SI	-0.11713	10.37	3.05728	27.06
UR	-0.65348	57.83	-0.79392	-270.57
SUM	-2.23287	197.61	1.10294	-97.61

Table 5: Characteristic effect, coefficient effect and proportion of each factor.

Varible	Characteristic effect	proportion%	coefficient effect	proportion%
C	0	0	-4.163	368.43
Y	-0.09168	8.14	0.51681	45.74
E	-1.37058	121.30	2.48577	-220.00
SI	-0.11713	10.37	3.05728	27.06
UR	-0.65348	57.83	-0.79392	-270.57
SUM	-2.23287	197.61	1.10294	-97.61

The panel data are used to analyze the impact of various influencing factors on the carbon emission intensity of low-carbon cities and non-low-carbon cities. Based on the measurement results, the difference in carbon emission intensity between low-carbon and non-low-carbon cities is decomposed into characteristic effect and coefficient effect by the Oaxaca-Blinder decomposition method. The contribution of various influencing factors to the difference in carbon emission intensity in terms of characteristic effect and coefficient effect is shown in table 5. The total gap between low-carbon cities and non-low-carbon carbon emission intensity is -1.17 of which the characteristic effect is -2.23. This explains 197.6% of the total gap and the unexplained part accounts for -97.6%. From 2007 to 2016, the characteristic effect appears in the difference between low-carbon and non-low-carbon cities, and the coefficient effect also has an important impact on the difference between the two types of cities.

The contribution of constant terms is the largest, 368.43%, which has a positive effect on the

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difference (Table 5). The unexplained part of constant terms increases the difference between low-carbon urban development. The coefficient effect of energy consumption intensity and urbanization level reduces the difference in carbon emission intensity between low-carbon and non-low-carbon cities, and the coefficient effect of economic development level and industrial structure also increases the difference.

5. Conclusion

The difference in carbon emission intensity is affected by economic development level, energy consumption intensity, industrial structure, and urbanization rate. The government needs to increase funds for energy conservation and emission reduction technologies. In particular, in industries with high energy consumption, the government needs to accelerate scientific and technological innovation, improve carbon production capacity, and ultimately achieve the development of a new type of industrialization.

The O-B decomposition result shows that the urbanization rate is the main factor affecting the difference in carbon emission between low-carbon and non-low-carbon cities. Urbanization at different stages has different impacts on carbon intensity and emissions. While improving the level of urbanization, non-low-carbon cities need to promote the use of new energy, technological progress, and innovation.

Economic development and industrial structure optimization are also conducive to narrowing the gap between low-carbon and non-low-carbon cities in carbon emission intensity. We need to recognize the connotation and requirements of low-carbon city development, reduce energy consumption and pollutant emission, and improve low-carbon productivity while developing the economy. In the transformation process of non-low-carbon cities, the corresponding policy indicators and evaluation system can be used to achieve rapid transformation and narrow the difference between low-carbon cities and non-low-carbon cities.

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