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Original Research

The Causality Relationships between Energy-related CO_2 Emissions and its Influencing Factors with Linear and Nonlinear Granger Causality Tests

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Abstract

At present, research on relationships between carbon dioxide emissions and its influencing factors are concerned with linear causality relationships, and most literature has focused on the economic field to find its influencing factors. This article aims to investigate the causality relationships between carbon dioxide emissions and its influencing factors in China through the traditional Granger causality test and the Hiemstra and Jones test. The paper not only considers economic factors, but also takes social factors into consideration. It has been concluded that linear Granger causality relationships exist from CO_2 emissions to GDP, gross national income, and freight traffic volume. Compared with linear relationships, unidirectional nonlinear Granger causality relationships run from CO_2 emissions to resident consumption levels, and also from the urban population to CO_2 emissions. Moreover, there are bidirectional nonlinear causality relationships between CO_2 emissions and GDP, and between CO_2 emissions and the possession of private automobiles. Finally, based on the above conclusions, this article analyzes energy-saving and emission reduction measures as proposed by the Chinese government, and puts forward policy recommendations to reduce carbon dioxide emissions.

Keywords: linear Granger causality test, nonlinear Granger causality test, carbon dioxide emissions, influence factors

Introduction

With continuous development of the economy and society, greenhouse gas emissions, global warming, ecosystem degradation, and other environmental problems have been increasingly serious. The emission of carbon dioxide is known as the main source of greenhouse gases [1-2]. Therefore, how to realize sustainable economic development, meanwhile, while effectively reducing carbon dioxide emissions has become a major problem facing the world today.

The United Nations Climate Change Conference in 2015 aimed at controlling the emissions of carbon through an agreement to curb global warming and avoid

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temperature increases above two degrees compared with the pre-industrial level. This conference passed the Paris Agreement, which suggests that parties should participate in global climate change action through the independent contribution approach. Developed countries will continue to take the lead in emissions reduction and strengthen support to the developing countries in capital, technology, and capacity building to help the latter countries mitigate or adapt to climate change. Thus, the reduction of carbon dioxide emissions has become a critical task for all countries in the world.

China is the largest developing country in the world, and rapid economic growth has allowed China to surpass the United States, thereby becoming the largest emitter of carbon dioxide. How to reduce the carbon emissions of China has become a hot topic in recent years. It is worth noting that the Chinese government has proposed a series policies to respond to climate change and assume its responsibilities. For example, energy consumption must be reduced by 16% and CO_2 emissions per unit GDP must be lowered by 17% during 2011-15 in the "Outline of National Economy and Social Development Plan in the Twelfth Five-Year Plan." Moreover, the target that CO_2 emissions per unit gross domestic product (GDP), namely carbon intensity, should be cut by 40-45% in 2020 compared with 2005 was regarded as a goal of the Thirteenth Five-Year Plan (2016-20).

Under this background, it has important academic value and practical significance of in-depth research of the relationship between carbon dioxide emissions and its influencing factors, which will provide reference for theoretical analysis and an empirical test for the selection and arrangement of policy.

Literature Review

Many studies have researched carbon dioxide emissions and its related factors. The driving factors behind carbon dioxide emissions in China could be broken down into three main drivers: economic growth, energy structure, and carbon dioxide emissions efficiency [3]. Another view proposed that it could also be categorized into energy structure, energy intensity, economic structure, and economic output effects. Especially economic output effect and energy intensity effect were the first two main drivers [4]. The relationship between carbon dioxide emissions and economic growth varied from region to region, and there was no universal model fitting every country. Governments should make policies according to the situation of itself [5]. Besides, there was evidence to support the bidirectional causality between CO_2 emissions and capital, the unidirectional causal relationship from labor to CO_2 emissions in the short run, and the unidirectional causality from GDP to CO_2 emissions in the long run [6]. There was bidirectional causality between CO_2 emissions and economic growth and unidirectional causality from CO_2 emissions to health expenditures [7]. As transportation is a significant source of greenhouse gas emissions, researchers have explored the different CO_2 emissions of different types of vehicles [8]. The relationship between urbanization, energy consumption, and CO_2 emissions in different provinces of China also has been explored, and it was discovered that there are significant differences between provinces [9]. Mutual relationships between a set of economic and financial development factors and CO_2 emissions were found, and scholars did further research to analyze the long-term relationship, the short-run dynamics, causality direction, and relative contributions [10].

Clearly the analysis of influencing factors of carbon dioxide emissions often needs to be judged through causality relationships between variables. Although it can be made preliminarily according to economic theory, it is difficult to make a reasonable judgment because of inconsistent assumptions. Even completely opposite judgments could be made.

The Granger causality relationship test used actual observation data to test the causality between variables from the statistical view and gave a definition of causality relationship which was called the Granger causality relationship in view of the prediction [11]. For the unclear causality relationships between variables in economic phenomenon, this method could be carried on and is widely used in economics.

But due to the impact of fluctuations in economic cycle, macroeconomic regulations and control policies, oil crisis of economic events, and fluctuations in international oil prices, technology progress, adjustment of industrial structure, and the relationships between carbon dioxide emissions and its influencing factors are not invariable, and may include a significant nonlinear relationship which the linear test cannot find. As a result, on the basis of existing research, it is of great significance to discuss nonlinear influence and explore factors beyond linear effect factors.

Beak and Broke proposed a non-parametric statistical method to capture the nonlinear causality (which a traditional linear causality test could not find [12]), and Hiemstra and Jones modified it to overcome the limitations of the traditional Grange causality test method [13].

In recent years, the nonlinear Granger causality test has been used as a method in some articles to explore nonlinear relationships. Some scholars have tried to investigate the relationship of energy consumption and income based on the fact that the relationships were different by using various models, and the relationships were specific in different countries [14]. Others applied linear and nonlinear causality tests to investigate the causal relationship between energy consumption and economic growth by obtaining sample data from newly industrialized counties in Asia as well as the United States in 2008 [15].

Most previous studies have focused on the field of economics and research the relationships between carbon emissions and economic factors [16-17]. However, CO_2 emissions are affected not only by economic factors. Social factors are also likely to have an important impact on carbon emissions in real life.

This article mainly investigates the causality relationships between CO_2 emissions and its influencing factors through the traditional Granger causality test and the Hiemstra and Jones tests. It is to be noticed that we not only think about generally studied economic factors, including China's gross domestic product, gross national income, and resident consumption level, but also take such social factors as urban population, freight traffic volume, gross output value of construction industry, and possession of private automobiles into consideration.

Material and Methods

In this paper we use the linear and nonlinear Granger causality test to investigate the causality relationship between carbon dioxide (CO_2) emissions and different economic and social factors in China while providing advice for the effective reduction of carbon dioxide emissions. Specifically, economic factors contain China's gross domestic product, gross national income, and resident consumption level. Social factors include the urban population, freight traffic volume, gross output value of the construction industry, and the possession of private automobiles.

Data

Sample Selection

According to data availability, except for the possession of private automobiles, this paper selects data from 1980 to 2014 as the sample interval, which includes 35 observations. Due to the lack of information, we chose data about the possession of private automobiles from 1985 to 2014. All data are at annual frequency and obtained from the China Statistical Yearbook and the China Energy Statistics Yearbook. Definitions and abbreviations of all relevant variables used in the study are shown in Table 1.

Sample Data Processing

In order to decrease the obvious heteroscedasticity phenomena of data, this paper first applies logarithmic transformation to the data.

Next, considering the problem of spurious regression, unit root tests are conducted for all time series to ensure that they are stationary before applying the linear and nonlinear Granger causality tests. In this paper, we conducted the augmented Dickey-Fuller (ADF) test [18] and the Phillips-Perron (PP) test, which are generally used to examine the stationarity of series [19]. Results of unit root tests are shown in Table 2.

According to Table 2, it is obvious that from the ADF test, the hypothesis of a unit root for series cannot be rejected significantly when we examine the level value. When we test the first difference, we have found that almost all series are still nonstationary besides GDP. In terms of the PP test, results show that all series have a unit root at the level value and the first difference of most series are unstable except for UP and FTV. However, we could indicate from the table that all series in the second difference appear to be stationary – at least at a 5% level of significance.

In this paper, the linear and nonlinear Granger causality tests are used to test the second difference sequence to determine the causality relationship between carbon dioxide emissions and different influencing factors.

Table 1. Definitions of all relevant variables used in the study.

Variables	Abbreviation	Definition	Unit of Measurement
China's Gross Domestic Product	GDP	Calculated according to the market price of China's final results of production activities of all the permanent units in a certain period	Billion Yuan
National Gross Income	GNI	The final results of the initial distribution of income in China in a year	Billion Yuan
Resident Consumption Level	RCL	The consumption expenditure of the resident population on average of China	Yuan
Urban Population	UP	The entire resident population residing in urban areas	10^4 Persons
Freight Traffic Volume	FTV	The weights of the actual delivery of goods within a certain period	10^4 Tons
Gross Output Value of Construction Industry	GCI	The total of construction products and services of construction enterprises in the form of money in a certain period	Billion Yuan
Possession of Private Automobile	PPA	The number of local private car license plates that have been registered in the traffic department of public security at the end of the reporting period	10^4
Carbon Dioxide Emissions	CE	Total emissions as calculated from the consumption of primary energies, including coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and nature gas	Tons

Table 2. Results of unit root tests.

	GDP	GNI	RCL	UP	FTV	GCI	PPA	CE
ADF								
Level	-1.2838	-1.1006	-1.7933	-1.6875	-2.4782	-0.2943	4.3210	-1.9879
First difference	-3.5908*	-3.3421	-3.8239	-3.0896	-4.9543	-2.4238	2.8946	-1.8691
Second difference	-4.0492**	-5.4968**	-4.2808**	-10.884**	-4.5829**	-3.6670*	-4.5848**	-3.4890**
PP								
Level	-1.4335	-1.4474	-1.4583	-1.8659	-1.8820	5.7391	9.3555	-1.8983
First difference	-2.9450	-3.0265	-2.5923	-3.8447*	-4.9504**	-1.7041	0.4461	-2.5638
Second difference	-4.9122**	-5.1033**	-5.8847**	-10.824**	-16.907**	-3.3199**	-3.9546*	-4.8268**

Notes: ** and * indicate significance at the 1% and 5% levels, respectively.

Linear Granger Causality Test

Definitions

The linear Granger causality test is the generally used standard Granger causality test. The linear relationship between the current value of a variable and the past value of another variable is detected through it [20]. More specifically, the Granger causality relationship between two economic variables, named *X* and *Y*, is defined as the predictive value of variable *Y* and could be better forecast with past information of both variable *X* and variable *Y* than only with that of variable *Y* itself, which means that variable *X* helps explain future changes in variable *Y*, then we prove there is a Granger relationship between variables *X* and *Y*.

Assume two stationary ergodic time series denoted by X_t and Y_t. The bivariate information set I_{t-1} contains *i*-length lagged past information of X_t, say X_{t-1} = (X_{t-1}, X_{t-2},..., X_{t-i}, *i*>0 and *j*-length lagged past information of Y_t, say X_t, say Y_{t-1} = (Y_{t-1}, Y_{t-2},..., Y_{t-i}, *j*>0. Let $F(X_t | I_{t-1})$ be the conditional probability distribution of X_t on the condition of binary information set I_{t-1}. Then $F(X_t \mid I_{t-1} - Y_{t-j})$ presents the conditional probability distribution of X_t given the past information only about series X_t. If:

$$F(X_t | I_{t-1}) > F(X_t | I_{t-1} - Y_{t-j})$$

…the conclusion that time series Y_t is the Granger cause of X_t could be brought forth. It is the same if:

$$F(Y_t | I_{t-1}) > F(\boxed{Y}_t | I_{t-1} - X_{t-i})$$

… in which case the time series X_t is the Granger cause of Y_t. It is worth noting that if the two kinds of feedback exist simultaneously, the bidirectional causality between time series X_t and Y_t exists.

Testing

In empirical analysis, the linear Granger causality test and the direction of its variables are realized through the vector auto-regressive model (VAR):

$$X_t = \sum_{i=1}^{m} \alpha_i X_{t-i} + \sum_{j=1}^{n} \beta_j Y_{t-j} + \varepsilon_t \tag{1}$$

$$Y_t = \sum_{k=1}^{p} \alpha_k X_{t-k} + \sum_{l=1}^{q} \beta_l Y_{t-l} + \eta_t \tag{2}$$

…within which $\varepsilon_t \sim N(0, \delta_\varepsilon^t)$ and $\eta_t \sim N(0, \delta_\eta^t)$. In this process, Akaike information criterion (AIC) is used to determine the best lag length, and the linear Granger causality test is conducted under the condition of best lag length.

In order to investigate whether there is a Granger causality relationship from Y_t to X_t, the following hypothesis is tested:

$$H_0 \square \beta_1 = \beta_2 = ... = \beta_j = 0$$

If there are at least a parameter value of β_j not zero, which indicates that the equation of null hypothesis does not hold, it proves that Y_t does strictly Granger cause X_t.

Nonlinear Granger Causality Test

Granger pointed out that the nonlinear mode of bivariable and multivariable better constructed the real world, which was almost certainly nonlinear [21]. Originally the Granger causality test is defined based on the distribution of variables, considering the effect of nonlinear Granger causality, not just about the linear causality relationship between the mean value of variables. Baek and Brock propose a nonparametric statistical method to capture nonlinear causality that the traditional linear causality test cannot find. Hiemstra and Jones relaxes the assumption that a variable must be independent and identically distributed (i.i.d) in the Baek and Brock causality test and allows each series to be weakly or short-term dependent.

Given X_t and Y_t to be two strictly stationary and weakly dependent time series, by defining the *m*-length lead vector of X_t by X_t^m, and the *Lx*-length and *Ly*-length lag vectors of X_t and Y_t, respectively, by X_{t-Lx}^{Lx} and X_{t-Ly}^{Ly}, we obtain the following representations.

$$X_t^m = (X_t, X_{t+1}, \cdots, X_{t+m-1}), m = 1,2,\cdots, t = 1,2,\cdots$$

$$X_{t-Lx}^{Lx} = (X_{t-Lx}, X_{t-Lx+1}, \cdots, X_{t-1}), Lx = 1,2,\cdots,$$
$$, t = Lx+1, Lx+2, \cdots$$

$$Y_{t-Ly}^{Ly} = (X_{t-Ly}, X_{t-Ly+1}, \cdots, X_{t-1}), Ly = 1,2,\cdots,$$
$$t = Ly+1, Ly+2, \cdots$$

Given *m*, *Lx* and *Ly* >1, the bandwidth e>0. If:

$$\begin{aligned}&\Pr(\|X_t^m - X_s^m\| < e \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < e)\\ &= \Pr(\|X_t^m - X_s^m\| < e \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e)\end{aligned} \tag{3}$$

…where Pr(•) represents probability and ‖•‖ is the maximum norm. The left-hand side of equation (3) shows the conditional probability of the distance between two *m*-length lead random vectors being within bandwidth *e* on the condition that the distance between two arbitrary vectors, *Lx*-length lag vectors of X_t and *Ly*-length lag vectors of Y_t, falls in bandwidth within *e*. The right-hand side of equation (3) is similar to the left-hand side, besides the condition that should be the distance only between two *Lx*-length lag vectors of X_t being within bandwidth *e*.

When it comes to a statistical test, it is advisable to replace conditional probability in equation (3) with joint probability. Let:

$$\begin{aligned}&C1(m+Lx, Ly, e) = \Pr(\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\| < e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < e)\\ &C2(Lx, Ly, e) = \Pr(\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < e)\\ &C3(m+Lx, e) = \Pr(\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\| < e)\\ &C4(Lx, e) = \Pr(\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e)\end{aligned} \tag{4}$$

Then $C1(m+Lx, Ly, e)/C2(Lx, Ly, e)$ and $C3(m+Lx, e)/C4(Lx, e)$ respectively represent the ratio of joint probability distribution of different sides of equation (3). Considering *m*, *Lx* and *Ly*≥1 and bandwidth *e*>0, equation (3) could also be expressed as:

$$\frac{C1(m+Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m+Lx, e)}{C4(Lx, e)}$$

Setting Kernel function to be K(Z_1, Z_2, e). When the maximum norm distance between Z_1 and Z_2 of the two variables falls within *e,* the weight of the function is 1; otherwise, the weight is 0. Then there is another expression of equation (4):

$$\begin{aligned}&C1(m+Lx, Ly, e) = \frac{2}{n(n-1)}\sum\sum_{t<s} K(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e) \times K(Y_{t-Lx}^{Ly}, Y_{s-Lx}^{Ly}, e)\\ &C2(Lx, Ly, e) = \frac{2}{n(n-1)}\sum\sum_{t<s} K(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e) \times K(Y_{t-Lx}^{Ly}, Y_{s-Lx}^{Ly}, e)\\ &C3(m+Lx, e) = \frac{2}{n(n-1)}\sum\sum_{t<s} K(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e)\\ &C4(Lx, e) = \frac{2}{n(n-1)}\sum\sum_{t<s} K(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e)\end{aligned} \tag{5}$$

Among which *t,s* = max*(Lx,Ly)*+1,...,*T*-*m*-1,*n* = *T*+1-*m*-max*(Lx,Ly)*. With a shift of function Kernel, it is able to exclude the values that are under the condition that the distance between two variables surpasses bandwidth *e.*

Using the joint probability in equation (5), the null hypothesis that *Y* does not Granger cause *X* being rejected or not is determined by whether the following equation:

$$\sqrt{n}\left[\frac{C1(m+Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \frac{C3(m+Lx, e, n)}{C4(Lx, e, n)}\right] \sim$$
$$\sim N(0, \sigma^2(m, Lx, Ly, e)) \tag{6}$$

…is established.

To investigate the nonlinear causality between variables X_t and Y_t, this paper applies the vector auto-regressive (VAR) model at first to estimate the residuals of two variables, denoted by ε_t and η_t, which are used to eliminate linear causality. Then the residuals are employed to Hiemstra-Jones nonlinear Granger causality test to examine the nonlinear causality between variables. By such processing, we could consider that any predictive ability detected in the nonlinear test could be regarded as nonlinear.

Nonlinear Granger Causality Test Considering ARCH Effect

Aiming to check the robustness of heteroscedasticity, the autoregressive conditional heteroskedasticity (ARCH) effect of sample data should be considered. Hsieh has observed that many of the nonlinear structures in data are related to the ARCH effect [22]. The assumption of the existence of the ARCH effect is considered as the size of the residual is related to the previous residual value. So the nonlinear Granger causality relationships in residual series which are obtained from the estimation of VAR model between CO_2 emissions and the influence factors are likely to attribute to the ARCH effect. In this case, the nonlinear causality relationships examined from the Hiemstra and Jones test possibly could only be the nonlinear relationships between the lag vectors of residual series of CO_2 emissions and the residual series of different influence factors, not the real nonlinear causality relationships.

Therefore, after the nonlinear causality test, a Q-statistic test should be carried out to check the existence of autocorrelation of residual series of CO_2 emissions and that of its influencing factors. If the autocorrelation phenomena do exist, then we adjust the residual series with the GARCH (1, 1) model and obtain new residual series, which are then used for the Hiemstra and Jones test to examine the nonlinear causality relationships. If not, there is no need to make adjustments.

Results

Linear Granger Causality Test

According to equations (1) and (2), we examine the linear Granger causality relationships between CO_2 emissions and the different influencing factors in this part through the unrestrained VAR model (Table 3).

Table 3 shows that we could not reject most null hypotheses at any regular conventional significance level. The linear Granger causality relationships between CO_2 emissions and most influence factors do not exist, except that there are linear causality relationships from CO_2 emissions to freight traffic volume at 1% significance level, and from CO_2 emissions to GDP and national gross income at 5% significance level.

Table 3. Linear Granger causality test between CO_2 emissions and influence factors.

Null hypothesis	F-statistic	Prob.
GDP does not Granger cause CE	1.05319	0.4502
CE does not Granger cause GDP	3.14761	0.0438*
GNI does not Granger cause CE	0.97410	0.4944
CE does not Granger cause GNI	3.83764	0.0233*
RCL does not Granger cause CE	1.42479	0.3142
CE does not Granger cause RCL	1.23561	0.3860
UP does not Granger cause CE	1.25089	0.3796
CE does not Granger cause UP	0.27492	0.9569
FTV does not Granger cause CE	0.15619	0.9917
CE does not Granger cause FTV	9.94833	0.0019**
GCI does not Granger cause CE	0.00042	0.9838
CE does not Granger cause GCI	3.96502	0.0559
PPA does not Granger cause CE	0.54055	0.7662
CE does not Granger cause PPA	1.90551	0.1847

Notes: ** and * indicate significance at the 1% and 5% levels, respectively.

Nonlinear Granger Causality Test

The nonlinear causality relationships between CO_2 emissions and its influencing factors are tested through the modified Beak and Brock nonlinear causality test proposed by Hiemstra and Jones and illustrated in equation (6). In the test process, variables are obtained from ε_t and η_t, which are residual series in the VAR model. Referring to Hiemstra and Jones, we fix the values for the head length $m = 1$, the common lag lengths $Lx = Ly$ from 1 to 5, and a common scale parameter of $e = 1.5\sigma, \sigma = 1$ [23].

Table 4 shows the results of Hiemstra and Jones test, and *HJ* denotes the *T*-value in equation (6).

Table 4 indicates that from the Hiemstra and Jones test there are unidirectional nonlinear causalities running from CO_2 emissions to residents consumption level, and from the urban population to CO_2 emissions. Meanwhile, the result shows that bidirectional nonlinear causalities exist between CO_2 emissions and GDP, and between CO_2 emissions and the number of private automobiles.

Nonlinear Granger Causality Test Considering ARCH Effect

After examining the residual series of CO_2 emissions and that of its influence factors (which have nonlinear Granger causality relationships with CO_2 emissions), it is suggested that no residual series has an ARCH effect. Therefore, results of nonlinear causality relationships between CO_2 emissions and different influencing factors obtained from previous section are reliable and no adjustments are necessary.

Discussion

Based on the results shown above, further analysis should be done to ensure that the results are consistent with the actual situation.

This paper aims at finding social and economic influencing factors of carbon emissions through linear and nonlinear Granger causality tests, and putting forward policy suggestions to reduce carbon emissions. So only social and economic factors that affect the carbon emissions are further analyzed.

Fitting curves are used to illustrate the causality relationships between carbon dioxide emissions and its influencing factors specifically.

From Fig. 1 we could investigate the impact of GDP on carbon dioxide emissions, generally experiencing a process from rapid to slow.

Fig. 2 shows that from 1980 to 2008, China's GDP growth was relatively slow. But with the growth of GDP,

Table 4. Nonlinear Granger causality test between CO_2 emissions and influence factors.

Lx = Ly	HJ				
	1	2	3	4	5
GDP does not Granger cause CE	-0.001015	0.124026	-0.724064	-1.285045	2.349734*
CE does not Granger cause GDP	1.275314	0.900802	-0.379893	-1.915688	-2.141478*
GNI does not Granger cause CE	0.232877	-0.259049	-1.382743	-1.113652	-0.076728
CE does not Granger cause GNI	0.503685	0.602932	1.176442	1.071874	0.82219
RCL does not Granger cause CE	-0.067023	1.615396	1.108969	1.369673	1.028219
CE does not Granger cause RCL	-1.836628	-2.52367*	-2.174318*	-0.363853	-0.498391
UP does not Granger cause CE	-0.356241	-1.409022	-1.410007	-1.646572	-2.177883*
CE does not Granger cause UP	-1.158132	-1.127682	-1.252923	-0.290485	0.542911
FTV does not Granger cause CE	0.509035	0.964845	0.835455	0.143998	0.040515
CE does not Granger cause FTV	-1.439233	-0.902249	-0.567652	-0.735825	-0.050745
GCI does not Granger cause CE	-1.95006	-1.453969	-2.0549	-1.648554	
CE does not Granger cause GCI	-0.012741	0.491618	1.222561	-0.397605	
PPA does not Granger cause CE	1.304438	0.69254	0.222049	-0.402223	-3.476193**
CE does not Granger cause PPA	-1.710685	-0.78899	-1.226994	-0.402178	-3.303126**

Notes: ** and * indicate significance at the 1% and 5% levels, respectively.

carbon dioxide emissions increased significantly, which was consistent with the actual development of China. In the early stage of reform and opening up, China vigorously developed its economy, including the addition and expansion of many highly polluting and high energy-consuming enterprises, so in the early stage of economic development the amount of carbon dioxide emissions grew rapidly.

However, after 2008 the successful hosting of the 29th Beijing Olympic Games greatly enhanced China's influence in the world. China's economy had developed rapidly, and the GDP had improved significantly. Under the influence of global warming the Chinese government took lots of energy-saving and emissions-reducing measures and achieved remarkable results. As the improvement of technology and energy structure adjusted, the economy developed rapidly and the increase of carbon dioxide emissions had a sharp slowdown, and in the future this continued to be stable or even decreased.

Fig. 3 shows that the impact of the size of the urban population on carbon dioxide emissions at the beginning

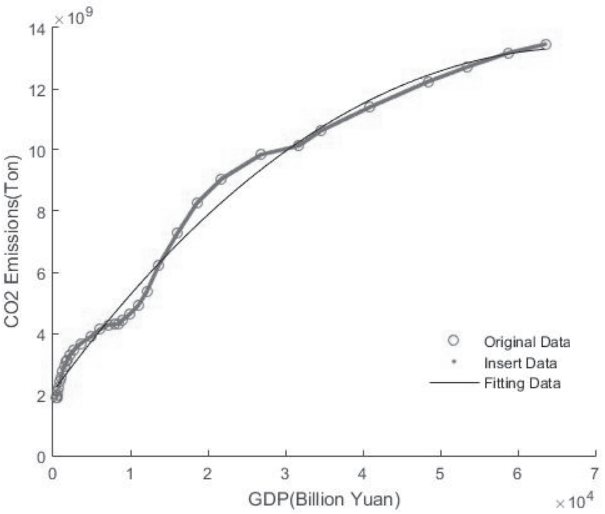

Fig. 1. Nonlinear Granger causality relationships between CO_2 emissions and GDP.

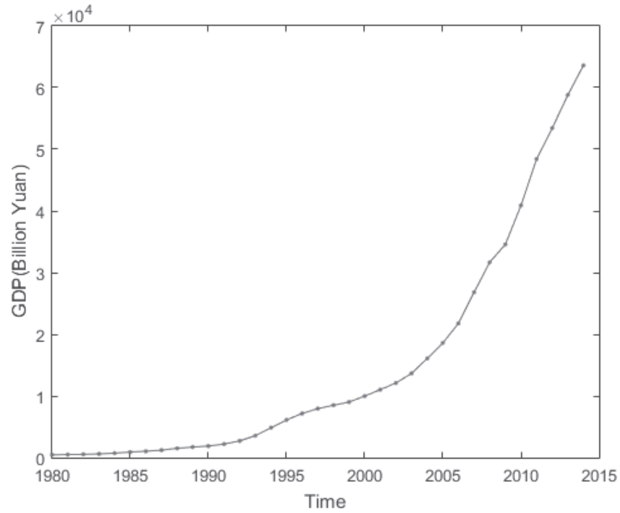

Fig. 2. GDP in China from 1980 to 2015.

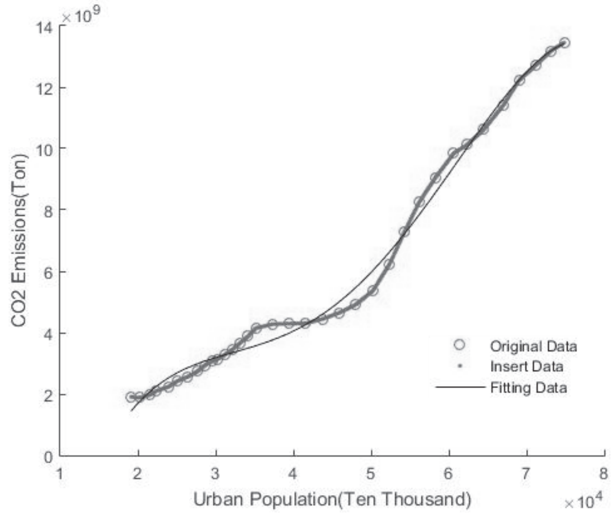

Fig. 3. Nonlinear Granger causality relationships between CO_2 emissions and the urban population.

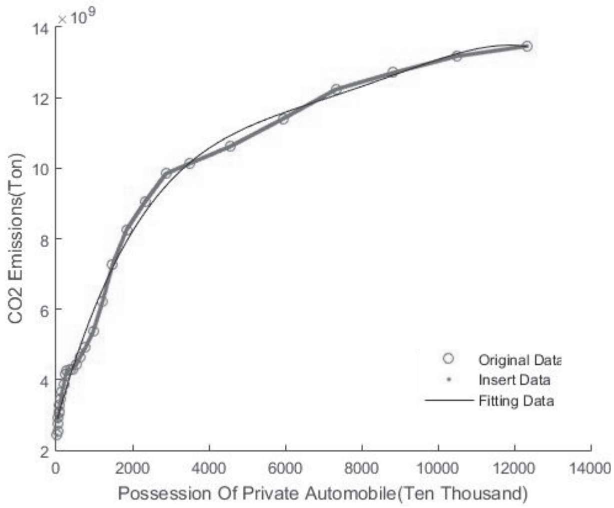

Fig. 5. Nonlinear Granger causality relationships between CO_2 emissions and possession of private automobiles.

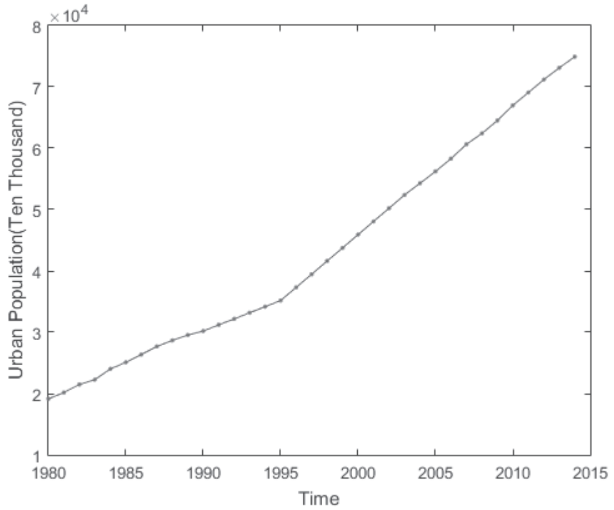

Fig. 4. The urban population in China from 1980 to 2015.

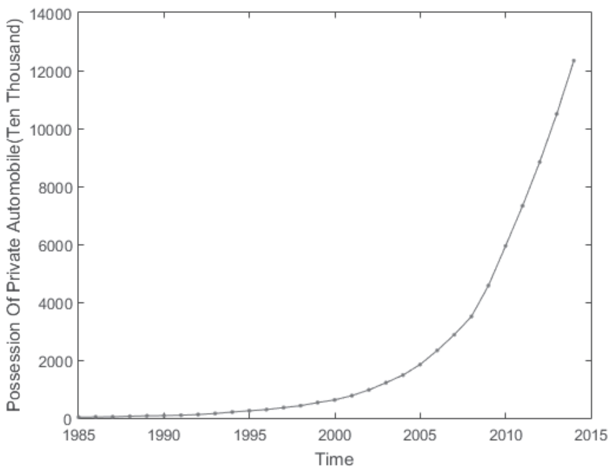

Fig. 6. Possession of private automobiles in China from 1985 to 2015.

is not obvious, but it becomes clearly evident starting in 2003.

In the process of urbanization in China (Fig. 4), the level of urbanization was low at first. As a result, even though there was population shift from rural to urban, the urban people still engaged in simple production activities, which would not cause a substantial increase in carbon emissions.

With the improvement of the level of urbanization in China, when the urban population of reached 500 million people, the increase of the urban population brought large-scale population aggregation and more economic activity. However, people's unawareness of environmental protection caused the promotion of the economy at the expense of the environment, which resulted in more energy consumption and carbon emissions. So the impact of the urban population on carbon dioxide emissions significantly increased at this stage.

Fig. 5 illustrates that the effect of the number of private cars on carbon dioxide emissions experiences a process from fast to slow.

Combined with Fig. 6, we could analyze that when China's ownership of private cars was at a low level, China's economy was still in the initial stages of development, and people were unaware of the importance of environmental protection to economic development. Increases in the number of private cars would result in a large number of polluting gas emissions. Therefore, it significantly increased the amount of carbon dioxide emissions and resulted in environmental pollution.

With economic development, the global warming situation was increasingly grim, and the whole country strengthened the work of energy conservation and emission reduction. The Chinese government had formulated a series of policies and measures to insure system implementation. However, in 2006 the country did not achieve the goal of energy saving and pollution reduction, which increased the difficulty of energy-saving and emission reduction work as part of China's 11^{th} Five-Year Plan. Since 2007, the impact of the country's policy on energy conservation and emission reduction was particularly far-reaching for the auto industry, which needed to improve production technology, and the car needed to reduce fuel consumption. Therefore, as shown in Fig. 6, in 2007, when the amount of private car ownership reached 30 million, along with the development of energy-saving vehicles and new energy automotive industry, the impact of private car ownership on carbon dioxide emissions gradually slowed.

Conclusions

Results and further analysis show that the causality relationships between GDP, the number of urban population, and the possession of private automobiles are nonlinear, which could not be found only through the linear Granger causality test. Besides, the nonlinear relationships are in accordance with reality. Therefore, this paper combines the linear and nonlinear Granger causality test to study the carbon dioxide emissions and its influencing factors has important significance.

Based on the above results, the following policy recommendations are put forward.

The nonlinear causality relationship from GDP to CO_2 emissions suggests that economic growth is not synchronized with the same increase rate in carbon emissions. Adjusting the industry and energy consumption structure is advisable. Government should control the expansion of energy-intensive industries and build the high-tech and knowledge economy to accelerate the third industry, in the meantime promoting hydro-energy, wind power, solar, and nuclear energy instead of fossil energy.

The nonlinear causality relationship running from the urban population to CO_2 emissions indicates that the accelerated urbanization process in China does increase CO_2 emissions. So it is reasonable to improve urban population awareness of energy conservation and emission reduction, and advocate green life and green travel, such as the use of energy-saving appliances, recycling and reuse of items, and public transportation priorities.

The nonlinear Granger causality relationship from the possession of private automobiles to CO_2 emissions is presented with technology improvement, but the growth number of private cars does not necessarily cause an increase in CO_2 emissions. It remains important to actively promote electric vehicles, vehicle power batteries, and other new power research to establish a green transportation system.

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