Correlation between CO_2 emissions and Gasoline to Diesel Ratio: evidence from China provinces

by

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Abstract

This paper utilized 1997-2016 provincial panel data to verify Environmental Kuznets Curve (EKC) for Carbon Dioxide (CO2) emissions in China. And to explore the underlying motivation, the correlation between CO2 emissions and Gasoline to Diesel Ratio (GDR) had also been investigated. The regression results show per capita CO2 emissions forms an inverted U-shape curve with respect to Gross Domestic Product (GDP) per capita. But because the historical data only formed the left side of the curve, and the right side is waiting for the future data. So the hypothesis of EKC only partially holds. This paper also demonstrate the regression results are independent from the number of GDP, but CO2 emissions has a high correlation with GDR. 1% GDR increase couples with 0.118186% and 0.114056% CO2 emissions decrease by panel Fully Modified Ordinary Least Squares (FMOLS) regression and panel Dynamic OLS (DOLS) regression method, respectively. As GDR can partially represent the economic structure and its transition in China, an interesting hypothesis can be put forward it is not the number of GDP, but the economic structure and its transition that determined the provincial differences of the regression results. The last part of this paper also discussed GDR's representation ability to economic structure and some hypotheses about that.

1. Introduction

At present, many evidences show Carbon Dioxide (CO2) emissions is a reason for global warming and fossil fuel consumption is the main reason for CO2 emissions (Olivier et al., 2013). As one of the largest fossil fuel consumer and the largest coal consumer, China and its CO2 emissions continues being hot-points among economic, energy and environment researches.

In the past 30 years, China has experienced economy, energy consumption and CO2 emissions boost. In 2010, China became the world's second largest economy. From 1987, China has become the world's largest coal consumer. From 2005 China continues to consume more than 40% of the world's annual coal production, and from 2011, more than 50%. In 2009, China became the world's largest energy consumer and CO2 emitter

(Pao et al., 2012). As a responsible country, China paid much attention on CO2 reduction — has funded a number of researches on carbon dioxide abatement, and has formulated and implemented a number of related policies on economic planning and energy utilization to reduce CO2 emissions.

These researches and policies are fruitful. In some China provinces, per capita CO2 emissions growth rate begins to decrease. Based on this phenomenon, some scholars stated a hypothesis that the per capita CO2 emissions in China will form an inverted U-shape curve with respect to GDP growth (Dong et al., 2017; Jalil and Mahmud, 2009; Kang et al., 2016; Riti et al., 2017). This hypothesis is called the Environmental Kuznets Curve (EKC) for CO2 emissions in China.

To verify the EKC hypothesis and investigate the reason of the CO2 emissions growth rate reduction, this paper utilizes the 1997-2016 provincial panel data in China and designed a new econometric model and introduced a new index —— Gasoline to Diesel Ratio (GDR) into the econometric model. The experimental result shows EKC for CO2 emissions is just partially hold. Because the actual CO2 emissions has not declined yet, even though the panel data regression shows an inverted U-shape curve. The up to now historical data only formed the left side of this curve, and the right side of the curve is still empty. So the per capita CO2 emissions may not reduce in the future. That means the per capita CO2 emissions may also possible to grow unlimited, or limited until a certain limit in the future, forming an S-type Growth Curve, but not a U-shaped curve. This prediction of CO2 growth trend is innovated and fills some gaps in the field of EKC for CO2 emissions in China.

The investigation of correlation between CO2 emissions and GDR is also an innovation of this paper. To explore the underlying motivation of CO2 growth rate reduction, a new index —— Gasoline to Diesel Ratio (GDR) has been introduced into the econometric model. As the household cars in China meanly use gasoline, and almost no diesel at all, while industrial and commercial transportation in China mostly use diesel, and almost no gasoline at all. To some extent, GDR can represent the economic structure in China. So this paper, from a special perspective, can partially explain the reason of recent years' per capita CO2 emission growth rate reduction in some China provinces. The quantitative regression shows GDR has a strong correlation with per capita CO2 emissions. By panel Fully Modified Ordinary Least Squares (FMOLS) and panel Dynamic OLS (DOLS) regression, 1% GDR increase couples with 0.118186% or 0.114056% CO2 emissions decrease, respectively.

The regression results show the provincial differences of relationship between GDP growth and CO2 emissions. The provincial level regression results show relationships between GDP growth and CO2 emissions are independent of the number of GDP, but relate to the provincial economic structure, perhaps also energy structure, their transition and their interactions. The last part of this paper discussed the influence factors of GDR's representation ability to economic structure and economic transition. These discussions about GDR, economic structure and economic transition are meaningful and also innovations of this paper.

The rest of this paper is written as follows. Section 2 is 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 of this paper.

2. Literature review

First born in 1955, the concept of Kuznets Curve (KC) was first been used by Kuznets (1955) to describe the correlation between income inequality and economic growth with an inverted U-shaped curve. The curve used by Kuznets was named the Kuznets Curve (KC). From 1990s, some scholars began to use KC in pollutant emissions and environment protecting researches. It prompted the birth of the term Environmental Kuznets Curve (EKC). Grossman and Krueger (1991) first found pollutant emissions has an inverted U-shaped relation with respect to per capita income. Panayotou (1993) fisrt used EKC to name this phonomenon. After that, EKC was investigated by many scholars and some basic features of EKC have been found out. Some of the features are of reference significance to this paper. Among them, Dinda (2004) pointed out that a country's fortunes change, from clean agrarian economy to polluting industrial economy to clean service economy, and people's increasing preference for environmental quality with income growth, is the real reason for EKC. Dinda's view-point can explain the reason of China's consistency of panel data to EKC. Because at present, China is finishing its industrilization, and on the stage of a economy transition from industrial to service and Chinese people are more care about environment quality. Stern (2004) proposed that some developing countries refers developed countries' experience and standards when addressing environmental problems, and sometimes perform better than early experienced countries. China, as a developing country, really has taken this kind of experience and standards from developed countries. So, as Stern said, China may performance better in CO2 reduction.

Then EKC was used to research CO2 emissions, and this kind of research was called EKC for CO2 emissions. As global warming was increasingly attracting publics' attention in 1990s. It is natural for scholars to use EKC to examine the relation between CO2 emissions and per capita income. In 1997, the journal Environment and Development Economics, belong to Cambridge University Press, set up a special issue on EKC (Barbier, 1997). In this special issue, Moomaw and Unruh (1997) first used EKC to investigate relation between CO2 emissions and GDP growth. And Moomaw and Unruh's research gave out some very important rules about EKC for CO2 emissions. Besides the a second order polynomial relation, an N-shaped curve, Moomaw and Unruh, used 16 countries' data, also demonstrated that CO2 emissions has a third order polynomial relation, an N-shaped curve, with per capita GDP. That means either U-shaped or N-shaped was not decided by the data itsself, but by the regression model that been used. So neither U-shaped nor the N-shaped relationship could been used to forecast the CO2 emissions with respect to GDP in the future. Moomaw and Unruh' research also had some deficiencies. Moomaw and Unruh proposed that EKC showed the phonomenon of CO2 decrease, but the real reason underling the surface was some critical historic events and subsequent policies, such as the 1970s' Oil Crisis. But we think this view point could explain some discontinuous CO2 reduction, but did not show the fundamental influence of economic and energy transitions to CO2 emissions. After Moomaw and Unruh, other scholars aslo did some important researches. Related to EKC for CO2 emissions, Sun (1999) said it merely reflected the peak-theory of energy intensity. Sun's view could explain some of the truth, but obviously his paper did not consider the ecomomic and energy structure transitions, and their impact on CO2 emissions. After this early research, many different empirical researches on EKC for CO2 emissions were done for various countries, regions, OECD countries, developing countries and so on (Acaravci and Ozturk, 2010; Ang, 2007; Apergis and Payne, 2009; Arouri et al., 2012; Friedl and Getzner, 2003; Galeotti et al., 2006; Halicioglu, 2009; Iwata et al., 2012; Lantz and Feng, 2006; Saboori et al., 2012). Kaika and Zervas (2013) make a summary of this kind of research —— (i) EKC researches suggest each countries to focus on economic growth and the environmental trauma will be solved during the development; (ii) EKC researches utilize data from various countries and types of environmental degradation, and find the mean reasons for EKC are income, economic and energy structurue, energy density, policy and governance, consumer preferences, international trade (pollution haven hypothesis) and so on.

In recent years, As China becomes a major CO2 emitter, the EKC for CO2 emissions in China has attracted many scholars to research. Jalil and Mahmud (2009) used time series data of China from 1975 to 2005, and added energy consumption and foreign trade as independent variables, coupled with CO2 emissions and income, to verify EKC for CO2 emissions in China. They found economic growth is the Granger causality of CO2 emissions, and trade just has a positive but insignificant impact. Kang et al. (2016) used 1997-2012 panel data from China provinces, and specially compared the non-sptial and spatial panel model. Kang found that eastern China has shaper CO2 increase than western, and compared to urbanization and coal consumption, trade has little influence on CO2 emissions. With using 1995–2014 data from China provincial level, Dong et al. (2017) not only examined the EKC for CO2 emissions, but also investigated the impact of natural gas consumption on CO2 emissions. Dong found EKC hypothesis meanly holds in eastern and central China provinces, and natural gas consumption has a significant positive influence on CO2 reduction. Dong also found the existence of EKC for certain province is independent from GDP. Wang et al. (2017) used 2000-2013 provincial panel data in China, to especially investigate the income/urbanization impact on industrial CO2 emissions in China. Wang found the inverted U-shaped curve only holds in electricity and heat sector, and urbanization in manufacturing sector. As the different impact in sectors, Wang suggested specific policy design for different sectors. With 1970-2015 time series data, Riti et al. (2017) employed different estimation techniques and gained the same result —— EKC for CO2 emission holds in China and the turning point will be around \$744665. Riti said their result of turning point is different from other researches meanly because the different data source, scope of data, variables selection and so caused sensitivity of the result. But as Chinese scholars, we think Riti's turning point is so much high. GDP per capita in China is just \$7816 in 2016. That means Riti's turning point is 95 times more than 2016's GDP number, and that seems quite impossible for present China. But in our research, even thoungh the turnning point not came yet, but it is coming. So there may be some mis-understanding or decimal point errors in Riti's research.

In summary, previous research on EKC has achieved a great deal of excellence. These studies used a variety of data and regression methods, especially regression methods which can be said to be too complicated, gorgeous and extravagant, sometimes even beyond the actual needs of research, and sometimes even increasing the amount of unnecessary calculations (lucky, they are done by computers). However, in fact, the actual problem has not been solved perfectly. Although it can be concluded that China's CO2 emissions meet the quadratic curve with a negative quadratic coefficient, this quadratic curve is meaningless in predicting China's future CO2 emissions. Just as Moomaw and Unruh (1997) said, "neither the 'U'- nor the 'N'-shaped can provide a reliable indication". According to the summary of the existing literature, adding new variables —— variables that can reflect China's economic structure and energy structure —— to study the real causes and to forecast the future of CO2 emissions changes in China will become most meaningful. This kind of research will not only benefit China's CO2 emissions projections, but also help the government to formulate relevant policies to guide economic transition and energy transition.

3. Methodology

3.1 Variables

As statistical analysis showed a high correlation between CO2 emissions and GDR. This paper chose GDR as an independent variable. GDR was meanly used in petro-chemical industry, representing the production structure of a refinery or a petro-chemical facility. Because the household cars in China meanly use gasoline, and almost no diesel at all, while industrial and commercial transportation in China all use diesel mostly. To some extent, GDR can reflect the ratio of industrial and commercial transportation to household car use and reflects the economic structure in China. So this paper used GDR as one of the independent variables. In order to verify the EKC hypothesis for CO2 in China, other variables in this paper are GDP per capita and its square.

3.2 Model

The econometric model in this paper was shown in Formula 1.

$$\ln PCCE = a \times \ln PCGDP + b \times (\ln PCGDP)^2 + c \times \ln GDR + r \qquad (1)$$

PCCE represents per capita CO2 emissions. PCGDP represents the per capita GDP of various provinces. $PCGDP^2$ represents the square of PCGDP. GDR represents the gasoline to diesel ratio of various provinces. And a, b, c are the parameters that need to be estimated. And r is the residue of estimation.

If the regression coefficient of GDP square is negative —— that means CO2 emissions forms an inverted U-shaped curve with respect to GDP —— EKC hypothesis will be **partially** proven. The reason of **partially** is that, the inflection point has not appeared at present and needs to be verified by future data. Once the inflection point appears and the trend of per capita CO2 emissions begins to decrease, the EKC can be fully proven.

Used the natural exponential (EXP) function on formula (1), the result is shown in Formula 2.

$$\mathrm{PCCE} = (PCGDP)^{a} \times (PCGDP)^{b\times \ln PCGDP} \times (GDR)^{c} \times EXP(r) \qquad (2)$$

Formula 2 shows the real relationship of the variables that reflected by Formula 1, and will be very useful in the discussion.

3.2.1. Unit root test and panel co-integration test

Variables in this paper were individually subject to LLC unit root test (Levin et al., 2002) and ADF-fisher test (Maddala and Wu, 1999) with test for root in level and 1st difference, respectively. And all variables together, depending on the results of unit root test, were subject to panel Pedroni co-integration test (Pedroni, 1999) with deterministic trend of individual intercept, individual intercept & individual trend and no intercept or trend, respectively.

3.2.2. Panel long-run parameter estimates

The estimate methods used in this paper were Co-integrating regression method of Fully-modified Ordinary Least Squares (FMOLS) by Pedroni (2000) and Dynamic Ordinary Least Squares (DOLS).

3.3 Data

This paper uses panel data of China's 30 provinces from 1997 to 2016. The data sources are National Bureau of Statistics in China and various Provincial Bureau of Statistics in China. The data of CO2 emissions was calculated meanly with the method proposed by Dong et al. (2017), with some modification on it——Dong's method calculated CO2 emissions by end-side energy consumption data, while this paper uses the primary energy consumption data, because it can more clearly reflect the industrial CO2 emissions in various provinces, especially for electronic generation industry. The data of GDP use the RMB unit, YUAN, and are normalized to 1997 prices. The per capita CO2 emissions and per capita GDP data were calculated by division with provincial population data of each year. The GDR data were directly calculated by the gasoline and diesel consumption data of each province. The statistic table, distribution curve, and scatter plot are shown in Table 1 and Figure 1.

Tab.1 Statistic Table of variables from 30 China provinces in 1997-2016

Stats Results	ln PCCE	ln PCGDP	(ln PCGDP)^2	ln GDR
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

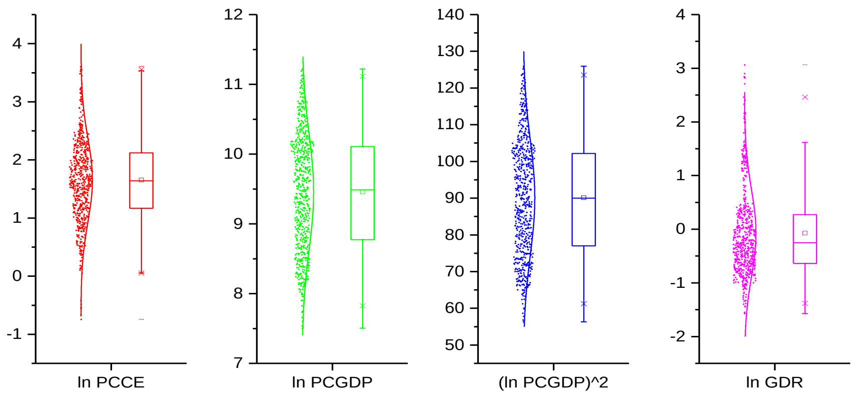

Fig.1 Box Chart of variables from 30 China provinces in 1997-2016

4. Empirical results and discussion

4.1 Results of unit root tests

Table 2 shows the results of unit root tests of all variables by LLC test and ADF-fisher test with intercept, intercept & trend and none, respectively. Only “ln PCGDP” and “(ln PCGDP) ^{2}” passed the LLC test at levels, so all variables are not stationary at levels. But all variables passed the LLC test and ADF-fisher test at 1st difference, so all variables are stationary at 1st difference.

Tab.2 Results of unit root test.

Variable	Level			1st difference		
	Intercept & trend	Intercept	None	Intercept & trend	Intercept	None
LLC test						
ln PCCE	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 GDR	2.631	-0.355	-0.079	-16.809***	-18.561***	-22.178***
ADF-Fisher test						
ln PCCE	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	14.3822	45.674	89.946***	59.117
ln GDR	43.441	74.352	56.135	305.024***	361.043***	509.589***

Notes: ***, **, and * represent 1%, 5%, and 10% statistical significance. Optimal lag lengths were automatic selection of Schwarz info criteria.

4.2 Results of co-integration tests

Results of unit root tests shows all variables are stationary at 1st difference. So they were subject to Pedroni co-integration test and the results were shown in Table 3. By models with intercept, five of all seven results reject the non-co-integration hypothesis with a 95% confidence level. Hence the CO2 emissions, economic growth and gasoline to diesel ratio forms a long-term co-integration relationship.

Tab.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***

Notes: ***, **, and * represent 1%, 5%, and 10% statistical significance. Newey-West bandwidth and Bartlett kernel were used.

4.3 Estimates of long-run parameters

As the results shown above, samples and data of China provinces have passed the co-integration test, so the model in Formula 1 can be used for long-run parameter estimate. And with panel data and 30 provincial data, Table 4 shows the results by FMOLS method and DOLS method, respectively. The upper lines shows the estimate results of 30 provinces, and the last line shows the panel data estimate results.

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

Province	FMOLS			DOLS		
	ln PCGDP	(ln PCGDP)^2	ln GDR	ln PCGDP	(ln PCGDP)^2	ln GDR
Beijing	8.924*[1.981]	-0.438*[-1.987]	-0.946**[-2.675]	3.030[0.306]	-0.181[-0.382]	-0.654[-0.949]
Tianjin	6.275***[2.879]	-0.295**[-2.778]	0.112[0.575]	-0.629[-0.135]	0.0441[0.193]	-0.021[-0.054]
Hebei	1.802**[2.379]	-0.070*[-1.742]	-0.232***[-5.157]	1.366[1.068]	-0.041[-0.596]	-0.353**[-2.652]
Shanxi	-1.233[-1.074]	0.084[1.380]	-0.324***[-4.515]	-5.111***[-5.978]	0.299***[6.571]	-0.404***[-6.854]
Inner Mongolia	1.131[0.642]	-0.017[-0.190]	-0.043[-0.190]	-9.473***[-4.297]	0.558***[4.721]	0.478[1.569]
Liaoning	4.006***[5.861]	-0.181***[-5.226]	-0.125**[-2.385]	1.993[1.382]	-0.076[-1.026]	-0.0018[-0.013]
Jilin	-1.190[-1.081]	0.080[1.413]	-0.187**[-2.805]	-3.271[-1.737]	0.190[1.853]	-0.091[-1.469]
Heilongjiang	-1.986[-1.027]	0.136[1.341]	0.069[0.401]	-1.518[-0.529]	0.103[0.660]	0.378[0.531]
Shanghai	7.613***[4.896]	-0.365***[-4.969]	-0.151[-1.671]	10.436**[3.092]	-0.486**[-3.178]	-0.190[-0.475]
Jiangsu	2.710*[1.807]	-0.104[-1.350]	0.0066[0.023]	5.736*[1.929]	-0.281[-1.815]	0.970**[2.554]
Zhejiang	-9.144**[-2.488]	0.510**[2.715]	-2.000***[-4.717]	-12.654***[-5.950]	0.694***[6.253]	-2.588***[-9.263]
Anhui	0.791[1.254]	-0.009[-0.272]	-0.189**[-2.72]	-0.0050[-0.0029]	0.035[0.350]	-0.110[-0.590]
Fujian	5.568***[3.030]	-0.226**[-2.353]	-0.670**[-2.743]	7.028***[5.436]	-0.304***[-4.357]	0.0995[0.272]
Jiangxi	-1.213[-0.749]	0.097[1.101]	-0.173**[-2.134]	-1.602[-1.253]	0.125[1.836]	-0.064[-0.952]
Shandong	3.772[1.365]	-0.153[-1.092]	-0.243[-0.899]	-4.460[-1.093]	0.258[1.262]	-0.399[-0.617]
Henan	5.921***[3.991]	-0.288***[-3.607]	-0.188*[-1.969]	-3.232*[-2.192]	0.204**[2.509]	-0.301**[-2.794]
Hubei	4.999***[3.316]	-0.242***[-3.041]	-0.363[-1.180]	0.0014[0.0007]	0.0064[0.059]	0.865[1.682]
Hunan	4.578[1.001]	-0.218[-0.896]	-0.278[-0.547]	-4.227[-0.993]	0.260[1.125]	1.109[1.132]
Guangdong	5.616**[2.865]	-0.256**[-2.574]	0.438***[3.012]	11.429**[2.868]	-0.540**[-2.739]	0.652**[3.310]
Guangxi	2.640*[1.991]	-0.104[-1.427]	0.162[0.928]	-5.585*[-2.155]	0.358**[2.492]	0.844**[3.098]
Hainan	18.147**[2.452]	-0.892**[-2.273]	0.288[0.874]	61.823[1.342]	-3.254[-1.307]	2.463[1.218]
Chongqin	1.499[0.699]	-0.068[-0.624]	-0.444**[-2.828]	2.779[0.543]	-0.148[-0.510]	-0.378[-0.984]
Sichuan	9.685***[3.087]	-0.510***[-2.938]	0.637[1.443]	22.215**[2.745]	-1.214**[-2.711]	0.515[0.590]
Guizhou	5.440***[4.630]	-0.278***[-4.212]	0.429***[3.160]	-2.167[-1.174]	0.124[1.237]	0.137[1.050]
Yunan	12.497***[3.164]	-0.659***[-3.079]	-0.057 [-0.427]	4.756[0.784]	-0.234[-0.746]	-0.062[-0.182]
Shannxi	-0.295[-0.239]	0.062[0.952]	0.147[0.966]	-2.455[-0.385]	0.181[0.500]	0.281[0.522]
Gansu	1.294*[1.904]	-0.044[-1.163]	-0.067**[-2.150]	-1.455[-0.725]	0.120[1.039]	-0.0005[-0.005]
Qinghai	-5.466***[-2.904]	0.313***[3.166]	-0.323***[-3.915]	-7.096[-1.232]	0.390[1.250]	-0.488*[-2.268]
Ningxia	3.967[1.287]	-0.161[-1.022]	0.0130[0.058]	-8.793[-0.397]	0.565[0.464]	0.215[0.329]
Xinjiang	-8.126***[-4.206]	0.487***[4.869]	0.156[1.122]	-4.303[-0.663]	0.281[0.828]	0.348[0.718]
Panel	2.276***[4.749]	-0.090***[-3.604]	-0.118**[-2.495]	1.078[1.532]	-0.028[-0.751]	-0.114**[-1.965]

Notes: ***, **, and * represent 1%, 5%, and 10% statistical significance. Values in square brackets are t-statistics.

4.4 Discussion

Firstly, in this part, we give some basic formulas to illustrate the relationship between CO2 emissions, GDP, economic structure and energy structure. Formula 3 shows a simple relationship between CO2 emissions and GDP, which is CO2 emissions equals to GDP multiply CO2 density.

$$\mathrm{CO2} = \mathrm{GDP} \times \frac{CO2}{GDP} \tag{3}$$

If consider the energy consumption, formula 3 can be written as formula 4, which is CO2 emissions equals to GDP multiply energy density and multiply generalized carbon emission coefficient.

$$\mathrm{CO2} = \mathrm{GDP} \times \frac{ENERGY}{GDP} \times \frac{CO2}{ENERGY} \tag{4}$$

CO2 emissions can be classified by energy types, and energy consumptions also. So generalized carbon emission coefficient also can be written as formula 5.

$$\frac{CO2}{ENERGY} = \frac{CO2_{Coal}+CO2_{Oil}+CO2_{Gas}}{ENERGY_{Coal}+ENERGY_{Oil}+ENERGY_{Gas}+ENERGY_{Clean}} \tag{5}$$

Energy consumption can be classified by different industrial types, and GDP also. So generalized carbon emission coefficient also can be written as formula 6.

$$\frac{ENERGY}{GDP} = \frac{ENERGY_{Primary\ industry}+ENERGY_{Secondary\ industry}+ENERGY_{Tertiary\ Industry}}{GDP_{Primary\ industry}+GDP_{Secondary\ industry}+GDP_{Tertiary\ Industry}} \tag{6}$$

From formula 3 to 6, we know CO2 emissions can be influenced by GDP, economic structure and energy structure.

4.4.1 Inverted U-shaped or not is independent from GDP

If an estimation result of an individual province or the panel data is inverted U-shaped, table 5 shows the turning point number of that result —— expressed by nominal GDP per capita with the unit of China YUAN. And table 5 also shows the GDP per capita of various provinces of China in 1997 and 2016 to compare with the turning point number. From table 5, a very interesting phenomenon can be observed whether the relationship between CO2 emissions and GDP per capita is inverted U-shaped or not is independent from the GDP per capita in different provinces.

This conclusion is also logically right. The estimation results reflected a dynamic process. Whether a result is inverted U-shaped or not is not depend on the current GDP in the individual province, but depend on the transition process of economic transition or energy transition process of that province. The turning point numbers of different provinces are also different. That means reaching a certain number of GDP will not make the CO2 emissions decrease automatically. So all provinces and the China government should not only focus on the GDP number growth, but also on the economic transition and energy transition, if they want to reduce the CO2 emissions.

Tab.5 Relationship between EKC, Turning Point and nominal GDP

Province	FMOLS		DOLS		1997	2016
	IU or Not	TP(PCGDP)	IU or Not	TP(PCGDP)	PCGDP	PCGDP
Panel Data	IU	310036.2	NS		6448.08	53777.40
Beijing	IU	26561.41	IU	4316.351	16750.73	118127.61
Liaoning	IU	63978.24	IU	494766.9	8657.47	50815.21
Shanghai	IU	33818.63	IU	46010.53	23601.85	116440.70
Jiangsu	IU	455361.2	IU	27076.07	9345.75	96747.44
Fujian	IU	223817	IU	104737.3	8747.41	74369.08
Guangdong	IU	58032.01	IU	39434.94	11026.14	73511.15
Hainan	IU	26162.57	IU	13353.57	5533.78	44200.65
Chongqin	IU	61209.57	IU	11950.32	4963.02	58204.04
Sichuan	IU	13294.4	IU	9409.789	3845.16	39862.67
Yunan	IU	13118.66	IU	25910.23	4094.21	30996.48
Hubei	IU	30592.57	NS		4863.73	55506.17
Tianjin	IU	41589.09	NS		13269.99	114503.14
Hebei	IU	389036.50	NS		6059.43	42932.33
Shandong	IU	225662.9	U		7441.17	68386.94
Henan	IU	29129.71	U		4372.05	42458.86
Hunan	IU	36315.5	U		4407.22	46249.44
Guangxi	IU	325236.4	U		3922.40	37862.01
Guizhou	IU	17750.57	U		2234.58	33127.23
Ningxia	IU	224106.3	U		4237.55	46942.07
Inner Mongolia	NS		U		4959.20	71936.90
Anhui	NS		NS		3831.11	39392.54
Gansu	NS		U		3181.92	27587.62
Shanxi	U		U		4699.14	35443.81
Jilin	U		U		5572.07	54068.06
Heilongjiang	U		U		7111.44	40500.37
Zhejiang	U		U		10566.20	84528.37
Jiangxi	U		U		3869.33	40285.28
Shannxi	U		U		3819.61	50877.50
Qinghai	U		U		4088.51	43380.94
Xinjiang	U		U		6052.68	40240.62

Note: IU means Inverted U-shaped. U means U-shaped, NS means Not Significant. TP means Turning Point. PCGDP means GDP per capita (YUAN, nominal GDP per capita).

4.4.2 Inverted U-shaped or not is associated with provincial economic transition

Figure 2 shows a colored map of China provinces and Figure 2(1) and Figure 2(2) reflects the estimation results of relationship between GDP and CO2 emissions. In Figure 2(1) and Figure 2(2), provinces in green color means, in these provinces, CO2 emissions formed an inverted U-shaped curve with respect to GDP. Provinces in red color means the CO2 emissions formed a U-shaped curve. And provinces in yellow color means, the CO2 emissions formed neither an inverted U-shaped curve nor a U-shaped curve, but formed an approximately linear line.

According to formula 2, investigating the meaning of inverted U-shaped curve, U-shaped curve and linear line formed by CO2 emissions with respect to GDP, in Figure 2(1) and Figure 2(2), green provinces indicated their annual CO2 emissions growth rate are decreasing, and red provinces means their annual CO2 emissions growth rate are increasing, and yellow provinces means their CO2 emissions growth rate are almost not changing.

Combining the real situations of these various provinces in China, more interesting assumptions can be put forward. Green provinces happen to be the provinces that have begun their economic transition from an industrial economy to a service economy. Red provinces happen to be the provinces that the economic transition process are not significant and their industrial economy are still expanding. In particular, almost all energy production provinces in China are colored red. The yellow provinces happen to be the provinces that experience neither of the two patterns above. That means the yellow provinces experience economic transition and coupled with the industrial economy expanding.

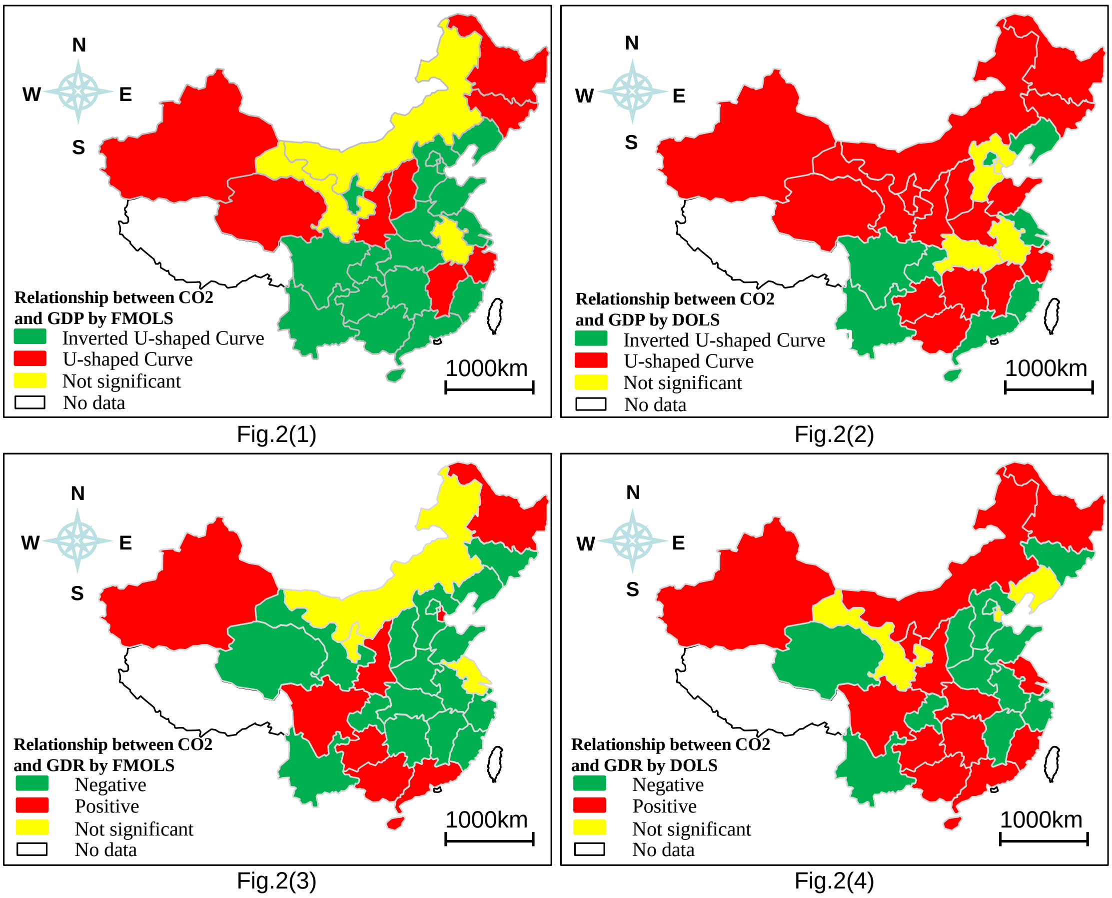

Fig.2 Colored maps of China provinces that reflect the estimation results

4.4.3 Correlation between CO2 and GDR is associated with the explanatory ability of GDR to provincial economic transition

Figure 2(3) and Figure 2(4) reflects the estimation results of relationship between GDR and CO2 emissions. In Figure 2(3) and Figure 2(4), provinces that in green color means, in these provinces, CO2 emissions has a negative correlation with GDR. In red color means CO2 emissions has a positive correlation with GDR. And in yellow color means neither negative nor positive, but means being irrelevant.

To explain the reason of the different colors, the meaning of GDR should be investigate first. In China household cars almost use gasoline, and almost no diesel. While industrial and commercial vehicles almost use diesel, and almost no gasoline. GDR reflects the ratio of industrial and commercial transportation energy consumptions to household transportation energy consumptions. To some extent, Changes of GDR are related to economic development and industrial transformation. For green provinces, the explanatory ability of GDR to provincial economic transition is stronger than that of yellow and red provinces.

On one hand, if a green province is in the process of industrialization, diesel consumption will growth faster than gasoline consumption, so GDR decreases, but CO2 emissions will increase because of the industrialization, so CO2 emissions have a negative correlation with GDR. On another hand, if a green province is in an economic transition process from an industrial economy to a service economy, gasoline consumption growth faster than diesel consumption, so GDR increases, but CO2 emissions will decrease because of the transition from an industrial economy to a service economy, so CO2 emissions also have a negative correlation with GDR. Red and yellow provinces are exceptions. For red and yellow provinces, the explanatory ability of GDR to provincial economic transition is weak, and CO2 emissions do not have a negative correlation with GDR.

Overall, compared with the yellow and red provinces, green provinces accounted for the majority, and the regression results from panel data being the same with green provinces also confirmed a negative correlation between GDR and CO2 emissions.

4.4.4 GDR's representation ability to economic transition is stronger for to-service transition provinces than industrialization provinces

Figure 2(1) reflects the estimation results of relationship between **GDP** and CO2 emissions by FMOLS. Figure 2(3) reflects the estimation results of relationship between **GDR** and CO2 emissions by FMOLS. Comparing Figure 2(1) with Figure 2(3), the coloring of these two different maps shows some similarities. The same similarities occurs when comparing Figure 2(2) with Figure 2(4). Combined with the analysis of 4.4.2 and 4.4.3, green color in Figure 2(1) and Figure 2(2) represents the provinces experiencing the transition from industrial economy to service economy, and green color in Figure 2(3) and Figure 2(4) represents the stronger representation ability of GDR to economic transition. According to the above phenomenon, it can be inferred that GDR is obviously more capable when characterizing the economy transition in to-service economy provinces. The ability to characterize provinces' industrialized process is weaker. This finding has some significance for the study of GDR to characterize economic transition.

On the other hand, it also shows that the consumption of gasoline and diesel in China's industrialization provinces is growing at the same time. For the provinces that have begun the to-service-economy transition, the growth rate of gasoline is significantly faster than diesel. This discovery also has some significance for studying the law of gasoline and diesel consumption in China.

4.4.5 Discussion summary

In summary, China is still a developing country, although some provinces in China have shown a trend of transition from a high-carbon economy to a low-carbon economy; in other provinces, the expansion of the high-carbon economy has not stopped yet.

From the overall perspective of China, the carbon emission growth rate has shown a downward trend, which proves that the whole country has begun the trend of economic transition, but this trend is still insignificant. From the perspective of panel data regression results, there is a quadratic parameter of -0.090 and -0.028 by FMOLS and DOLS, respectively. As this number is small, compared to most of the to-service transition provinces. So, for whole China, the inverted U-shaped curve of CO_2 emissions to GDP is not significant at all.

Farther more, the inflection point of China's CO_2 emissions has not appeared yet, so China's EKC for CO_2 emissions cannot be fully confirmed so far. This is also what the Chinese government needs to pay attention to. It is not that with the development of the economy, carbon emissions can be automatically reduced. But the economic transition that will reduce carbon emissions. At present, the Chinese government is already making efforts to promote China's economic transition and CO_2 reduction. This is the right decision. China should continue to work on this direction.

5. Conclusions and Deficiencies

This paper utilizes 1997-2016 panel data from 30 China provinces. The data was subjected to unit root test, panel co-integration test and of long-run parameter estimate. Historical data show that the growth rate of CO_2 has declined significantly, especially for some provinces in China. This paper hopes to verify this trend with EKC hypothesis. The purpose of studying the relationship between CO_2 and Gasoline to Diesel Ratio (GDR) is to try to explain the real reason of the CO_2 growth rate reduction. The conclusions of this paper are as follows.

(1) The result of regression shows per capita CO_2 emissions forms a quadratic curve with negative quadratic coefficient and a positive primary coefficient with respect to per capita GDP. It shows that the EKC hypothesis is partly true. However, although CO_2 growth rate has declined, CO_2 emissions has not declined yet, EKC hypothesis cannot be fully confirmed, which is similar to the conclusion of Moomaw and Unruh (1997).

(2) There is a significant correlation between CO_2 emissions and GDR. GDR has a negative impact on CO_2 emissions. To some extent, GDR has the explanatory ability to provincial economic transition. The regression results show the change of economic structure may be an important reason for CO_2 emission growth rate reduction.

(3) Both the inverted U-shaped relationship between CO_2 emissions and GDP per capita and the correlation between CO_2 emissions and GDR are independent from individual province GDP per capita. This conclusion is similar to that of Dong et al. (2017).

(4) This paper also discusses GDR’s explanatory ability to provincial economic transition. This discussion considers that correlation between CO_2 and GDR is associated with the explanatory ability of GDR to provincial economic transition. And GDR’s representation ability to economic transition is stronger for to-service-transition provinces than industrialization provinces.

This paper also has some deficiencies. This paper only focuses on the impact of economic transition on carbon emissions, but fails to clearly reflect the impact of energy transition and energy efficiency improvement on carbon emissions. However, China's energy transition and energy efficiency improvement can also be the reasons of China’s CO2 emission growth rate reduction. Therefore, in future research, we will study the impact of China's energy transition and energy efficiency improvement on China's CO2 emissions.

Acknowledgements

This study is supported by National Office for Philosophy and Social Sciences in China (No. 17BGL014). The authors also gratefully acknowledge the helpful reviews and comments from the editors and anonymous reviewers.

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