Gasoline to Diesel Consumption Ratio: A New Socioeconomic Indicator of Carbon Dioxide Emissions in China

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Abstract: In recent years, gross domestic product (GDP) has grown rapidly in China, but the growth rate of carbon dioxide (CO₂) emissions has begun to decline. Some scholars have put forward the environmental Kuznets curve (EKC) hypothesis for CO₂ emissions in China. This paper utilized the panel data of 30 provinces in China from 1997 to 2016 to verify the EKC hypothesis. To explore the real reasons behind the EKC, the index gasoline to diesel consumption ratio (GDCR) was introduced in this paper. The regression results showed that CO₂ emissions and GDP form an inverted U-shaped curve. This means that the EKC hypothesis holds. The regression results also showed that a 1% GDCR increase was coupled with a 0.118186% or 0.114056% CO₂ emission decrease with the panel fully modified ordinary least squares or panel dynamic ordinary least squares method, respectively. This means that CO₂ emissions negatively correlate with GDCR. From the discussion of this paper, the growth rate reduction of CO₂ emissions is caused by the economic transition in China. As changes of GDCR can, from a special perspective, reflect the economic transition, and as GDCR is negatively correlated with CO₂ emissions, GDCR can sometimes be used as a new socioeconomic indicator of carbon dioxide emissions in China.

Keywords: environmental Kuznets curve; carbon dioxide emissions; gasoline to diesel consumption ratio; China

1. Introduction

There is considerable evidence proving that global warming is very likely to be caused by carbon dioxide (CO₂) emissions and fossil fuel consumption is the main reason for CO₂ emissions [1,2]. In the past 30 years, China has experienced rapid growth in its economy and energy consumption. The problem of CO₂ emissions has become much more important for China [3].

In recent years, the gross domestic product (GDP) still grows rapidly in China, but the growth rate of CO₂ emissions has begun to decline for the whole of China and for some Chinese provinces [3]. Based on this, some scholars have hypothesized that the CO₂ emissions in China will form an inverted U-shaped curve with respect to GDP [4–6]. This hypothesis is called the environmental Kuznets curve (EKC) for CO₂ emissions in China.

This paper utilized the panel data from 1997 to 2016 of 30 provinces in China to verify the EKC hypothesis. To investigate the real reasons behind EKC and the underlying motivation of the reduction of the CO₂ emission growth rate, a new index—the gasoline to diesel consumption ratio (GDCR)—was introduced in this paper. The index, GDCR, means the ratio of gasoline consumption to diesel consumption of a particular region. In China, as passenger cars almost always use gasoline and...
commercial vehicles almost always use diesel, the changes of GDCR can reflect the economic transition in China. If the industrial economy grows, the usage of commercial vehicles (especially heavy trucks) will increase, so diesel consumption will increase and GDCR will decrease; if the service economy grows, the usage of passenger cars will increase, gasoline consumption will increase, and GDCR will increase. Therefore, from the perspective of the transportation utilization of different economic sectors, the changes of GDCR can reflect the economic transition in China, and the reflection of GDCR to economic structure is quite different from using the output value to represent the economic structure. The output value is only one of the dimensions, and the output value alone cannot represent the reason of the structural change of CO2 emissions. GDCR also cannot represent the change of CO2 emissions, but it can provide a new perspective for CO2 emission studies. Moreover, if the correlation between GDCR and CO2 emissions can be verified, GDCR may become a new indicator of CO2 emissions.

Figure 1 shows the historical data of the GDP, CO2 emissions, GDCR, diesel consumption, and gasoline consumption of the whole of China from 1997 to 2016. As shown in Figure 1, the CO2 emission growth rate began to decrease from 2011 with the rapid growth of GDP; GDCR formed a U-shaped curve over time, which was just the opposite of the CO2 emissions.

The initial idea of this paper was generated from plant optimization research for refineries. In the oil refining industry, the gasoline to diesel production ratio (GDPR) is an important index for facilities and for refineries. Refineries have to work hard to adjust the GDPR to meet the GDCR. In this research, we found that GDCR is influenced by changes in economic structure and can reflect the economic transition. Once we started to study the EKC for CO2 emissions in China, we thought of the index GDCR and began to consider the relationship between CO2 emissions and GDCR. This is the initial idea of this paper.

Previous studies of EKC for CO2 emissions have revealed the inverse U-shaped curve of CO2 emissions and GDP in China, but they have failed to reveal precisely all the indicators of CO2 emissions and do not use GDCR. This paper has introduced GDCR, and this is the main innovation of this paper. This paper will combine the environmental Kuznets curve of GDCR and CO2 emissions to prove the correlation between GDCR and CO2 emissions. This paper assumes that GDCR will be negatively correlated with CO2 emissions. In other words, the increase of gasoline consumption will reduce China’s CO2 emissions, and the reduction of diesel consumption will reduce China’s CO2 emissions. Therefore, GDCR becomes a new socioeconomic indicator of carbon dioxide emissions in China.

The rest of this paper is written as follows. Section 2 is the literature review. Section 3 describes the data, model, and regression methods. Section 4 shows the empirical results and the discussion, and Section 5 is the conclusion.
2. Literature Review

The concept of the Kuznets curve was introduced by Kuznets [7] to describe the inverted U-shaped relationship of income inequality and economic growth. From the 1990s, the Kuznets curve was used in pollutant emission studies. Grossman and Krueger [8] first proposed that pollutant emissions and per capita income form an inverted U-shaped curve. Panayotou [9] first used the term EKC to name this phenomenon. Since then, the EKC has been investigated by many scholars [10]. Among them, Dinda [11] pointed out that the economic transition and fortune changes of a country and people's increasing preference for environmental quality are the real reasons for the EKC.

Following its initial use for environmental quality, EKC was used to research CO$_2$ emissions; this kind of research was called EKC for CO$_2$ emissions. Moomaw and Unruh [12] first used EKC to study CO$_2$ emissions and GDP. Using data from 16 countries, they demonstrated that CO$_2$ emissions also prove a third-order polynomial relation, an N-shaped curve with GDP, in addition to a second-order polynomial relation, a U-shaped curve. This means that whether the curve is U-shaped or N-shaped may not be decided by the data, but by the type of the econometric model that has been selected. Subsequently, Sun [13] said that the EKC for CO$_2$ emissions merely reflected the peak theory of energy intensity. Sun's view could explain some fundamental influence of energy efficiency on CO$_2$ emissions, but obviously his paper did not consider the impact of economic transitions and energy transitions on CO$_2$ emissions. After these early studies, many different empirical studies of EKC for CO$_2$ emissions were conducted for various countries and regions. Using the panel data of five regions in Canada from 1970 to 2000, Lantz [14] studied the non-linear relationship between CO$_2$ emissions and their influencing factors, and proved that CO$_2$ emissions had nothing to do with per capita GDP, but had an inverted U-shaped relationship with population and a U-shaped relationship with technology. Saboori [15] used the data of Malaysia from 1980 to 2009 to verify the hypothesis of the environmental Kuznets curve, and proved that the relationship between carbon dioxide emissions and GDP is inverted U-shaped, which supports the EKC hypothesis. Galeotti [16] proved that the carbon emissions of OECD (Organization for Economic Co-operation and Development) countries are in line with EKC, while non-OECD countries show different situations according to different data sources. Using panel data from 11 OECD countries, Iwata [17] studied the role of nuclear energy in the environmental Kuznets curve of CO$_2$ emissions, and proved that Finland, Japan, South Korea, and Spain meet the EKC hypothesis, and also that nuclear energy can only reduce CO$_2$ emissions for some countries. Using data from 19 European countries, Acaravci [18] demonstrated the environmental Kuznets curve for carbon dioxide emissions in Denmark, Germany, Greece, Iceland, Italy, Portugal, and Switzerland. Using the data of 12 countries in the Middle East and North Africa (MENA) from 1981 to 2005, Arouri [19] proved that the hypothesis of environmental Kuznets curve holds for CO$_2$ emissions of MENA, but the turning point is very low and the inverted U-shaped relationship is not obvious. To summarize the above, generally speaking, the hypothesis of the environmental Kuznets curve of CO$_2$ emissions may be true for high-income countries, but not for low-income countries.

In recent years, as China has become a major carbon dioxide emitter, the EKC for CO$_2$ emissions in China has attracted much scholarly research. Kang, Zhao, and Yang [5] used panel data from the years 1997–2012 from Chinese provinces and compared the non-spatial and the spatial panel models. They found that Eastern China has had a sharper increase in CO$_2$ emissions than Western China and that, compared to urbanization and coal consumption, trade has had little effect on CO$_2$ emissions. Using provincial-level data of 1995–2014 in China, Dong, Sun, Hochman, Zeng, Li, and Jiang [4] not only examined the EKC for CO$_2$ emissions, but also investigated the influence of natural gas consumption on CO$_2$ emissions. They found that the EKC appears mainly for Eastern and Central provinces in China, and natural gas consumption shows a positive influence on CO$_2$ emission reduction.

All the above papers are about EKC, but to research the impact factors and indicators of CO$_2$ emissions, some scholars have tried from other perspectives and used other kinds of models. Among them, Fan, et al. [20] used the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model and found that population, income, and energy intensity (technology)
correlated strongly with CO₂ emissions. Li et al. [21] used the STIRPAT model and found that GDP, population, urbanization, economic structure, and technology level were factors impacting CO₂ emissions. Wang et al. [22] used an extended STIRPAT model and found that population, GDP, technology level, urbanization, economic structure, energy structure, and foreign trade were factors impacting CO₂ emissions. To summarize the studies of the impact factors of CO₂ emissions, there were some similarities of these studies. They used the same kind of models, either the STIRPAT model or the extended STIRPAT model; they found similar impact factors of CO₂ emissions, population, income (or GDP), energy intensity (technology level), urbanization, industrial structure, energy structure, foreign trade, and so on.

Another kind of reference of this paper are the studies of the gasoline to diesel consumption ratio (GDCR). When it comes to the literature review of the gasoline to diesel ratio, as far as we know, most of the papers with the keywords of either the gasoline to diesel ratio or diesel to gasoline ratio (or something like this) can be divided into two categories. One category is about the research of blended combustion for the internal combustion engine [23, 24]. The other category is about the research of product optimization for oil processing [25, 26]. The research with the keywords of the ratio of gasoline to diesel ratio (or something like this) seldom belongs to the field of macroeconomics. Chang and Zhang [27] found that emission allowance prices exhibit co-movement with diesel and gasoline prices in China using the GARCH (generalized autoregressive conditional heteroskedasticity) method with Copula function. Dahl [28] studied the price elasticity and income elasticity of gasoline and diesel, and gave policy suggestions for more than 100 countries. Karagiannis et al. [29] tested the short-term and long-term conduction effect of crude oil prices to gasoline and diesel retail prices in Germany, France, Italy, and Spain, but above all, their studies did not use the ratio of gasoline to diesel, or even the ratio of the price of gasoline and diesel. We have not yet found any macroeconomic research about GDCR.

In summary, previous research on EKC and CO₂ emissions have made a lot of achievements and have used various kinds of data and regression methods. However, the actual problem of finding the real reason behind EKC has not been solved. To the best of our knowledge, the relevant literature has not introduced the index of GDCR into the EKC and CO₂ emissions studies. Based on this, this paper introduces the GDCR.

3. Methodology

3.1. Variables

To verify the EKC hypothesis, this paper chose CO₂ emissions per capita as the dependent variable and GDP per capita and its square as independent variables [30]. Because CO₂ emissions are influenced by the economic transition and GDCR can reflect the economic transition from the perspective of transportation needs, GDCR was also chosen as one of the independent variables.

3.2. Model

Quantitative regression was used in the empirical study of this paper, and the first-order linear equation was chosen as the regression model. According to the selection of variables mentioned above, the econometric model is shown in Formula (1).

\[
\ln PCCDE = a \times \ln PCGDP + b \times (\ln PCGDP)^2 + c \times \ln GDCR + r
\]  

(1)

PCCDE represents per capita CO₂ emissions; PCGDP represents the per capita GDP; ln denotes the logarithm of the data; \((\ln PCGDP)^2\) represents the square of the logarithm of PCGDP; GDCR represents the gasoline to diesel consumption ratio; \(a\), \(b\), and \(c\) are the parameters that need to be estimated; and \(r\) is the residue of estimation.
In the regression results, if the parameter of the GDP square was negative, that means that CO$_2$ emissions and GDP formed an inverted U-shaped curve, so the EKC hypothesis held [31]; if the parameter of GDCR was negative, that means GDCR was negatively correlated with CO$_2$ emissions.

3.3. Data

There are 34 provinces in China, but the data of Hong Kong, Macao, Taiwan, and Tibet were vacant, so this paper used panel data of 30 provinces from 1997 to 2016 in China. The data source was the National Bureau of Statistics, China. The data of CO$_2$ emissions were calculated mainly using the method proposed by Dong, Sun, Hochman, Zeng, Li, and Jiang [4], with some modification: Dong’s method calculated CO$_2$ emissions by end-side energy consumption data, whereas this paper used the primary energy consumption data. The data of GDP used the unit of RMB (Unit of Chinese money), and they were normalized to 1997 prices. The statistic table, distribution curve, and scatter plot of the data are shown in Table 1 and Figure 2. As shown in Table 1, the number of observations was 600 and the statistical description of variables, such as standard deviation, kurtosis, and skewness, can be viewed from Table 1 and Figure 2.

| Stats Results | ln PCCDE | ln PCGDP | (ln PCGDP)$^2$ | ln GDCR |
|---------------|----------|----------|----------------|---------|
| Mean          | 1.698    | 9.553    | 91.881         | −0.104  |
| Median        | 1.685    | 9.612    | 92.386         | −0.283  |
| Maximum       | 3.609    | 11.221   | 125.919        | 2.847   |
| Minimum       | −0.742   | 7.604    | 57.828         | −1.572  |
| Std. Deviation| 0.712    | 0.790    | 15.054         | 0.802   |
| Skewness      | 0.058    | −0.074   | 0.068          | 1.182   |
| Kurtosis      | 3.424    | 2.141    | 2.153          | 4.278   |
| Cross sections| 30       | 30       | 30             | 30      |
| Observations  | 600      | 600      | 600            | 600     |

Figure 2. Box chart of variables from 30 China provinces in 1997–2016.

3.4. Statistical Test and Parameter Estimation

In order to test the stability of the sample sequence, the variables were subjected individually to the LLC (Levin-Lin-Chu) unit root test and the ADF-Fisher test in level and first difference, respectively. If the variables passed the LLC and ADF-Fisher tests, the variables were stationary. Then, all the variables together were subjected to a panel Padron co-integration test [32]. If the variables passed the panel Padron co-integration test, that means that there were co-integration vectors between variables and the variables could be regressed. The estimation methods used in this paper were the method of panel fully modified ordinary least squares (FMOLS) [33] and panel dynamic ordinary least squares (DOLS) [34].
4. Results and Discussion

4.1. Results of Unit Root Test

Table 2 shows the results of the unit root test by the LLC method and the ADF–Fisher method. Only "ln PCGDP" and "(ln PCGDP)^2" passed the LLC test at levels, and all variables passed the LLC test and ADF-fisher test at first difference. This means that all variables were stationary at first difference.

Table 2. Results of unit root test.

| Variable    | LLC test Level | Intercept & Trend | None | Intercept & Trend | None | Intercept & Trend | None |
|-------------|----------------|-------------------|------|-------------------|------|-------------------|------|
| ln PCGDE    | 2.958          | -0.800            | 4.997| -5.765 ***        | -6.181 *** | -10.965 ***   |
| ln PCGDP    | 2.147          | -6.471 ***        | 9.291| -3.393 ***        | -3.584 *** | -3.907 ***   |
| (ln PCGDP)^2| 0.119          | -5.151 ***        | 8.442| -3.093 ***        | -3.903 *** | -3.562 ***   |
| ln GDCR     | 2.631          | -0.355            | -0.079| -16.809 ***      | -18.561 *** | -22.178 *** |

ADF–Fisher test

| ln PCGDE    | 45.306         | 23.978            | 14.281| 109.649 ***      | 158.540 *** | 229.143 *** |
| ln PCGDP    | 48.361         | 51.064            | 8.277 | 48.590           | 90.594 ***  | 62.954      |
| (ln PCGDP)^2| 61.344         | 42.921            | 14.382| 45.674           | 89.946 ***  | 59.117      |
| ln GDCR     | 43.441         | 74.352            | 56.135| 305.024 ***      | 361.043 *** | 509.589 *** |

Note: ***, **, and * represent 1%, 5%, and 10% statistical significance.

4.2. Results of Co-Integration Test

The results of the unit root test showed that all variables were stationary at first difference. Then, they were subjected to a Pedroni co-integration test; the results are shown in Table 3. For the model with the intercept, five of the seven results negated the non-co-integration hypothesis with a 95% confidence level. Hence, there was a long-term co-integration relationship among CO2 emissions, GDP, and GDCR.

Table 3. Results of panel Pedroni co-integration test.

| Test         | Intercept & Trend | Intercept | None |
|--------------|-------------------|-----------|------|
| Panel v-Statistic | 0.943         | 1.739 **  | 1.281 *  |
| Panel rho-Statistic | 3.492         | 0.980     | 0.336  |
| Panel PP-Statistic | -2.279 **     | -2.777 ***| -1.715 **|
| Panel ADF-Statistic | -7.467 ***    | -6.977 ***| -3.843 ***|
| Group rho-Statistic | 4.615         | 2.843     | 2.563  |
| Group PP-Statistic | -2.994 ***    | -2.581 ***| -1.059 |
| Group ADF-Statistic | -7.983 ***    | -7.578 ***| -3.310 ***|

Note: ***, **, and * represent 1%, 5%, and 10% statistical significance.

4.3. Results of Parameter Estimation

As the test results show, the panel data of the China provinces passed the co-integration test. Table 4 shows the results of the parameter estimation obtained by the FMOLS method and the DOLS method. The regression results of the panel data showed that the CO2 emissions formed an inverted U-shaped curve with respect to GDP. This means that the EKC hypothesis held.

The regression results of the panel data also showed that a 1% GDCR increased couples with 0.118186% or 0.114056% decreases in CO2 emissions by the panel fully modified ordinary least squares (FMOLS) or panel dynamic OLS (DOLS) method, respectively. This means that GDCR negatively correlated with CO2 emissions.
was neither negative nor positive, but irrelevant.

Sustainability 2020, 12, 5608

Table 4. Parameters of long-run estimation of China provinces and panel data.

| Province    | PCGDP (in Log) | CO₂ emissions (in Log) |
|-------------|----------------|------------------------|
| Beijing     | 8.924 [1.961]  | -0.438 [-1.987]        |
| Tianjin     | 6.275 [2.079]  | -0.295 [-2.728]        |
| Hebei       | 1.862 [2.579]  | -0.070 [-1.742]        |
| Shanxi      | -1.233 [-1.074] | 0.084 [1.380]          |
| Inner Mongolia | 1.131 [0.642]  | -0.017 [-1.900]        |
| Liaoning    | 4.906 [5.861]  | -0.181 [-5.226]        |
| Jilin       | -1.190 [-1.081] | 0.080 [1.613]          |
| Heilongjiang| -1.986 [-1.027] | 0.136 [1.341]          |
| Shanghai    | 7.613 [4.896]  | -0.365 [-4.469]        |
| Jiangsu     | 2.710 [1.807]  | -0.104 [-1.300]        |
| Zhejiang    | -9.144 [-2.489] | 0.510 [2.715]          |
| Anhui       | 0.791 [2.254]  | -0.099 [-0.272]        |
| Fujian      | 5.968 [3.030]  | -0.226 [-2.533]        |
| Jiangxi     | -1.213 [-0.749] | 0.097 [1.101]          |
| Shanxi      | 3.772 [1.365]  | -0.153 [-1.092]        |
| Henan       | 9.921 [3.991]  | -0.288 [-3.607]        |
| Hubei       | 4.998 [3.316]  | -0.242 [-3.043]        |
| Hunan       | 4.578 [1.001]  | -0.218 [-0.896]        |
| Guangdong   | 5.616 [2.865]  | 0.256 [-2.574]         |
| Guangxi     | 2.640 [1.991]  | -0.104 [-1.427]        |
| Hainan      | 18.147 [2.452] | 0.892 [-2.223]         |
| Chongqing   | 1.499 [0.699]  | -0.066 [-0.624]        |
| Sichuan     | 9.685 [3.087]  | -0.510 [-2.938]        |
| Guizhou     | 5.440 [4.630]  | -0.278 [-4.232]        |
| Hunan       | 12.497 [3.164] | -0.659 [-3.079]        |
| Shanxi      | 0.295 [-0.229] | 0.062 [0.952]          |
| Guizhou     | 1.294 [1.904]  | 0.044 [-1.163]         |
| Qianghai    | -5.466 [-2.904] | 0.313 [-1.166]        |
| Ningxia     | 3.967 [1.297]  | -0.161 [-1.022]        |
| Xiangjiang  | -8.126 [-4.236] | 0.487 [4.469]          |
| Panel       | 2.276 [4.749]  | -0.090 [-3.604]        |

Note: ***, **, and * represent 1%, 5%, and 10% statistical significance. T-statistics are shown in square brackets.

For 30 provinces in China, the regression results were quite different. Figure 3 shows the colored map of various provinces; Figure 3a,b show the relationship between GDP and CO₂ emissions; Figure 3c,d show the relationship between GDCR and CO₂ emissions. Figure 3 shows a colored map of China’s provinces. In Figure 3a,b, in the green provinces, the CO₂ emissions formed an inverted U-shaped curve with respect to GDP. In the red provinces, the CO₂ emissions formed a U-shaped curve, and in the yellow provinces, the CO₂ emissions formed neither an inverted U-shaped curve nor a U-shaped curve, but an approximately linear line. In Figure 3c,d, in the green provinces, the CO₂ emissions had a negative correlation with GDCR. In the red provinces, the CO₂ emissions had a positive correlation with GDCR, and in the yellow provinces, the correlation between CO₂ emissions and GDCR was neither negative nor positive, but irrelevant.

4.4. Results of Residual Test

The residuals of the FMOLS and DOLS were subjected to a unit root test, LLC, ADF-Fisher, and PP-Fisher. The results of the residual stationarity test are shown in Table 5. As shown in Table 5, the residuals of the FMOLS and DOLS passed the unit root test. Therefore, the residuals were stationary sequences, proving the real existence of the co-integration relationship between variables.

Table 5. Results of residual stationarity test.

| Test          | FMOLS       | DOLS        |
|---------------|-------------|-------------|
| LLC-Statistic | -5.90949 *** | -18.1992 *** |
| ADF-Fisher-Statistic | 133.160 *** | 370.581 *** |
| PP-Fisher-Statistic  | 151.438 *** | 408.667 *** |

Note: ***, **, and * represent 1%, 5%, and 10% statistical significance.
provinces, the CO$_2$ emissions formed an inverted U-shaped curve with respect to GDP. In the red provinces, the CO$_2$ emissions formed a U-shaped curve, and in the yellow provinces, the CO$_2$ emissions formed neither an inverted U-shaped curve nor a U-shaped curve, but an approximately linear line. In Figure 3(c) and Figure 3(d), in the green provinces, the CO$_2$ emissions had a negative correlation with GDCR. In the red provinces, the CO$_2$ emissions had a positive correlation with GDCR, and in the yellow provinces, the correlation between CO$_2$ emissions and GDCR was neither negative nor positive, but irrelevant.

Figure 3. Colored maps of China provinces that reflect the estimation results. Note: the “not significant” means that the absolute value of the parameter of GDP square or GDCR was less than 0.1, and that means the impact of the variable on CO$_2$ emissions was not significant, which were signed as “not significant”).

4.5. Discussion

From the regression results, some meaningful conclusions can be drawn. Firstly, as GDCR can represent the economic transition and GDCR correlates strongly with CO$_2$ emissions, to some extent, GDCR becomes a new socioeconomic indicator of CO$_2$ emissions in China. Other discussions are shown as follows.

(1) Relationship of CO$_2$ emissions and GDP is independent from the value of GDP

When studying the EKC for CO$_2$ emissions in China, Dong [4] points out that the existence of EKC has nothing to do with the per capita GDP of each province. As a result of this paper, Table 6 shows the types of result curves of CO$_2$ emissions and GDP, the turning point of EKC, and the GDP of the years 1997 and 2016. Figure 4 shows the scatter plots of Table 6. The horizontal axis of Figure 4 shows whether the CO$_2$ emissions of a province conform to the Kuznets curve, and the vertical axis of Figure 4 shows the per capita GDP of the province. In Figure 4, no matter whether the amount of the GDP of an individual province is large or small, the result curve will be either a U-shaped curve or an inverse U-shaped curve, and no matter whether the result curve is U-shaped or inverse U-shaped, the amount of GDP may be either large or small. This means that the relationships between CO$_2$ emissions and GDP are independent from the amount of GDP.

(2) Relationship of CO$_2$ emissions and GDP are associated with economic transition

When studying EKC for air pollutant emissions, Dinda [11] pointed out that a country’s fortunes change—for example, from a clean agrarian economy to a polluting industrial economy to a clean service economy—is the real reason for the EKC. Table 7 shows the relationship between CO$_2$ emissions and GDP, the relationship between CO$_2$ emissions and GDCR, and the percentage of the GDP of various industries of 1997 and 2016.
Table 6. The types of regression curves, turning point, and GDP.

| Province      | FMOLS | DOLS | 1997 | 2016 |
|---------------|-------|------|------|------|
| Type          | TP    | Type | TP   | PCGDP | PCGDP |
| Panel Data    | IU    | 310,036.2 | NS   | 6448.08 | 53,777.40 |
| Beijing       | IU    | 26,561.41 | IU   | 4316.351 | 16,750.73 |
| Liaoning      | IU    | 63,978.24 | IU   | 494,766.9 | 8657.47 |
| Shanghai      | IU    | 33,818.63 | IU   | 46,010.53 | 53,777.40 |
| Jiangsu       | IU    | 455,361.2 | IU   | 27,076.07 | 9454.75 |
| Fujian        | IU    | 223,817 | IU   | 104,737.3 | 74,369.08 |
| Guangdong     | IU    | 58,032.01 | IU   | 39,434.94 | 73,511.15 |
| Hainan        | IU    | 26,162.57 | IU   | 13,353.57 | 44,200.65 |
| Chongqing     | IU    | 61,209.57 | IU   | 11,950.32 | 58,204.04 |
| Sichuan       | IU    | 13,294.4 | IU   | 9409.789 | 39,862.67 |
| Yunnan        | IU    | 13,118.66 | IU   | 25,910.23 | 30,996.48 |
| Hubei         | IU    | 30,592.57 | NS   | 4863.73 | 55,506.17 |
| Tianjin       | IU    | 41,589.09 | NS   | 13,269.99 | 114,503.14 |
| Hebei         | IU    | 389,036.5 | NS   | 6059.43 | 42,932.33 |
| Shandong      | IU    | 225,662.9 | U    | 7441.17 | 68,386.94 |
| Henan         | IU    | 29,129.71 | U    | 4325.05 | 42,458.86 |
| Hunan         | IU    | 36,315.5 | U    | 4407.22 | 46,244.94 |
| Guangxi       | IU    | 325,236.4 | U    | 3922.40 | 37,862.01 |
| Guizhou       | IU    | 17,750.57 | U    | 2234.58 | 33,127.23 |
| Ningxia       | IU    | 224,106.3 | U    | 4237.55 | 46,942.07 |
| Inner Mongolia| NS    | U     | U    | 4959.20 | 71,936.90 |
| Anhui         | NS    | NS    | NS   | 3831.11 | 39,392.54 |
| Gansu         | NS    | U     | U    | 3181.92 | 27,587.62 |
| Shanxi        | U     | U     | U    | 4699.14 | 35,443.81 |
| Jilin         | U     | U     | U    | 5572.07 | 54,068.06 |
| Heilongjiang  | U     | U     | U    | 7111.44 | 40,500.37 |
| Zhejiang      | U     | U     | U    | 10,566.20 | 84,528.37 |
| Jiangxi       | U     | U     | U    | 3869.33 | 40,285.28 |
| Shanxi        | U     | U     | U    | 3819.61 | 50,877.50 |
| Qinghai       | U     | U     | U    | 4088.51 | 43,380.94 |
| Xinjiang      | U     | U     | U    | 6052.68 | 40,240.62 |

Note: IU means inverted U-shaped. U means U-shaped, NS means not significant. TP is represented by GDP per capita and means the turning point of EKC. The calculation of turning points uses the symmetry axis formula of quadratic function. 1997 and 2016 are the first and last years of GDP data used in this paper. China’s GDP continued to grow from 1997 to 2016. From 1997–2016, the GDP datum of 1997 is just the minimum value of all data, and the GDP datum of 2016 is the maximum value.

Figure 4. Scatter plot of the type of result curves and PCGDP. Note: IU means inverted U-shaped. U means U-shaped, NS means not significant. PCGDP means GDP per capita (YUAN, nominal GDP per capita).
Table 7. Regression results and economic structure.

| Provinces     | Relationship between Variables | Percentage of Different Industries |
|---------------|--------------------------------|-----------------------------------|
|               | CDE and GDP                    | CDE and GDCR                      | Primary Industry | Secondary Industry | Tertiary Industry |
|               | FMOLS DOLS                     | FMOLS DOLS                        | 1997    | 2016 Difference | 1997    | 2016 Difference | 1997    | 2016 Difference |
| Whole China   | IU NS N N                      | 17.90% 8.13% −9.77%              | 47.10% 40.07% −7.03% | 35.00% 51.80% 16.80% |
| Beijing       | IU IU N N                      | 3.72% 0.51% −3.21%               | 37.64% 19.26% −18.38% | 58.64% 80.23% 21.59% |
| Liaoning      | IU IU N NS                     | 13.24% 9.77% −3.47%              | 46.68% 38.69% −9.99% 38.08% 51.55% 13.47% |
| Shanghai      | IU IU N N                      | 2.09% 0.39% −1.71%               | 51.59% 29.83% −21.76% | 46.32% 69.78% 23.46% |
| Jiangsu       | IU IU NS P                     | 13.51% 5.27% −10.24%             | 51.07% 44.73% −6.34% | 33.42% 50.00% 16.38% |
| Fujian        | IU IU N P                      | 20.09% 8.20% −11.88%             | 42.31% 48.92% 6.60% | 37.60% 42.88% 5.28% |
| Guangdong     | IU IU P P                      | 12.58% 4.57% −8.01%              | 47.65% 43.42% −4.22% | 39.77% 52.01% 12.24% |
| Hainan        | IU IU P P                      | 36.12% 23.40% −12.72%            | 20.22% 22.35% 2.13% | 43.66% 54.25% 10.59% |
| Chongqing     | IU IU N N                      | 20.35% 7.35% −13.00%             | 43.08% 44.52% 1.44% | 36.57% 48.13% 11.56% |
| Sichuan       | IU IU P P                      | 27.16% 11.93% −15.23%             | 39.04% 40.84% 1.80% | 33.81% 47.23% 13.43% |
| Yunnan        | IU IU N N                      | 23.09% 14.84% −8.25%             | 44.38% 38.48% −5.90% | 32.53% 46.68% 14.15% |
| Hubei         | IU NS N P                      | 26.88% 11.20% −15.68%             | 37.52% 44.86% 7.34% | 35.99% 43.94% 8.34% |
| Tianjin       | IU NS P NS                     | 5.50% 1.23% −4.27%               | 53.46% 42.33% −11.12% | 41.05% 56.44% 15.39% |
| Hebei         | IU NS N N                      | 19.27% 10.89% −8.38%             | 46.92% 47.57% −1.35% | 31.81% 41.54% 9.73% |
| Shandong      | IU U N N                       | 18.28% 7.25% −11.03%             | 46.19% 46.08% −2.07% | 33.57% 46.68% 13.10% |
| Henan         | IU U N N                       | 24.96% 10.59% −14.37%             | 46.96% 47.63% 1.57% | 28.98% 41.78% 12.80% |
| Hunan         | IU U N P                      | 30.03% 11.34% −18.69%             | 36.56% 42.28% 5.72% | 33.40% 46.37% 12.97% |
| Guangxi       | IU U P P                      | 32.07% 15.27% −16.80%             | 33.79% 45.17% 11.38% | 34.14% 39.56% 5.42% |
| Guizhou       | IU U P P                      | 33.75% 15.68% −18.07%             | 35.86% 39.65% 3.79% | 30.39% 44.67% 14.29% |
| Ningxia       | IU U NS P                     | 19.98% 7.62% −12.35%             | 39.48% 46.97% 7.49% | 40.45% 45.40% 4.86% |
| Inner Mongolia| NS U NS P                     | 27.96% 9.03% −18.93%             | 36.62% 47.18% 10.57% | 35.42% 43.78% 8.36% |
| Anhui         | NS NS N N                     | 31.37% 10.32% −20.85%             | 35.31% 48.43% 13.12% | 33.32% 41.05% 7.72% |
| Gansu         | NS U NS NS                    | 23.97% 13.66% −10.31%             | 42.57% 34.94% −7.63% | 33.47% 51.41% 17.94% |
| Shanxi        | U U N N                       | 13.00% 6.01% −6.98%               | 47.94% 38.54% −9.40% | 39.06% 55.45% 16.39% |
| Jilin         | U U N N                       | 25.14% 10.14% −15.00%             | 38.72% 47.41% 8.69% | 36.14% 42.45% 6.31% |
| Heilongjiang  | U U P P                       | 17.25% 17.36% 0.10%               | 53.72% 28.60% −25.12% | 29.03% 54.04% 25.01% |
| Zhejiang      | U U N N                       | 13.21% 4.16% −9.05%               | 54.51% 44.86% −9.66% | 32.28% 50.99% 18.71% |
| Jiangxi       | U U N N                       | 29.59% 10.30% −19.30%             | 42.18% 47.73% 13.55% | 36.23% 41.97% 5.75% |
| Shannxi       | U U P P                       | 18.73% 8.73% −10.00%              | 41.60% 48.92% 7.32% | 39.67% 42.35% 2.68% |
| Qinghai       | U U N N                       | 20.61% 8.60% −12.01%              | 37.79% 48.59% 10.80% | 41.60% 42.81% 1.21% |
| Xinjiang      | U U P P                       | 26.90% 17.09% −9.81%              | 37.06% 37.97% 0.73% | 36.04% 45.12% 9.08% |

Note: CDE means CO$_2$ emissions. IU means inverted U-shaped. U means U-shaped, NS means not significant. N means negative, P means positive. Difference means difference between 2016 and 1997.
Considering the change of the percentage of each industry of an individual province shown in Table 7, the 30 provinces in China can be classified into five categories. This classification is shown in Table 8. In Table 8, each category corresponds to a unique form of economic transition. The classification of provinces is actually the classification of the mode of economic transition.

Table 8. Classification of 30 provinces in China by type of economic transition.

| Transition | Type of Provinces | Example Provinces |
|------------|------------------|-------------------|
| I2S        | Developed provinces | Beijing, Shanghai, Tianjin |
| A2I, I2S   | Quasi-developed provinces | Jiangsu, Zhejiang, Guangdong |
|            |                   | Henan, Hebei, Shandong, Shanxi, Shanxi, Liaoning, Jilin, Inner Mongolia, Hunan, Hubei, Jiangxi, Anhui, Guangxi, Fujian, Chongqing, Sichuan |
| A2I        | Developing provinces | Gansu, Yunnan, Heilongjiang, Guizhou, A2S, I2S Xinjiang, Hainan |
| A2S, I2S   | Quasi-developing provinces | Ningxia, Qinghai |
| A2S        |                  | Xinjiang, Hainan |

Note: I2S means economic transition from industry to service; A2I means economic transition from agriculture to industry; A2S means economic transition from agriculture to service.

The relationship between CO$_2$ emissions and GDP in the regression results can be partly explained by this classification. In the economic transition from agriculture to industry (A2I), the CO$_2$ emissions will increase with GDP growth; in the economic transition from industry to service (I2S), the CO$_2$ emissions will be decrease with GDP growth. For an individual province, if it experiences the I2S after the A2I, the regression curve of this province will be inverted U-shaped, and that means the EKC hypothesis holds for this province. For provinces with other modes of economic transition, the U-shaped curve or inverted U-shaped curve can be explained for similar reasons, and the details are shown in Table 9. Table 9 shows the relationship of regression curves and economic transition modes. In Table 9, each particular mode of economic transition corresponds to some particular modes of regression curves. That means the type of the regression curve of CO$_2$ emissions and GDP are associated with the economic transition.

Table 9. Relationship of regression curve and economic transition mode.

| Economic Transition | Curve of CDE and GDP | Example Provinces |
|---------------------|---------------------|-------------------|
| I2S                 | IU                  | Beijing, Shanghai |
| A2I, I2S            | IU or NS            | Jiangsu, Guangdong |
| A2S, I2S            | NS                  | Gansu             |
| A2S                 | U or NS             | Xinjiang          |
| A2I                 | U                   | Shanxi, Jilin     |

Note: CDE means CO$_2$ emissions. IU means inverted U-shaped. U means U-shaped, NS means not significant.

(3) Negative correlations of CO$_2$ emissions and GDCR are because of economic transition

If a province is in the economic transition from agriculture to industry, diesel consumption will grow faster than gasoline consumption, so GDCR decreases but CO$_2$ emissions will increase because of the industrialization. Thus, CO$_2$ emissions have a negative correlation with GDCR.

For the same reason, if a province is in the economic transition from industry to service, gasoline consumption will grow faster than diesel consumption, so GDCR increases but CO$_2$ emissions decrease because of the economic transition. Thus, CO$_2$ emissions also have a negative correlation with GDCR. These rules are shown in Table 10. As shown in Table 10, for provinces that are experiencing economic transition from agriculture to industry, such as Fujian and Qinghai, the GDCR of these provinces will decrease, and the CO$_2$ emissions will increase, so the correlation of GDCR and CO$_2$ emissions is negative. This is similar for provinces that are experiencing economic transition from industry to service.
### Table 10. Relationship between economic transition and correlation of GDCR and CO₂ emissions.

| Transition | GDCR | CDE | Correlation | Example Provinces          |
|------------|------|-----|-------------|----------------------------|
| A2I        | Decrease | Increase  | Negative     | Fujian, Qinghai, Hubei, Anhui |
| I2S        | Increase | Decrease  | Negative     | Beijing, Shanghai, Liaoning, Shanxi |

Note: CDE means CO₂ emissions. Transition is short for economic transition; correlation means the correlation of GDCR and CO₂ emissions; A2I means economic transition from agriculture to industry; I2S means economic transition from industry to service.

### 5. Conclusions

Data of recent years show that the growth rate of CO₂ emissions has declined for the whole of China and some of the China provinces. This paper utilized the panel data to verify the EKC hypothesis. To explore the real reason behind EKC and the underlying motivation of the growth rate reduction of CO₂ emissions, the index GDCR was introduced in this paper. The index, GDCR, means the ratio of gasoline consumption to diesel consumption of a particular region. This paper combines the environmental Kuznets curve for CO₂ emissions and GDCR to prove the correlation between GDCR and CO₂ emissions. The conclusions are as follows.

1. The EKC hypothesis for CO₂ emissions holds in China.
2. GDCR can be a new socioeconomic indicator of CO₂ emissions in China.
3. The relationship between CO₂ emissions and GDP is independent from GDP.
4. The relationship of CO₂ emissions and GDP is associated with economic transition.
5. The negative correlation of CO₂ emissions and GDCR is because of economic transition.

In summary, this paper shows that the EKC hypothesis holds. This means that CO₂ emissions may decrease with GDP growth, but GDP growth is a necessary—but not sufficient—condition for CO₂ emission reduction. CO₂ emissions are not determined by GDP, but associated with economic transition. Thus, to effectively decrease CO₂ emissions and to solve the problem of global warming, the government still needs to formulate relevant policies to transform the economic structure of China.

This paper also has some deficiencies. This paper has only focused on the impact of economic transition, but fails to reflect the impact of energy transition and energy efficiency. In future research, we will study the impact of energy transition and energy efficiency on CO₂ emissions further.

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