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Dynamic relationship between urban carbon dioxide emissions and economic growth

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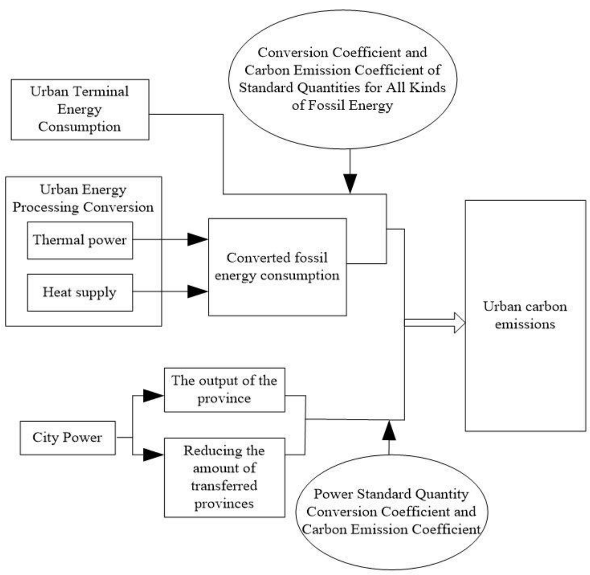
Graphical abstract



Abstract

Urban economic development cannot be separated from energy consumption, and energy consumption directly leads to a large number of carbon emissions. It is of great significance to study the relationship between carbon dioxide emissions and economic growth for the implementation of energy conservation, emission reduction and the development of low-carbon economy in cities. A new method of dynamic relationship between urban carbon dioxide emission and economic growth is put forward. The carbon dioxide emission data in cities are calculated by using urban carbon dioxide emission measurement method. The data of economic attributes are obtained by using classification algorithm under uncertain data flow environment. Based on this data, a decoupling model of carbon emission and economic growth is constructed to measure economic growth elasticity of urban carbon emissions; Granger causality test model is established to analyze the Granger causality between urban carbon dioxide emissions and economic growth. The experimental results show that the growth rate of urban economy is obviously faster than that of carbon emissions. Economic growth is the Granger causality of carbon dioxide emissions. On the contrary, the implementation of carbon emission reduction measures will not hinder economic growth.

Keywords: City, carbon dioxide, emissions, economic growth, decoupling model, Granger, causality.

1. Introduction

With the continuous development of human economy, environmental problems such as global warming and ecosystem deterioration caused by the intensification of greenhouse gas emissions are becoming increasingly serious (Dali and Kamarudin, 2018; Lee *et al.*, 2017). According to the 2007 assessment report of the United Nations Intergovernmental Panel on Climate Change, global temperatures have risen by an average of 0.13°C every 10 years in the past 50 years, it is almost twice as much as in the past 100 years. The report also points out that other greenhouse emissions from human activities are likely to be the main causes of global temperature rise, resulting in more frequent occurrence of extreme climatic phenomena such as drought, rainstorms, snowstorms, heat waves and tropical cyclones (Focas, 2017; Singh, 2020).

Thus, how to effectively reduce greenhouse gas emissions while achieving sustainable economic development has become a major issue facing all countries in the world today (Schuster *et al.*, 2016). In this context, it is of great academic value and practical significance to study the relationship between "economic growth" and "carbon dioxide emissions". It will provide a theoretical analysis and empirical basis for policy authorities to choose and arrange future energy and environmental economic policies (Azhar and Zainuddin, 2020; Mozina *et al.*, 2018; Xu *et al.*, 2016). This paper puts forward a new method of dynamic relationship between carbon dioxide emission and economic growth in cities. Considering the new trend of international development of low-carbon economy in the future, this paper makes an empirical study on the internal dynamic relationship between carbon emission and economic growth through decoupling and Granger causality, which provides a theoretical basis for strengthening the construction of low-carbon cities and realizing the sustainable development of economy and society (Chaabouni, 2016; Khanchoul *et al.*, 2018).

2. Dynamic relationship between carbon dioxide emissions and economic growth in cities

2.1. Calculating method of urban carbon dioxide emission

According to the IPCC Carbon Emission Computation Guidelines (2006) and the characteristics of China's urban energy statistics, the calculation formula of urban carbon emissions is expressed as follows:

$$C_{it} = \frac{44}{12}\times\left(\sum_{j=1}^{17} Z_{ijt} + \sum_{j=1}^{17} D_{ijt} + \sum_{j=1}^{17} R_{ijt} + O_{it} - I_{it}\right)$$
$$= \frac{44}{12}\times\left(\begin{array}{l} \sum_{j=1}^{17} ZE_{ijt}\times\delta Z_{ijt}\times\eta Z_{ijt}+\sum_{j=1}^{17} DE_{ijt} \\ \delta D_{ijt}\times\eta D_{ijt}+\sum_{j=1}^{17} RE_{ijt}\times\delta R_{ijt}\times \\ \eta R_{ijt}+\left(OE_{it}-IE_{it}\right)\times\delta E_t\times\eta E_t \end{array}\right) \quad (1)$$

In the formula, C_{it} is the NO_2 emission of city *i* at time *t*, Z_{ijt}, D_{ijt} and R_{ijt} are the carbon emission of the *j*-th terminal energy consumption at time *t* in city *i*, the carbon emission of thermal power generation in energy processing conversion, and the carbon emission of heat supply in energy processing conversion. O_{it} and I_{it} are respectively the carbon emissions of the electricity output of the province and the carbon emissions of the electricity import of the other provinces in the city i at time t. ZE_{ijt}, DE_{ijt} and RE_{ijt} are respectively the energy consumption at the *j*-th terminal of the cityat time *t*, the energy consumption of thermal power generation in energy processing and conversion, and the energy consumption of heating in energy processing and conversion. δZ_{ijt}, δD_{ijt} and δR_{ijt} are the corresponding conversion coefficients of energy consumption standard quantities, and ηZ_{ijt}, ηD_{ijt} and ηR_{ijt} are the corresponding carbon emission coefficients of energy consumption. OE_{it} and IE_{it} are the local and the provincial power transfers in time *t* of city *i* respectively. δE_t and ηE_t are the standard conversion coefficient and carbon emission coefficient of China's power consumption in time *t*.

The conversion coefficients of standard energy consumption in terminal energy consumption, thermal power generation and heating process, as well as the conversion coefficients and carbon emission coefficients of standard energy consumption in and out of interregional power transfer are calculated using the following formulas:

$$\delta Z_{ijt} = \frac{\mathrm{ZEB}_{jt}}{\mathrm{ZES}_{jt}}, \delta D_{ijt} = \frac{\mathrm{DEB}_{jt}}{\mathrm{DES}_{jt}},$$
$$\delta R_{ijt} = \frac{\mathrm{REB}_{jt}}{\mathrm{RES}_{jt}}, \delta E_{ijt} = \frac{\mathrm{ZEEB}_{t}}{\mathrm{ZEES}_{t}}; \quad (2)$$
$$\eta E_{it} = \frac{\frac{44}{12}\times\sum_{j=1}^{17} DE_{jt}\times\delta D\times\eta D_{jt}}{\mathrm{ZEEB}_t}$$

In the formula, δZ_{ijt}, δD_{ijt} and δR_{ijt} are the conversion coefficients of standard quantity. For different regions, the conversion coefficients of standard quantity are the same in the same year. ZEB_{jt} and ZES_{jt} are the standard quantity and physical quantity of the *j*-th terminal energy consumption at time *t*, DEB_{jt} and DES_{jt} are the standard quantity and physical quantity of the *j*-th energy consumption in thermal power generation process at time *t*, REB_{jt} and RES_{jt} are the standard quantity and physical quantity of the *j*-th energy consumption in heating process at time *t*, respectively. Quantity and physical quantity. δE_t is the standard conversion coefficient of power terminal energy at time *t*, ZEEB_t and ZEES_t are the standard quantity and physical quantity of power terminal energy consumption at time *t*, respectively. ηE_{it} is the carbon emission coefficient of electric power at time *t*. Thermal power generation in China is mainly generated by burning fuel. Its carbon emission coefficient is determined by the proportion of energy consumption in the process of thermal power generation (Chen and Chen, 2016; Russo *et al.*, 2015). Due to the influence of energy consumption structure, power production technology and other factors, the carbon emission coefficient of electric power varies greatly every year. Therefore, it is necessary to calculate different carbon emission coefficients at different time intervals for different regions when power is transferred into and out. The total amount of energy carbon emissions consumed by thermal power generation in energy processing and conversion is divided by the end energy consumption as the carbon emission coefficient of electric power (Feng *et al.*, 2016; Souse *et al.*, 2015).

The calculation process of urban carbon emissions is shown in Figure 1.

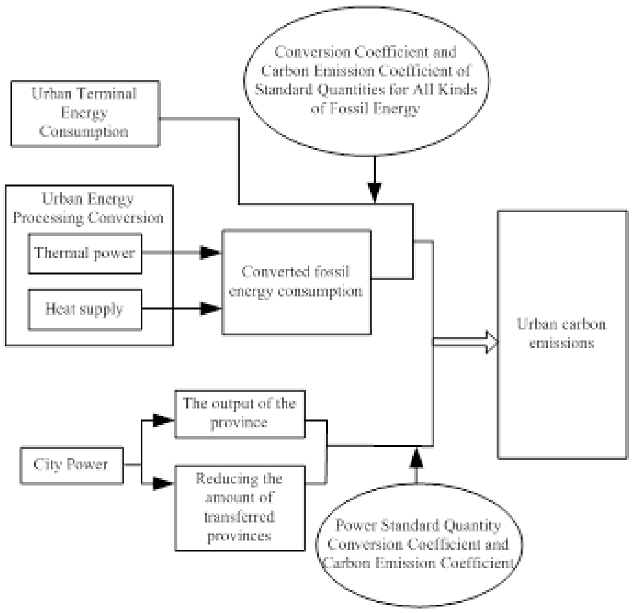


Figure 1. Flow chart of urban carbon emission measurement

2.2. Classification algorithms in uncertain data stream environment

From the data available in China, the data of carbon dioxide emissions from various provinces have been not yet published, so in order to study the dynamic relationship between urban carbon dioxide emissions and economic growth, estimating China's carbon dioxide emissions has become a problem that must be taken seriously (Gao, 2015; Huang *et al.*, 2015; Wang *et al.*, 2015). co_2 emission sources can be divided into two categories, one is the emission of natural environment, the other is the carbon dioxide generated by human production activities. Soil, forest, ocean and so on are the sources of natural environment emissions. People's various production activities around the world are the sources of anthropogenic emissions. Economic growth can not be separated from anthropogenic factors. Therefore, this paper mainly studies the carbon dioxide produced by economy. Before studying the dynamic relationship between urban carbon dioxide emissions and economic growth, it is necessary to classify urban carbon dioxide emissions data to obtain data on carbon dioxide generated by economic growth (Xie *et al.*, 2017; Yu *et al.*, 2015; Zhang *et al.*, 2015).

Data flow model has a wide range of applications in various fields, such as the Internet of Things, finance, the Internet and so on. With the progress of technology, people find that data in these areas are generally uncertain due to repeated measurements, privacy protection and data loss. The uncertainty of data results in that the values of data items can not be expressed by single values, but by multiple values and corresponding probability distributions (Yang *et al.*, 2018).

In this paper, the classification algorithm under uncertain data flow environment is used to classify the data of carbon dioxide emissions related to economic attributes of cities in China. Uncertainty can be found in the numerical attributes of carbon dioxide emissions, as well as in the nominal attributes of economic growth (Ain *et al.*, 2019; Mcpherson *et al.*, 2015; Yasin *et al.*, 2018). The uncertainty attribute set of urban carbon dioxide emission data is as follows:

$$A^u = \{A_1^u, A_2^u, \ldots, A_k^u\} \tag{3}$$

A^u represents the uncertain attribute set of urban carbon dioxide emission data, A_i^u represents the ith uncertain attribute of A^u, A_{it}^u represents the attribute value of uncertain attribute A_t^u in the t-th sampling of urban carbon dioxide emission data, and k represents the number of uncertain attributes of urban carbon dioxide emission data, $i \in [1,k]$.

The uncertain attribute value A_{it}^u of urban carbon dioxide emission data includes a range of values and the probability distribution over the range. If A_i^u is a numerical property, its range of values is expressed by [a_{it}, b_{it}], and the probability distribution is expressed by a probability density function $g_{it}(x)$.

In the data of urban carbon dioxide emission under the big data environment, the uncertain data stream of carbon dioxide emission is a series of incoming samples of uncertain data on carbon dioxide emissions, which is expressed by formula (2):

$$D^u = \{D_1^u, D_2^u, \ldots, D_t^u, \ldots\} \tag{4}$$

Where, D_t^u represents the uncertain data sample of carbon dioxide emissions. Each uncertain data sample D_t^u contains an attribute vector A^u and a category y^u, namely:

$$D_t^u = (A^u, y^u) \tag{5}$$

Where, $y^u \in C^u = \{C_1^u, C_2^u, \ldots, C_{|C|}^u\}$ indicates the category of sample D_t^u of carbon dioxide emission data.

The purpose of this paper is to construct a classifier for the uncertain data stream D^u of the dynamic relationship between urban carbon dioxide emissions and economic growth, and give a correct classification for the subsequent carbon dioxide data sample $D_t^u = (A^u, y^u = ?)$. In the big data environment, in the uncertain data stream system, data continuously arrives at the system, but the data cannot be obtained all at once, and only be scanned once. Therefore, this paper constructs an incremental classification model, i.e. incremental decision tree model,and uses this model to transform the uncertain attribute A^u of urban carbon dioxide emission data into a class probability distribution $\{\Pr(C_1^u), \ldots, \Pr(C_{|C|}^u)\}$, so thatat any time, according to the model, the data sample D_t^u under subsequent carbon dioxide emission reduction constraints is predicted to belong to the following categories:

$$y^u = \arg\max_{c=1,\ldots,|C|} \{\Pr(C_c^u)\} \tag{6}$$

Where, c is the quantity words of the categories of urban carbon dioxide emission data.

Formula (6) can be used to accurately classify and obtain carbon dioxide emission data related to economic growth attributes.

2.3. Construction of a model for the relationship between urban carbon emissions and economic growth

Based on the data of carbon dioxide emission from economic attributes obtained in the previous section, the relationship model between urban carbon emission and economic growth is constructed, and the dynamic relationship between urban carbon dioxide emission and economic growth is analyzed comprehensively.

2.3.1. Construction of decoupling model of carbon emission and economic growth

(1) Construction of decoupling model

There are two common decoupling models: Tapio model and OECD model. The division of elastic index in Tapio model is more precise, and it reflects the decoupling state of economic growth and carbon emissions in different regions at different times or in same region at different times. Tapio model has low demand for time base period selection and is not easily affected by the dimension of indexes (Fikriah *et al.*, 2019; Wei, 2018). Therefore, on the basis of the data of carbon dioxide emissions related to economic growth attributes obtained by formula (6), a Tapio model is constructed to study the decoupling relationship between carbon emissions and economic growth in four cities, and to measure the economic growth elasticity of urban carbon emissions.

$$w_n = y^u \frac{R\Delta C}{R\Delta \mathrm{GDP}} = \frac{(C_n - C_{n-1}) / C_{n-1}}{(\mathrm{GDP}_n - \mathrm{GDP}_{n-1}) / \mathrm{GDP}_{n-1}} \quad (7)$$

In this formula, w_n is the decoupling elasticity index, $R\Delta C$ is the growth rate of carbon emissions, that is, the change rate of carbon emission level in the *n*-th year relative to the *n*-1-thyear, $R\Delta$GDP is the change rate of a city's GDP in the *n*-th year relative to the *n*-1-thyear, and *C* is the carbon emission factor.

(2) Representation of decoupling state

According to the different characteristics of the decoupling elastic index, Tapio classifies the decoupling states into eight types, which are described in Table 1.

China is in the process of rapid economic development, the economic growth rate must be greater than zero, so there are four decoupling states: strong decoupling, weak decoupling, growth linkage and negative decoupling of expansion (Fang *et al.*, 2015; Kuusela and Amacher, 2016).

Table 1. Tapio (2005) elastic classification of decoupling

Decoupling state		Δco_2	ΔGDP	Elastic levele	Meaning
Negative decoupling	Strong negative decoupling	>0	<0	<0	Economic Recession and Increased Carbon Emissions
	Weakly negative decoupling	<0	<0	0<*t*<0.8	Carbon emissions fell less than the economic downturn
	Extended negative decoupling	>0	>0	*t*>1.2	Carbon emissions increase more than economic growth
Decoupling	Strong decoupling	<0	>0	<0	Economic Growth, Carbon Emissions Decline
	Weak decoupling	>0	>0	0<*t*<0.8	The increase of carbon emissions is less than that of economic growth
	Recessive decoupling	<0	<0	>1.2	Carbon emissions have fallen more sharply than economic recession
Link	Growth link	>0	>0	0.8<*t*<1.2	The growth rate of carbon emissions is basically the same as that of economic growth
	Declining links	<0	<0	0.8<*t*<1.2	The decline in carbon emissions is basically consistent with the extent of the economic recession

2.3.2. Granger causality test model

(1) Unit root test

The purpose of unit root test is to check the stability of time series and avoid the occurrence of pseudo-regression in analysis. It is also the premise of analyzing whether there is co-integration relationship and Granger causality among variables. This paper adopts ADF test method, which is developed from DF test (Dickey-Fuller test). DF test is only applicable to the first-order autoregressive process, and ADF test can be applied to the stationarity test of multi-order *AR*(*p*) process (Alshehry and Belloumi, 2015; Vogt *et al.*, 2015).

The principle of ADF test takes the first order autoregressive sequence as an example: $x_t=\varphi x_{t-1}+\alpha$.

The characteristic equation of the sequence is $\lambda-\varphi_1=0$.

When the eigenvalue φ_1 is in the unit circle, the sequence is stationary; conversely, the sequence is non-stationary (Mohajeri *et al.*, 2015).

Original hypothesis H_0: sequence x_t is nonstationary; alternative hypothesis H_1: sequence x_t is stationary.

The statistics *t* is test: $t(\varphi_1)=(\hat{\varphi}_1-\varphi_1)/S(\varphi_1)$, where $\hat{\varphi}_1$ is the least square estimate of parameter $\hat{\varphi}_1$:

$$S(\hat{\varphi}_1)=\sqrt{\frac{S_T^2}{\sum_{t=1}^{T} x_{t-1}^2}}, S_T^2=\frac{\sum_{t=1}(x_t-\varphi_1\hat{x}_{t-1})}{T-1} \quad (8)$$

Where, $S(\hat{\varphi}_1)$ eigenvalue estimator and *S* represent the parameters of least squares estimate. When $\varphi_1=0$, the limit distribution of $t(\varphi_1)$ is called standard normal distribution; when $|\varphi_1|<1$, the asymptotic limit distribution of $t(\varphi_1)$ is called standard normal distribution; when $|\varphi_1|=1$, the asymptotic distribution of $t(\varphi_1)$ is no longer normal distribution.

We call $\tau=\frac{|\hat{\varphi}_1|-1}{S(\hat{\varphi}_1)}$ the ADF test statistics. When the significant level is α, τ_α is called the α position point of ADF test. That is, when $\tau\leq\tau_\alpha$, we reject the original hypothesis, which means that the sequence is remarkably stable. On the contrary, we accept the original hypothesis, which means that the sequence is not stable.

Before the ADF test, we can make a preliminary judgment on the time series. The time series diagram can be used to preliminarily judge whether the time series is unstable. In order to avoid the fluctuation of the data to a large extent, we can easily get the stationary series. In this paper, we take the logarithm of GDP and carbon dioxide emission co_2 respectively, which can be recorded as $LNCO_2$ and LNGDP.

(2) Co-integration test

Co-integration test is the causality test of non-stationary sequence. Co-integration means that there exists a common random trend. Co-integration processing is mainly to test whether there is a stable relationship between variables and to prevent pseudo-regression caused by non-stationary sequence (Bonal *et al.*, 2015). If a linear combination of two random walk variable sequences is stable, then the two sequences are co-integrated, and the single integer order of the two sequences is the same, which is the necessary condition for the co-integration between the two sequences.

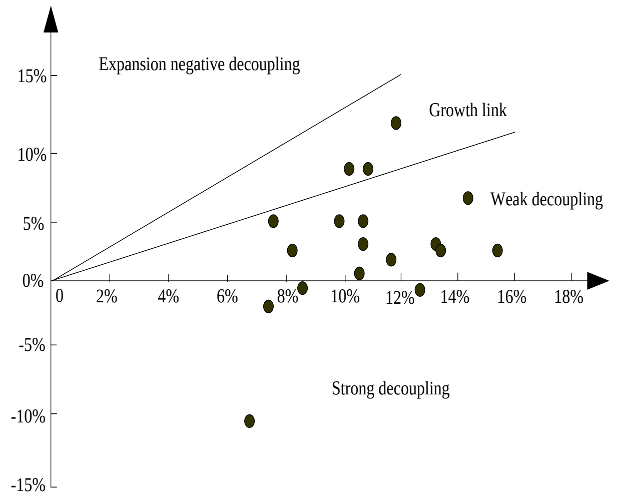


Figure 2. Decoupling of Carbon Emissions and Economic Growth in Shanghai from 1995 to 2014

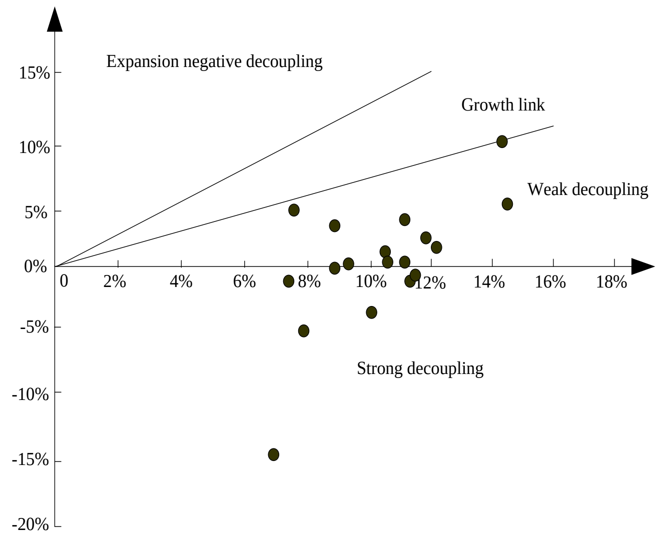


Figure 3. Decoupling of Carbon Emissions and Economic Growth in Beijing from 1995 to 2014

If two sequences of x_t and y_t are known to be non-stationary, but they are all d-order mono-integer sequences, then it can use the stationary test of residual ε_t of co-integration regression equation (OLS):$x_t=\alpha+\beta y_t+\varepsilon_t$ to judge the co-integration relationship of x_t and y_t. If x_t and y_t do not exist co-integration, then any linear combination of them is non-stationary, that is, residual $\varepsilon_t$must also be non-stationary. Therefore, if the test shows that the residual ε_t is stable, then we can consider that there is a co-integration relationship between x_t and y_t.

(3) Granger causality test

Granger test is only a prediction of stationary time series. Assuming that there are two economic variables C (carbon emissions) and G (GDP), under the condition that both information are included at the same time, the prediction effect of variable C is generally better than that only using the past information of C to predict. That is, variable G helps to improve the interpretation and prediction accuracy of variable C, then it is considered that there is Granger causality between variable *X* and *Y* (Ahmad *et al.*, 2015; Ismail *et al.*, 2015; Liu *et al.*, 2019; Mi *et al.*, 2019; Wang *et al.*, 2018; Yu *et al.*, 2018, 2019). The two-variable autoregressive model is as follows:

$$C_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i G_{t-i} + \sum_{i=1}^{m} \beta_i G_{t-i} + \varepsilon_t \tag{9}$$

$$C_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i G_{t-j} + \sum_{j=1}^{m} \beta_j G_{t-j} + \varepsilon_t \tag{10}$$

The co-integration factor $\beta_i(i=1,2,\ldots,m)=0$ should be tested, that is, “G is not the cause of C changing”, and the original hypothesis $\beta_i(i=1,2,\ldots,m)=0$ should be rejected, that is, the Granger causality from G to C should be affirmed; similarly, the Granger causality from Y to X should be verified by the hypothesis $\beta_i(i=1,2,\ldots,m)=0$.

3. Results

3.1. Decoupling analysis of carbon emissions and economic growth

Based on the above decoupling models, the decoupling status of carbon emissions and economic growth in Shanghai, Beijing, Tianjin and Chongqing from 1995 to 2014 is calculated and described in Figures 2-5.

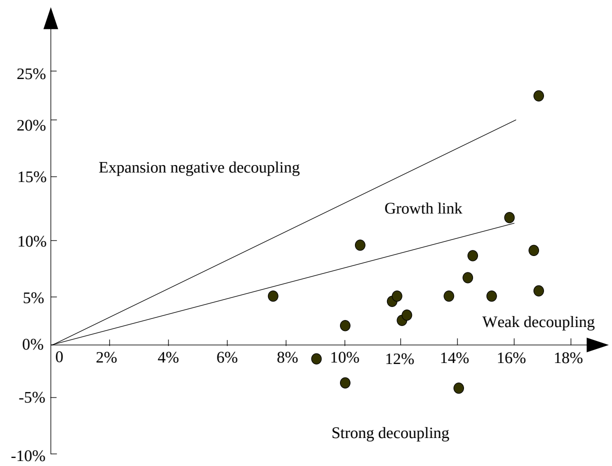


Figure 4. Decoupling of Carbon Emissions and Economic Growth in Tianjin from 1994 to 2014

From the analysis of Figures 2-5, we can see that most of the years in cities are in a weak decoupling state, indicating that the economic growth rate is obviously faster than the increase rate of carbon emissions. Among them, Beijing has the best decoupling status, the year of strong decoupling is more, and its decoupling elasticity coefficient is small. From the time series, decoupling shows a good momentum of development. Since 2008, the number of years of strong decoupling has increased, indicating that Beijing's energy saving and emission reduction policy has achieved good results. The decoupling status of Shanghai is similar to that of Beijing. Over the years, the decoupling status is located in weak and strong decoupling areas, which indicates that the rapid economic growth has not brought about excessive growth of carbon emissions. The decoupling status of Tianjin and Chongqing is comparatively consistent, and the decoupling status varies greatly from year to year in terms of time series; from the overall distribution, the weak decoupling status is not obvious in most years, and the value of decoupling coefficient is larger, indicating that economic growth is accompanied by an increase in carbon emissions. This is related to the rapid development of the two cities and the important position of the secondary industry in the three industries. Secondary industry is the main source of energy consumption and the source of increasing carbon emissions.

3.2. Granger test

3.2.1. ADF test: A case study of shanghai

In order to ensure the stationarity of time series data, the stationarity tests of $LNCO_2$ and LNGDP in four mega-cities (Beijing, Shanghai, Tianjin and Chongqing) are carried out respectively. The ADF test method is adopted in this paper. The lag period is 2. The test principle refers to the above requirements. Table 2 shows the results of ADF test in Shanghai.

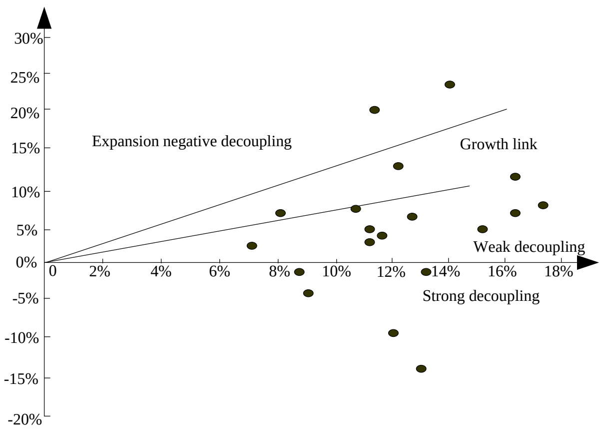


Figure 5. Decoupling of Carbon Emissions and Economic Growth in Chongqing from 1995 to 2014

Table 2. ADF Unit Root Test Results in Shanghai

Variable	ADF test value	Critical value (1%)	Critical value (5%)	Critical value (10%)	Judgement conclusion
LNGDP	0.992746	-4.532598	-3.673616	-3.277364	Nonstationary
LNGDP first-order difference	-2.303840	-4.532598	-3.690814	-3.286909	Nonstationary
LNGDP second Order Difference	-5.647835	-4.667883	-3.733200	-3.310349	Stable
$LNCO_2$	-0.157.26	-4.532598	-3.673616	-3.277364	Nonstationary
$LNCO_2$ first-order difference	-3.984466	-4.571559	-3.690814	-3.286909	Nonstationary
$LNCO_2$ second Order Difference	-5.800843	-4.667883	-3.733200	-3.310349	Stable

The analysis of Table 2 shows that the statistic is 0.992746 at 5% significant level, and its P value is greater than the significant level α. Therefore, we accept the original hypothesis that the GDP time series data are non-stationary, and the LNGDP first-order difference still accepts the original hypothesis. When the second-order difference is used for LNGDP, the statistic at the 5% significant level is -5.647835, which is less than the significant level α. The original hypothesis is rejected, that is, LNGDP is a second-order mono-integer sequence with a significant level of 1%. Similarly, $LNCO_2$ is a second-order mono-integer sequence with a significant level of 1%. Similarly, LNGDP and $LNCO_2$ are second-order mono-integer sequences at 1% significant level in Beijing. Tianjin is at 1% significant level, both of them are second-order mono-integer sequences. Chongqing's LNGDP is a second-order mono-integer sequence and $LNCO_2$ is a first-order mono-integer sequence.

3.2.2. Co-integration test analysis: A case study of Shanghai

Table 3 is the result of co-integration regression between carbon emissions and GDP in Shanghai; Table 4 is the ADF test result of co-integration regression residual of carbon emissions and GDP in Shanghai.

According to ADF test results, if LNGDP and $LNCO_2$ are stationary time series at different significance levels, it indicates that there may be a long-term stable equilibrium relationship of co-integration. Therefore, co-integration test can be used. The co-integration regression results of Shanghai are as Table 3. Eviews software is used to do co-integration analysis of LNGDP and $LNCO_2$ time series data. Taking $LNCO_2$ as dependent variable and LNGDP as independent variable, Least Square Estimation regression analysis is carried out to obtain the co-integration regression equation as follows:

$$\mathrm{LNCO_2} = 6.845602 + 0.348285\mathrm{LNgdp} + u_t \tag{11}$$

R^2=0.96, F=416.84, DW=0.875660. The coefficient of the independent variable has passed the test, which shows that the regression equation has a high significance. From the co-integration equation, the estimated coefficient of GDP growth is 0.348285, which means that for every unit of GDP increase, carbon dioxide emissions will increase by 0.348285. The ADF test of the residuals shows that the residuals are stationary.

3.2.3. Granger causality test

According to the above principle, Granger causality test is carried out for $LNCO_2$ and LNGDP in four cities respectively. Complying with SC and AIC minimization criteria, it can determine that the lag time of Granger causality test is 2. The test results are shown in Table 5.

The significance probability of the two hypotheses in Shanghai is greater than 0.05, so the original hypothesis is accepted, that is, there is no causal relationship between GDP growth and carbon dioxide emissions in Shanghai. At the same time, it reflects that Shanghai's economic growth is on the path of sustainable development. Sustained economic growth will not lead to an increase in carbon dioxide emissions, nor will carbon dioxide emissions lead to economic growth. Beijing's test results are similar to Shanghai's, while Tianjin and Chongqing's test results are consistent, that is, there is a one-way Granger causality between economic growth and carbon emissions. Economic growth is the Granger cause of carbon dioxide emissions, otherwise it is not true. Carbon emission reduction measures will not hinder economic growth in the long run.

Table 3. Co-integration regression results of carbon emissions and GDP in Shanghai

Variable	Coefficient	Std. error	*t*-Statistic	Prob.
LNGDP	0.348285	0.017059	20.41676	0
C	6.845602	0.151398	45.21582	0
R-squared	0.958606	Mean dependent var	9.929445	
Adjusted R- squared	0.956306	S. D. dependent var	0.221274	
S. E. of regression	0.046253	Akaike info criterion	-3.214735	
Sum squared resid	0.038508	Schwarz criterion	-3.115162	
Log likelihood	34.14735	Hannan— Quinn criter	-3.195298	
F-statistic	416.8439	Durbin — Watson stat	0.87566	
Prob (F-statistic)	0			

Table 4. ADF test results of co-integration regression residual of carbon emissions and GDP in Shanghai

	t-Statistic	Prod.*
Augmented Dickey-Fuller test statistic	-4.058087	0.0004
Test critical values:	1% level	-2.699769
	5% level	-1.961409
	10% level	-1.606610

Table 5. Granger causality test results

	Original hypothesis	*F* statistical value	Saliency probability	Test conclusion
Shanghai City	LNGDP does not Granger Cause $LNCO_2$	0.43285	0.6557	Accept
	$LNCO_2$ does not Granger Cause LNGDP	3.30919	0.0689	Accept
Beijing City	LNGDP does not Granger Cause $LNCO_2$	1.78051	0.2073	Accept
	$LNCO_2$ does not Granger Cause LNGDP	0.20417	0.8179	Accept
Tianjin City	LNGDP does not Granger Cause $LNCO_2$	9.99341	0.0024	Refuse
	$LNCO_2$ does not Granger Cause LNGDP	3.07741	0.0805	Accept
Chongqing City	LNGDP does not Granger Cause $LNCO_2$	6.10705	0.0135	Refuse
	$LNCO_2$ does not Granger Cause LNGDP	0.44601	0.6496	Accept

4. Discussion

This paper discusses the relationship between carbon emissions and various factors of urban economic development. The details are as follows:

(1) The first is economic growth. Economic growth is an important indicator to measure the level of economic development. Based on experience, in the early stage of industrialization, the per capita carbon emissions of a country increase substantially with the economic growth. Because economic growth in the early stage of industrialization needs to use more fossil energy. After industrialization, the degree of correlation between economic growth and carbon emissions will be reduced. Looking from the history of economic development, the first two industrial revolutions have made the economy grow at an unprecedented rate. During this period, the large use of fossil energy has led to a sharp increase in carbon dioxide emissions. In recent years, with the rapid economic growth of developing countries, the demand for fossil energy continues to expand. Developing countries are in a period of rapid economic growth, and carbon dioxide emissions are also increasing rapidly. In order to achieve the level of developed countries' economic growth in the future, we need enough space for carbon emissions in the process of future economic development. With the economic growth, the accumulation of carbon emissions is also a long process.

(2) Factor of industrial structure. Changes in industrial structure in the economy will affect carbon dioxide

emissions. Secondary industry is the main sector of carbon dioxide emissions. The higher the proportion of secondary industry is, the more the carbon dioxide emissions are. The theory of industrial structure evolution holds that the industrial structure corresponds to the economic development and keeps changing, and the industrial height keeps evolving from the lower level to the higher level. With the economic development, the labor force first transfers from the primary industry to the secondary industry; the expansion of the secondary industry: with the continuous development of the economy, the tertiary industry is in the dominant position, the efficiency of energy utilization gradually improves, and people have a clean environment. The per capita carbon emissions may decrease as the demand of the environment increases. The expansion of tertiary industry: the scale of primary industry decreases, while the scale of secondary and tertiary industry expands. In the more developed countries and regions, the proportion of primary industry is relatively small, while the proportion of secondary and tertiary industries is relatively large. Generally speaking, the causal relationship between carbon dioxide emissions and output may be obvious in countries with a relatively large proportion of secondary industry. Empirically, the proportion of secondary industry may be positively correlated with carbon emissions. On the contrary, in developing countries and regions, the proportion of primary industry is relatively large, while the proportion of secondary and tertiary industries is relatively small. The carbon emissions per unit output of the first and third industries are lower than that of the second industry. With the development of industrial structure, the carbon emissions of the economy may show some regularity. Compared with developed countries, China's industrial structure has a relatively high proportion of secondary industry, which will increase carbon emissions to a certain extent.

(3) Urbanization level. The level of urbanization is also an obvious factor affecting carbon dioxide emissions. The level of urbanization is a quantitative index to measure the degree of urbanization development, which is expressed by the proportion of urban population in a certain region to the total population. The process of urbanization requires a large amount of energy input, which will produce a large amount of carbon emissions. A relatively high urbanization rate requires a large amount of carbon dioxide emissions. The level of urbanization in a country is closely related to its economic development. Compared with developed countries, China is in the period of urbanization. In order to reach the level of urbanization in middle-income countries, a large amount of energy input is needed and necessary infrastructure construction is carried out. A large amount of energy input will bring about an increase in carbon dioxide emissions. At the same time, rural residents in China will increase their carbon dioxide emissions. In the process of urbanization, a large number of people migrate from rural areas to cities. This huge increase in urban population will also increase carbon dioxide emissions.

5. Conclusions

Based on the research contents of this paper, the following conclusions and suggestions are obtained:

(1) The dynamic relationship between carbon dioxide emissions and economic growth is studied in this paper, which provides a reliable basis for the implementation of energy saving and emission reduction and the development of low-carbon economy. Through comparative analysis and empirical research, the decoupling status of carbon emissions and economic growth in four cities is mainly weak decoupling, among which Beijing has the best decoupling status, and the trend of decoupling has gradually changed from weak decoupling to strong decoupling. The decoupling status of Tianjin and Chongqing has changed greatly in each year. Through Granger causality test, it is found that the results of Shanghai and Beijing are comparatively consistent, indicating that there is no Granger causality between carbon emissions and economic growth, while Tianjin and Chongqing show a one-way Granger causality between economic growth and carbon emissions, indicating that in the long run, the growth of carbon emissions will not lead to economic growth, that is, implementing strong energy saving and emission reduction measures will not lead to economic downturn in the long run

Through the analysis of the differences between the economic structure and carbon emissions within the city, the rapid economic growth does not necessarily lead to an increase in energy consumption, it mainly depends on whether the industrial structure is reasonable or not and whether the energy efficiency is constantly improving. Shanghai and Beijing have a relatively high level of economic development and pay more attention to the quality of economic development. The increase of energy consumption does not necessarily lead to an increase in carbon emissions, but mainly depends on the improvement of energy consumption structure. Coal-based energy consumption structure in Tianjin and Chongqing will inevitably lead to a large increase in carbon emissions.

(3) Cities are the most concentrated areas in China's economic development and people's lives, as well as the most concentrated areas in energy consumption and pollutant emissions. Therefore, the development of low-carbon economy requires attention to the construction of low-carbon cities. Among them, the government plays a main role in the construction of low-carbon cities, and is also the promoter of fostering low-carbon economy in the transformation of economic structure. To achieve low-carbon city, we must strive to implement low-carbon economy and realize low-carbon life. To achieve low-carbon urban economic development, efforts can be made from four aspects: transformation of economic development mode, adjustment of economic development structure, economic development energy and policy support for new technologies of energy saving and emission reduction. To achieve low-carbon urban social life, it is necessary to actively publicize and popularize the concept of low-carbon life, realize low-carbon urban

planning, promote building energy saving and realize green building, so as tostreng then urban greening construction to improve urban forest coverage.

(4) China's mega-cities play a guiding role in leading regional economic and social development. Building a low-carbon city is a systematic project, which requires extensive and deep participation of the government, enterprises and the public. The super-metropolis should make clear its overall orientation of economic development, construct a perfect urban development system, scientifically plan the urban development route, actively and reasonably construct the transportation system of the super-metropolis, realize the benign economic interaction with the surrounding areas, and lead the low-carbon construction of the surrounding urban agglomerations. By adjusting the energy consumption structure, optimizing the industrial structure and improving the efficiency of resource use, the level of carbon emissions can be reduced to the greatest extent. We should continue to strengthen the development and utilization of new energy sources, increase the ratio of renewable energy sources, such as promoting clean transformation of heating coal to gas, and encouraging the development and application of renewable energy technologies. At the same time, we should improve the relevant policies, regulations and standards of energy conservation and emission reduction, establish and improve the regulatory and decision-making mechanisms of megacities, such as strengthening the assessment and supervision of energy conservation and emission reduction targets, and establishing regional energy management linkage mechanism and consumption forecasting and early warning mechanism.

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