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
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 of 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\textsubscript{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\textsubscript{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.

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Abbreviation</th>
<th>Definition</th>
<th>Unit of Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>China’s Gross Domestic Product</td>
<td>GDP</td>
<td>Calculated according to the market price of China’s final results of production activities of all the permanent units in a certain period</td>
<td>Billion Yuan</td>
</tr>
<tr>
<td>National Gross Income</td>
<td>GNI</td>
<td>The final results of the initial distribution of income in China in a year</td>
<td>Billion Yuan</td>
</tr>
<tr>
<td>Resident Consumption Level</td>
<td>RCL</td>
<td>The consumption expenditure of the resident population on average of China</td>
<td>Yuan</td>
</tr>
<tr>
<td>Urban Population</td>
<td>UP</td>
<td>The entire resident population residing in urban areas</td>
<td>10\textsuperscript{4} Persons</td>
</tr>
<tr>
<td>Freight Traffic Volume</td>
<td>FTV</td>
<td>The weights of the actual delivery of goods within a certain period</td>
<td>10\textsuperscript{4} Tons</td>
</tr>
<tr>
<td>Gross Output Value of Construction Industry</td>
<td>GCI</td>
<td>The total of construction products and services of construction enterprises in the form of money in a certain period</td>
<td>Billion Yuan</td>
</tr>
<tr>
<td>Possession of Private Automobile</td>
<td>PPA</td>
<td>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</td>
<td>10\textsuperscript{4}</td>
</tr>
<tr>
<td>Carbon Dioxide Emissions</td>
<td>CE</td>
<td>Total emissions as calculated from the consumption of primary energies, including coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and nature gas</td>
<td>Tons</td>
</tr>
</tbody>
</table>

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.
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 $X_{t-i} = (X_{t-1}, X_{t-2}, ..., X_{t-i})$, $i > 0$ and $j$-length lagged past information of $Y_t$, say $Y_{t-j} = (Y_{t-1}, Y_{t-2}, ..., Y_{t-j})$, $j > 0$. Let $F(X_t | I_{t-1})$ be the conditional probability distribution of $X_t$ given the conditional information set $I_{t-1}$. Then $F(X_t | I_{t-1} - Y_{t-j})$ 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 $Y$ is the Granger cause of $X$, could be brought forth. It is the same if:

$$F(Y_t | I_{t-1}) > F(Y_t | I_{t-1} - X_{t-i})$$

...in which case the time series $X$ is the Granger cause of $Y$. 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):

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

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

...within which $\varepsilon_t \sim N(0, \delta^2)$ and $\eta_t \sim N(0, \delta^2)$. 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:

$$H_0 \sqsupseteq \beta_j = ... = \beta_j = 0$$

If there are at least a parameter value of $\beta_j$ 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 $Y_{t-Ly}^{Ly}$, we obtain the following representations.

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

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

$$\text{Pr}\left[\left\|X_{t}^{m} - X_{t}^{*}\right\| < e, \left\|X_{t-Lx}^{Lx} - X_{t-Lx}^{*}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{t-Ly}^{*}\right\| < e\right]$$

$$= \text{Pr}\left[\left\|X_{t}^{m} - X_{t}^{*}\right\| < e, \left\|X_{t-Lx}^{Lx} - X_{t-Lx}^{*}\right\| < e\right]$$

(3)

...where $\text{Pr}(\cdot)$ represents probability and $\|\cdot\|$ 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.

$$C1(m + Lx, Ly, e) = \text{Pr}\left[\left\|X_{t}^{m} - X_{t}^{*}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{t-Ly}^{*}\right\| < e\right]$$
$$C2(Lx, Ly, e) = \text{Pr}\left[\left\|X_{t-Lx}^{Lx} - X_{t-Lx}^{*}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{t-Ly}^{*}\right\| < e\right]$$
$$C3(m + Lx, e) = \text{Pr}\left[\left\|X_{t-Lx}^{Lx} - X_{t-Lx}^{*}\right\| < e\right]$$
$$C4(Lx, e) = \text{Pr}\left[\left\|X_{t-Lx}^{Lx} - X_{t-Lx}^{*}\right\| < e\right]$$

(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 $Ly \geq 1$ 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):

$$C1(m + Lx, Ly, e) = \frac{2}{n(n-1)} \sum_{t,s = T-m,...,T} K(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e) \times K(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)$$
$$C2(Lx, Ly, e) = \frac{2}{n(n-1)} \sum_{t,s = T-m,...,T} K(X_{t-Lx}^{Lx}, X_{t-Lx}^{Lx}, e) \times K(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)$$
$$C3(m + Lx, e) = \frac{2}{n(n-1)} \sum_{t,s = T-m,...,T} K(X_{t-Lx}^{Lx}, X_{t-Lx}^{Lx}, e)$$
$$C4(Lx, e) = \frac{2}{n(n-1)} \sum_{t,s = T-m,...,T} K(X_{t-Lx}^{Lx}, X_{t-Lx}^{Lx}, e)$$

(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:

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

(6)

...is established.

To investigate the nonlinear causality between variables $X_t$ and $Y_t$, this paper applies the vector autoregressive (VAR) model at first to estimate the residuals of two variables, denoted by $\epsilon_t$ and $\eta_t$, 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions and most influence factors do not exist, except that there are linear causality relationships from CO₂ emissions to freight traffic volume at 1% significance level, and from CO₂ emissions to GDP and national gross income at 5% significance level.

Nonlinear Granger Causality Test

The nonlinear causality relationships between CO₂ 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 et, ηt, 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 length Lx = Ly from 1 to 5, and a common scale parameter of e = 1.5σ, σ = 1 [23].

Table 4 shows the results of the 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 CO₂ emissions to residents consumption level, and from the urban population to CO₂ emissions. Meanwhile, the result shows that bidirectional nonlinear causalities exist between CO₂ emissions and GDP, and between CO₂ emissions and the number of private automobiles.

Nonlinear Granger Causality Test Considering ARCH Effect

After examining the residual series of CO₂ emissions and that of its influencing factors (which have nonlinear Granger causality relationships with CO₂ emissions), it is suggested that no residual series has an ARCH effect. Therefore, results of nonlinear causality relationships between CO₂ 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,
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 of economic development was highly significant. The number of urban residents increased steadily, and the amount of carbon dioxide emissions increased accordingly. However, after 2008 the Chinese government took measures to control urban population growth and the amount of carbon dioxide emissions showed a downward trend.

Table 4. Nonlinear Granger causality test between CO$_2$ emissions and influence factors.

<table>
<thead>
<tr>
<th>Lx = Ly</th>
<th>GDP does not Granger cause CE</th>
<th>CE does not Granger cause GDP</th>
<th>GNI does not Granger cause CE</th>
<th>CE does not Granger cause GNI</th>
<th>RCL does not Granger cause CE</th>
<th>CE does not Granger cause RCL</th>
<th>UP does not Granger cause CE</th>
<th>CE does not Granger cause UP</th>
<th>FTV does not Granger cause CE</th>
<th>CE does not Granger cause FTV</th>
<th>GCI does not Granger cause CE</th>
<th>CE does not Granger cause GCI</th>
<th>PPA does not Granger cause CE</th>
<th>CE does not Granger cause PPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.001015</td>
<td>1.275314</td>
<td>0.232877</td>
<td>0.503685</td>
<td>-0.067023</td>
<td>-1.836628</td>
<td>-0.356241</td>
<td>-1.158132</td>
<td>0.509035</td>
<td>-1.439233</td>
<td>-1.95006</td>
<td>-0.012741</td>
<td>1.304438</td>
<td>-1.710685</td>
</tr>
<tr>
<td>2</td>
<td>0.124026</td>
<td>0.900802</td>
<td>-0.259049</td>
<td>0.602932</td>
<td>1.615396</td>
<td>-2.52367*</td>
<td>-1.409022</td>
<td>-1.127682</td>
<td>0.964845</td>
<td>-0.902249</td>
<td>-1.453969</td>
<td>0.491618</td>
<td>0.69254</td>
<td>-0.78899</td>
</tr>
<tr>
<td>3</td>
<td>-0.724064</td>
<td>-0.379893</td>
<td>-1.382743</td>
<td>1.176442</td>
<td>1.108969</td>
<td>-2.174318*</td>
<td>-1.410007</td>
<td>-1.252923</td>
<td>0.835455</td>
<td>-0.567652</td>
<td>-2.0549</td>
<td>1.222561</td>
<td>0.222049</td>
<td>-1.226994</td>
</tr>
<tr>
<td>4</td>
<td>-1.285045</td>
<td>-1.915688</td>
<td>-1.113652</td>
<td>1.071874</td>
<td>1.369673</td>
<td>-0.363853</td>
<td>-1.646572</td>
<td>-0.290485</td>
<td>0.143998</td>
<td>-0.735825</td>
<td>-1.648554</td>
<td>-0.397605</td>
<td>-0.402223</td>
<td>-0.402178</td>
</tr>
<tr>
<td>5</td>
<td>2.349734*</td>
<td>-2.141478*</td>
<td>-0.076728</td>
<td>0.82219</td>
<td>1.028219</td>
<td>-0.498391</td>
<td>-2.177883*</td>
<td>0.542911</td>
<td>0.040515</td>
<td>-0.050745</td>
<td>-0.076728</td>
<td>0.82219</td>
<td>0.040515</td>
<td>-0.303126**</td>
</tr>
</tbody>
</table>

Notes: ** and * indicate significance at the 1% and 5% levels, respectively.
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 assure 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 11th 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 CO₂ 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 CO₂ emissions indicates that the accelerated urbanization process in China does increase CO₂ 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 CO₂ emissions is presented with technology improvement, but the growth number of private cars does not necessarily cause an increase in CO₂ emissions. It remains important to actively promote electric vehicles, vehicle power batteries, and other new power research to establish a green transportation system.

Acknowledgements
This work was supported by the Social Science Foundation of Hebei Province of China, industrial carbon emissions forecast and emission reduction scenario design for key industries (HB15YJ040).

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