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Original Research

CO_2 Emissions in China's Yangtze River Economic Zone: A Dynamic Vector Autoregression Approach

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Abstract

China has become the world's largest carbon emitter, and coal consumption in the Yangtze River Economic Zone takes over more than one third of the total number in the country. Investigating the main influencing factors of the Yangtze River Economic Zone's CO_2 emissions is of vital importance to develop effective environmental policies. The vector autoregression model was applied in the present paper to analyze the driving forces in this area based on the pertinent data from 1985 to 2014. Results show that energy efficiency is the primary influencing factor of the region's carbon emissions, which plays a leading role in mitigating CO_2 emissions. Energy structure has an obviously positive impact on the zone's CO_2 emissions. Urbanization has continuously promoted coal consumption in this area. These findings are extremely helpful for related departments in the Yangtze River Economic Zone to develop appropriate policies pertaining to energy savings and emissions reduction.

Keywords: CO_2 emissions, China's Yangtze River Economic Zone, vector autoregression model, energy efficiency

Introduction

Human health is affected by all air pollution, but some emissions have more severe atmospheric conditions. In particular, carbon dioxide (CO_2) and other pollutants, which contribute to global warming, have recently attracted attention, because CO_2 is one of the most researched gases [1-2].

China has become the focus and main force of the world to shoulder the responsibility of reducing CO_2 emissions. China has produced the most carbon emissions in the world, and even in 2014 its total carbon emissions ran up to 11.5 billion tons – almost one third of the total emissions of the world. Undoubtedly, China's carbon emissions are getting more and more attention from all over the world. However, the difficulty in reducing carbon emissions is the continuing existence of large demand due to rapid urbanization and industrialization. Thus, China is trying hard to mitigate its CO_2 emissions.

The Yangtze River Economic Zone (YREZ) is one of the largest economic zones of the economic density in China. Both the proportion of population and GDP in the YREZ are more than 40 percent of the total number, and the CO_2 emissions in this area take over more than one third of the total number. The YREZ, linking the mainland's most developed core areas (the Chengdu

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Chongqing and Wuhan regions), includes almost half of China's hinterland. Thanks to the rich natural resources, solid industrial and manufacturing base, and comprehensive transportation system, this economic zone has developed into one of the strongest areas. Consequently, investigating the main influential factors of the YREZ's CO_2 emissions is of vital importance to develop appropriate policies pertaining to energy savings and emissions reduction.

Different methods of investigating CO_2 emissions have been used by scholars worldwide [3-4], and they might be divided into four types.

The first method is index decomposition analysis. This classical approach mainly analyzes the factors that affect carbon emissions from the historical data, as well as the impact of various factors on CO_2 emissions. Decomposition analysis was applied by Shahiduzzaman and Layton [5] to investigate the effect on CO_2 emissions brought by economic changes in the United States, and it was concluded that economic structure contributed significantly to carbon emissions in the US. Based on Kaya factors, Remuzgo and Sarabia [6] used the decomposition analysis method to study the international inequality in CO_2 emissions and they decomposed the man-made carbon emissions into four factors: carbon intensity, electricity intensity, labor productivity, and employment rate. Using the divisia index (LMDI) decomposition method, Moutinho et al. [7] explored the influential factors of changes in CO_2 emissions in four parts of Europe and concluded that energy structure is an essential driving force affecting carbon emissions. The same method was applied by Chen and Liang [8], who extended the change in China's carbon emissions into twelve influencing factors, including energy intensity, energy structure, economic structure, labor productivity, and so on. Structural decomposition analysis, using the input-output theory and linkage analysis, was applied by Chang and Lahr [9] to explore changes in China's production-source CO_2 emissions. According to their empirical results, economic scale and energy intensity played dominant roles in the change of carbon emissions.

The second approach is the bottom-up analysis. The input-output price method was used by Di Cosmo and Hyland [10] to simulate the impact of price increases of ETS allowance on the final commodity price. Three different environmental regulations were investigated in the study on how environmental regulations affect carbon emissions and energy intensity of China's power plants [11]. In addition, taking Beijing as an example, how industrial structure potentially affects carbon emissions was investigated by Mi et al. [12]. The combination of the bottom-up model and the scenario analysis model was designed by Zhang et al. [13] to predict future carbon emissions and to estimate the reduction possibility of the primary aluminum industry in China. And the results indicated that a series of measures, such as controlling ore quality, could effectively mitigate CO_2 emissions of industry in China.

The third method is system optimization. To investigate the impact of urbanization on energy structure and energy consumption, Li et al. [14] developed the urbanization-energy consumption-CO_2 emissions system dynamic model with the system dynamics method. A multi-objective optimization model was introduced by Kang and Liu [15] to explore the impact of the heat pump on economic efficiency and CO_2 emission reduction of the heat exchanger network. A bi-directional fixed effect model was constructed to study the impact of urban transportation on CO_2 emissions in China [16]. Four assessment methods, including average amount of mixed electricity and marginal mixed power, were discussed and an optimizing energy system model was applied to predict the carbon emissions of Germany in 2030 [17]. Zhao et al. [18] studied the carbon connection among different departments by combining the production model and the improved hypothesis extraction method.

The last is econometric models. The ARDL model was applied by Sohag et al. [19] to explore the effect of Malaysia's resident consumption structure on carbon emissions. The stochastic copula autoregressive model was used by Marimoutou and Soury [20] to study the impact of energy price on CO_2 emissions. A cross-section regression analysis was carried out between the emission reduction plan and the major indexes analyzed at the European level [21]. The effect of Iran's energy consumption structure on CO_2 emissions was investigated and the technical and scale benefits of the manufacturer were explored using the data envelopment analysis model [22]. Based on the DEA model, the Malmquist index method was used by Lin and Fei [23] to assess the CO_2 emissions associated with the agricultural sector in China. Using the STIRPAT dynamic model, Yuan et al. [24] explored the influential factors on CO_2 emissions associated with energy in China. Dividing China's 30 provincial administrative units into three different levels of economic growth zones based on the per capita GDP, Wang and Zhao [25] applied the Grey Forecast model in evaluating the impacts of CO_2 emissions associated with energy.

Though the driving factors of carbon emissions have been widely discussed, there are two differences between the present research and previous studies. The first is that existing literature has focused more on the national level and provincial level than a regional level, while the present paper focuses on the study of carbon emissions in a key economic zone and investigates the impacts of the influential factors on carbon emissions in the YREZ. The other is that linear models are adopted by most researchers to explore the relationship between CO_2 emissions and the influencing factors, while in this article the vector autoregressive (VAR) model, taking nonlinear relationship among variables into consideration, is applied to explore the impacts of major influencing factors on CO_2 emissions in the YREZ. The VAR model has been widely used by Lin and Xu [26-27] to investigate China's CO_2 emissions.

Table 1. Definition of relevant variables.

Variable	Definition	Unit
CE	CO_2 emissions in the YREZ	10^4tons
GDP	Per capita GDP in the YREZ	10^4yuan
ENE	Energy efficiency in the YREZ	Tce per percent
URB	Urbanization level in the YREZ	Percent
INS	Industrial structure in the YREZ	Percent
ENS	Energy structure in the YREZ	Percent

Table 2. Statistical description of the variables.

Variable	Unit	Mean	Std. dev.	Min	Max
CE	10^4 tons	105152.3	61846.13	38086.29	219318.9
GDP	10^4 yuan	1.2901	1.399	0.0783	4.7731
ENE	Tce per percent	7309.374	4778.021	1362.891	18172.48
URB	Percent	30.0812	8.8539	17.5643	46.2156
INS	Percent	46.1126	2.115	42.3278	49.9095
ENS	Percent	71.4009	7.0935	59.5561	86.3685

Material and Methods

Data Source and Description

The annual observations on CO_2 emissions, industrial structure, urbanization level, energy efficiency, and per capita GDP in the YREZ during 1985-2014 were selected in this article. All the data are obtained from the China Statistical Yearbook (1985-2015) and the provincial statistical yearbooks (1985-2015). Energy efficiency is obtained by dividing the total output by carbon consumption. Industrial structure is calculated as value-added of the second industry divide by local GDP. Urbanization level means the proportion of the urban population. The definitions and the statistical descriptions of the variables are shown in Tables 1 and 2.

According to the annual data of the variables, this paper analyzes their dynamic changes. As shown in Fig. 1, CO_2 emissions, with an annual growth rate of 8%, have been growing rapidly since 2002. Energy efficiency has a rapid growth rate thanks to the advance of modern science and technology. Overall, energy structure has been gradually optimized, and the share of coal consumption declined steadily from 86.37% in 1993 to 59.56% in 2014. Per capita GDP increased from 783 yuan in 1985 to 47,731 yuan in 2014, with a rapid average annual growth rate of 14.7%. Industrial structure presents a pattern of fluctuation, and the proportion of the second industry reached its peak (49.91%) in 2011. In addition, there has been a steady increase in urbanization level, with an average annual growth rate of 3.3%.

VAR Model

The VAR model was first introduced by Sims [28]. It takes the form of multiple simultaneous equations, and the endogenous variables in each equation form a regression with the lagged values of all endogenous variables to estimate the dynamic relationships between all the endogenous variables. According to existing studies, it has been concluded that large amounts of dynamic relationships do exist between CO_2 emissions and its influencing factors. Therefore, the VAR model is applied in the present paper to investigate the dynamic impacts of the driving factors on CO_2 emissions in the YREZ.

The mathematical expression of general VAR model is as follows:

$$y_t = v + A_t y_{t-1} + \ldots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \ldots + \\ + B_q x_{t-q} + \mu_t \; t \in \{-\infty, +\infty\} \quad (1)$$

…where y_t, (t = 1,... T) is a $K \times 1$ vector, A is $K \times K$ aparametric matrix, x_t is a vector of exogenous variable, and B is a $K \times M$ coefficients matrix to be estimated. μ_t represents the random error term.

It is a difficult and contradictory process to determine the lag length (p) when constructing a VAR model. If the selected lag period is too long, there would be too many parameters to estimate in the model, which might result in the decline of the freedom and the inefficiency of the model. On the contrary, if the lag period is too short, the residual might not reach the white noise and the results could cause biased estimates. Therefore, there is a need to reach a balance between lag periods and degree of freedom. The Swartz Criteria (SC) and Akaike information criterion (AIC) are usually used to help determine a proper lag period. The formula of the two statistics can be expressed as follows:

$$AIC = -2l/n + 2k/n \tag{2}$$

$$SC = -2l/n + k\log n/n \tag{3}$$

$$l = -\frac{nm}{2}(1+\log 2\pi) - \frac{n}{2}\log[\det(\sum_t \varepsilon_t \varepsilon_t^{'}/n)] \tag{4}$$

…where l represents a logarithmic likelihood function, k is the number of parameters to be estimated, and n indicates the number of observations.

Model Specification

The IPAT identity (I = PAT) is often used to investigate the effects of the different factors driving environmental pollution:

$$I = P \cdot A \cdot T \tag{5}$$

Dietz and Rosa [29] proposed the STIRPAT model based on the IPAT model, the model can be expressed as follows:

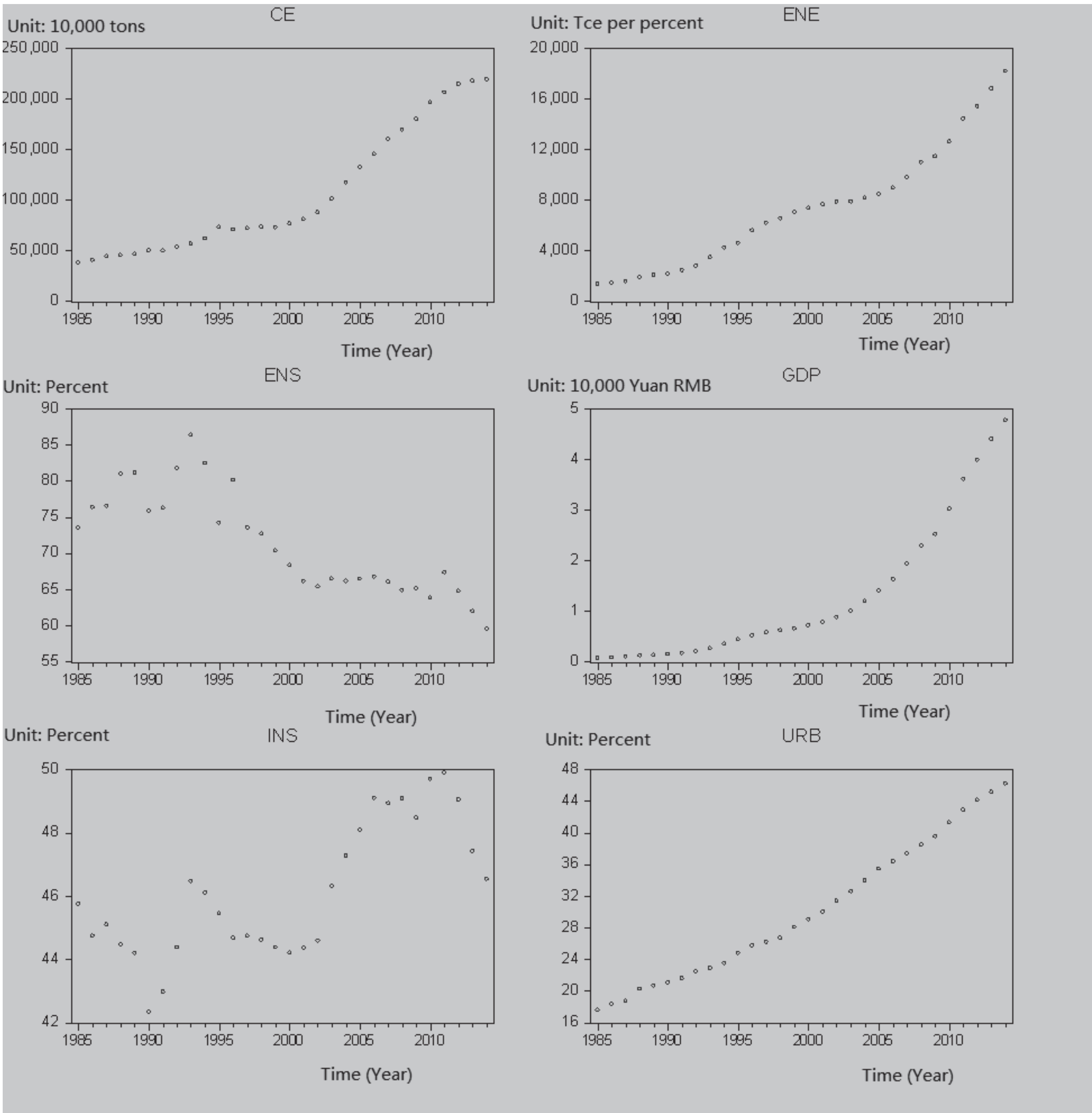

Fig. 1. Trends of CO_2 emissions, energy efficiency, energy structure, per capita GDP, industrial structure, and urbanization level, 1985-2014.

Table 3. Definition of relevant variables in the model.

Variable	Definition
I	The emission level of a pollutant
P	The size of the population
A	A country's affluence
T	Technological progress
a	The intercept term
b, c, d	The elasticities of environmental impacts of P, A and T respectively
ξ	The random disturbance

$$I_t = aP_t^b A_t^c T_t^d \xi_t \tag{6}$$

The definitions of the variables are shown in Table 3.

In order to avoid the possibility of heteroscedasticity, all the variables take a logarithmic form, and Eq. (10) can be written as:

$$LI_t = La + b(LP_t) + c(LA_t) + d(LT_t) + \xi_t \tag{7}$$

In order to analyze the influences of the driving forces on CO_2 emissions in the YREZ, Eq. (7) can be rewritten as:

$$LCE_t = La + b(LPOP_t) + c(LGDP_t) + d(LENE_t) + \xi_t \tag{8}$$

To further the study of the driving forces of the YREZ's CO_2 emissions, the model was expanded by adding URB, INS, and ENS to the model. Firstly, city is the center of population, transportation, construction, and industry. Urban areas and the rapid progress of industrialization and technology are leading to serious air pollution in urban areas [30-32]. The urbanization level in the YREZ increased from 17.6% in 1985 to 46.2% in 2014. An increasing urban population needs large amounts of urban housing and infrastructure and will result in an increase in CO_2 emissions. Therefore, it is essential to introduce URB into the model. Secondly, the second industry includes a majority of high energy-consuming industries. It is definitely that the proportion of the second industry has a positive impact on CO_2 emissions. Hence, INS is introduced into the model. Thirdly, as a major energy-consuming country in the world, China uses coal as its main energy source. Large amounts of coal use can lead for a significant increase in carbon emissions. Accordingly, the ENS is also involved in the model.

The expanded econometric model of CO_2 emissions in the YREZ is as follows:

$$LCE_t = La + \beta_1 LGDP_t + \beta_2 LENE_t + \beta_3 LURB_t + \\ + \beta_4 LIND_t + \beta_5 LENS_t + \xi_t \tag{9}$$

Results and Discussion

Unit Root Test

Time series analysis usually requires a stable sequence so that there is no existence of a stochastic trend or accurate trend. However, the majority of the time series might not be stationary, which may possibly result in biased analysis. The unit root test is used to test whether the variables have unit roots. Table 4 presents the findings of the different variables. The results indicate that none of the time series above is a stationary sequence. To address this issue, the first-order difference method is applied to change the time series into a stationary one. Test results of the first-order differential form are shown in Table 5. Data in Table 5 indicate that all the variables can reject the null hypothesis at different significance levels. This provides us with strong evidence to accept the conclusion that the first-order difference sequences are stationary, and the co-integration test can be proceed.

Table 4. Results of unit root test of all the variables.

	Series	ADF		DFGLS		KPSS	
		Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
Levels	CE	-1.5311	-2.0089	-2.0397**	-2.4186	0.5798**	0.1320*
	GDP	-1.7895	0.0499	-1.7797	-3.4723**	0.5701**	0.1689**
	ENE	3.6875	-1.9344	1.2281	0.2684	0.5869**	0.1560**
	URB	1.8214	-3.7071*	-0.2769	-2.2160	0.6098**	0.1581**
	INS	-1.6846	-2.4726	-1.6486*	-1.7642	0.4355*	0.161
	ENS	-0.5774	-2.4383	-0.6404	-2.6146	0.5399**	0.1005

***, **, * denote the null hypothesis of a unit root is rejected receptively at the 1%, 5%, and 10% significance levels

Table 5. Results of unit root test of variables in first-order difference.

	Series	ADF		DFGLS		KPSS	
		Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
Frist difference	CE	-3.4032***	-3.3243**	-1.6081*	-3.4649***	0.0971***	0.0841***
	GDP	-3.0592**	-3.3605**	-2.6995*	-3.2787**	0.1067***	0.0580***
	ENE	-3.4266**	-3.7630**	-3.3211***	-3.688**	0.2167***	0.0998***
	URB	-4.5549***	-4.5415***	-6.0825***	-4.6814***	0.2201***	0.1380**
	INS	-3.6972***	-3.6256**	-3.3665***	-3.6832**	0.0829***	0.0834***
	ENS	-5.7862***	-5.8304***	-5.4361***	-5.9109***	0.0230***	0.1338**

***, **,* are the same as for Table A1

Johansen Co-Integration Test

The co-integration test determines whether a set of non-stationary linear combinations have a stable equilibrium relationship. The Johansen test is a test of regression coefficient based on the VAR model and a test for multivariate co-integration. Table 6 presents the results of the Johansen test, which includes both the trace statistic and the max-eigen statistic. Trace test and max-eigenvalue test both indicate one co-integration equation at the 0.05 level. Thus, it is reasonable to conclude that there is only one co-integration equation among the variables.

Table 6. Johansen co-integration test.

Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	0.05 Critical value	Prob.**
None*	0.9108	125.8897	95.7537	0.0001
At most 1	0.5549	60.6397	69.8189	0.2162
At most 2	0.4643	38.7826	47.8561	0.2690
At most 3	0.3009	21.9310	29.7971	0.3023
At most 4	0.2430	12.2660	15.4948	0.1446
At most 5	0.1613	3.8415	4.7485	0.1293
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen statistic	0.05 Critical value	Prob.**
None*	0.9108	65.2550	40.0776	0.0000
At most 1	0.5549	21.8571	33.8769	0.6187
At most 2	0.4643	16.8516	27.5843	0.5927
At most 3	0.3009	9.6651	21.1316	0.7754
At most 4	0.2430	7.5181	14.2646	0.4298
At most 5	0.1613	3.8415	4.7478	0.1293

* denotes rejection of the hypothesis at the 0.05 level
** mackinnon-haug-michelis (1999) p-values.

Table 7. Lag selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	397.6888	NA	3.31e-21	-30.1299	-29.8396	-30.0463
1	446.9941	72.0617	1.29e-21	-31.1534	-29.1211	-30.5682
2	504.4972	57.5031	4.11e-22	-32.8075	-29.0332	-31.7206
3	596.1465	49.3496*	3.45e-23*	-37.0882*	-31.5719*	-35.4997*

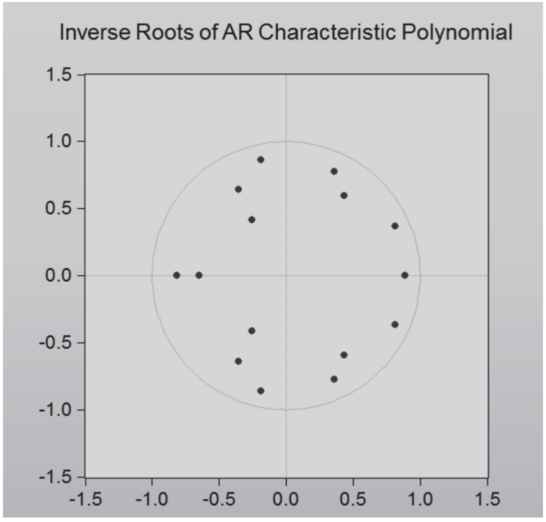

Fig. 2. VAR roots of characteristic polynomial.

Optimal Lag Order Selection

To make the conclusion of the model more convincing, it is of vital importance to coordinate the lag order and the degree of freedom. Table 7 shows the results of lag order selection under different criteria. "*" suggests lag order chosen by the corresponding criteria. Finally, 3 is selected as the optimal lag order.

VAR Specifications and Estimates

Taking all the relevant variables into account, the VAR model of the CO_2 emissions in the YREZ is constructed. Based on the criteria of AIC and SC, the estimates with their t-values and the standard errors of the model are presented in Table 8. It can be concluded that most of the t-values are significant,

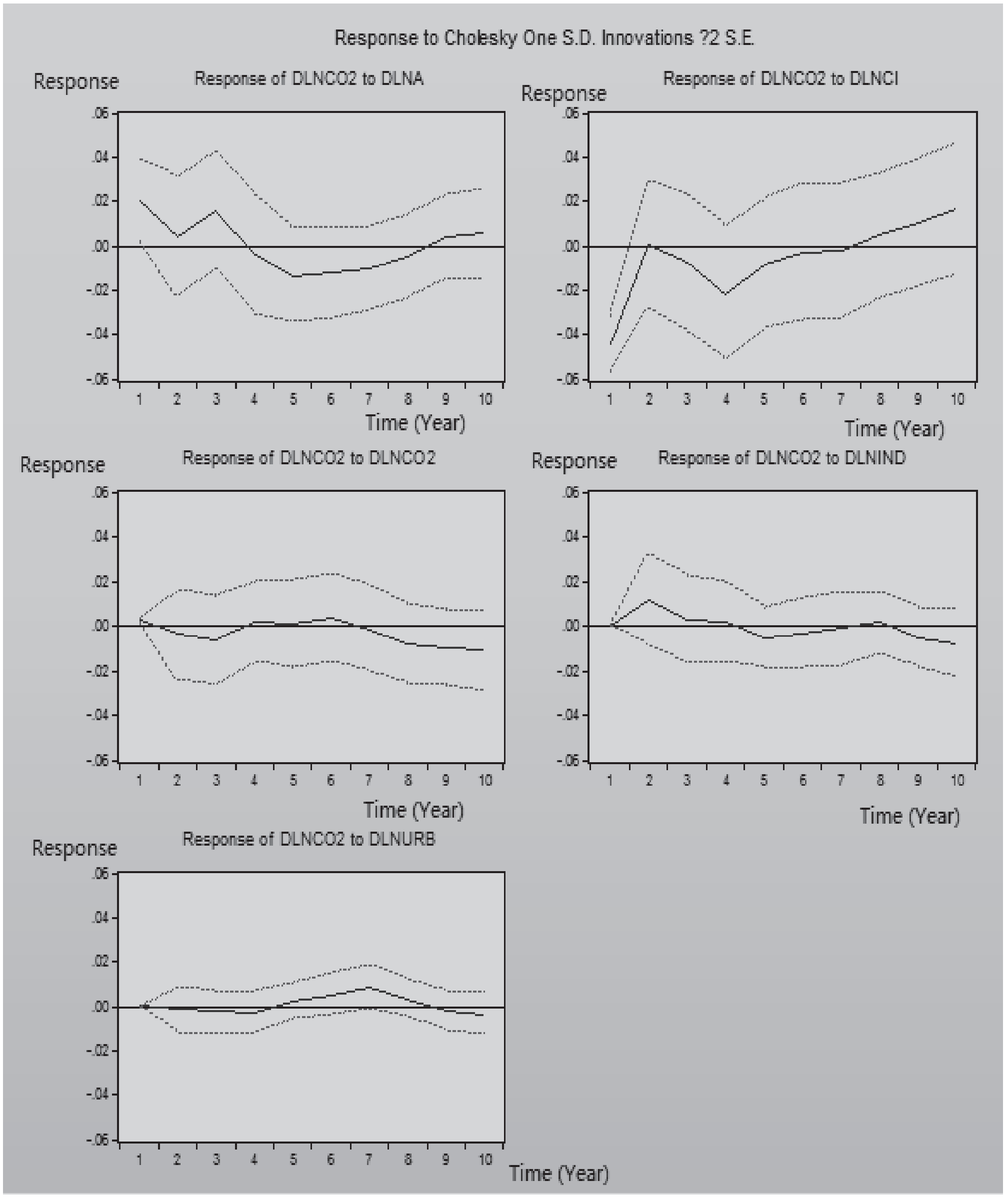

Fig. 3. Responses of the Yangtze River Economic Zone's CO_2 emissions to its driving factors.

Table 8. Vector autoregression estimates.

LNCE(-1)	-0.8441	LNENE(-1)	-1.5185	LNENS(-1)	0.0982
	(4.2612)		(3.4708)		(0.4513)
	[-0.1981]		[-0.4375]		[0.2176]
LNCE(-2)	0.0106	LNENE(-2)	6.2851	LNENS(-2)	0.1752
	(5.3244)		(4.6134)		(0.2142)
	[0.0020]		[1.3624]		[0.8177]
LNCE(-3)	3.3027	LNENE(-3)	-2.5370	LNENS(-3)	-2.5370
	(5.4277)		(4.4127)		(4.4127)
	[0.6085]		[-0.5749]		[-0.5749]
LNGDP(-1)	4.2402	LNURB(-1)	-0.3746	LNINS(-1)	0.0402
	(3.6689)		(0.2093)		(1.0092)
	[1.1557]		[-1.7893]		[0.0398]
LNGDP(-2)	-7.0139	LNURB(-2)	-0.5551	LNINS(-2)	-0.8827
	(4.9814)		(0.2642)		(1.0680)
	[-1.4080]		[-2.1013]		[-0.8266]
LNGDP(-3)	0.4504	LNURB(-3)	-0.0625	LNINS(-3)	2.6615
	(4.7603)		(0.3626)		(1.9440)
	[0.0946]		[-0.1725]		[1.3691]
C	22.6623	R^2	0.9982	SC	-2.4189
	(15.8407)	Adj_R^2	0.9941	AIC	-3.3308
	[1.4306]	SSR	0.014	SC	-2.4189

and the equation has high R^2 of 0.9982 and high adjusted R^2 of 0.9941.

AR Roots Test

The VAR model's stability requires that the reciprocal of the characteristic roots is less than 1. This implies that all the characteristic roots should be within the unit circle. The result of the AR root test is presented in Fig. 2. There is no root located outside the unit circle, which implies that the estimated VAR model meets the stability test. The adoption of the stability test ensures the following analysis based on the VAR model is more convincing and more effective.

Table 9. Estimates from variance decomposition.

Period	S.E.	LNCE	LNENE	LNENS	LNGDP	LNINS	LNURB
1	0.04159	100.0000	0.0000	0.0000	0.00000	0.0000	0.0000
2	0.04644	98.7066	0.0250	0.7424	0.3129	0.2118	0.0012
3	0.05256	95.7855	2.3760	0.8034	0.5906	0.4426	0.0020
4	0.06137	94.6877	3.4786	0.6427	0.7661	0.3614	0.0636
5	0.06926	78.5998	17.8354	1.4430	1.0235	0.9474	0.1510
6	0.07729	64.1503	10.0272	12.0819	1.5245	1.6173	10.5988
7	0.08396	54.7283	17.8684	12.1377	2.2860	1.5854	11.3943
8	0.08952	48.1442	22.0685	12.8986	3.7235	1.4115	11.7537
9	0.09141	46.2336	22.4531	13.7223	4.4746	1.3645	11.7518
10	0.09189	46.2214	22.0116	14.0211	4.6382	1.3718	11.7360

Impulse-Response Function

The impulse-response function is to find out the dynamic effects of the independent variables on the dependent variables. This methodology is used to present the response of one endogenous variable to an impact caused by an error term. Fig. 3 presents the responses of CO_2 emissions in the YREZ to the influencing factors – both short term and in the long run. One standard deviation shock to energy efficiency (ENE) increases carbon emissions briefly for about 4 years and then there is a negative response in the long run. One standard deviation shock to energy structure (ENS) seems to increase carbon emissions both in the short and long terms. CO_2 emission shows a small fluctuation in economic growth (LNGDP). In the early 2 years it has a negative impact but a positive response in the late years. One standard deviation shock to industrial structure (LNINS) seems to raise CO_2 emissions in the short term, but the impact will gradually be reduced and finally has a small opposite effect in the long run. The impulse response of the carbon emissions to urbanization level (LNURB) indicates that one standard deviation shock to URB tends to raise CO_2 emissions both in the short and long terms, but finally the impact will be very weak.

Variance Decomposition

Variance decomposition is used to describe the proportion of error variance of different impacting factors of carbon emissions in the YREZ. It is a description of the relative effect that can explain the contribution of each variable to the system variable. The results of variance decomposition are presented in Table 9. For the YREZ's carbon emissions, energy efficiency shock is the most important factor in explaining its variability. In the third period, energy efficiency shock accounts for around 2.5% of the forecast error variance and rises to 22% over the long term. The impact of energy structure ranks second. In the short term, the impact of energy structure is less than 1% of the predicted variance, while it reaches to 14% at long horizons. This is different from Lin's research [26], which suggested that energy structure shock would not play a crucial part in affecting carbon emissions. The next relative significant contributor is urbanization shock. Although the percentage of its predicted variance is far less than 1% in the short term, the number rises to 11% in the long run. However, economic progress and industrial structure shock account for around 4% and 1% of the predicted variance in the long run, respectively. This indicates that neither of them is a significant factor affecting carbon emissions in the YREZ.

Conclusions

According to time series data from 1985 to 2014, the present paper investigated the impacting factors of CO_2 emissions in China's YREZ based on the VAR model. It can be concluded from the results that energy efficiency, energy structure, and urbanization level are three key elements for reducing CO_2 emissions. These empirical results are crucial for policy makers of the YREZ, and the following policy recommendations might be helpful.

First, promote energy-saving technology research and improve energy efficiency. Priority should be given to research and the application of energy-saving technologies and emission reduction technologies. On the one hand, control the development of high-energy consuming industries. Including the energy-saving targets into the comprehensive evaluation of economic and social development and the annual assessment system would effectively improve the energy efficiency of high energy consuming industries. On the other hand, the government should increase the investment of advanced energy-saving technologies. By formulating fiscal policies, such as subsidizing related research institutions and enterprises, the government can encourage them to participate in the research and development of low carbon dioxide emission techniques. Moreover, it is necessary to strengthen technical exchanges with developed countries and introduce advanced foreign technologies of clean energy, such as clean coal technology and clean development mechanisms. Secondary combustion technology of exhaust gas and CO_2 recycling technology are two technologies under vigorous development that can significantly mitigate energy consumption. Government should encourage the R&D and use of these kinds of technologies.

Second, reduce the percentage of coal consumption to optimize the energy structure. Government should adopt targeted measures such as expanding the use of natural gas, hydropower, and nuclear power to optimize energy structure. In the first place, the central government is supposed to speed up the approval and construction of nuclear power plants, and strictly control the size and number of thermal power plants. Nuclear energy is a clean and pollution-free energy source, so expanding nuclear energy production and consumption will significantly reduce coal consumption. In addition, with the development of science and technology, bio-energy has gradually become an important source of renewable energy consumption. Moreover, the government ought to gradually release coal prices to connect with the international market. This will encourage the related enterprises to seek ways to improve productivity, thereby reducing coal consumption and carbon emissions.

Third, a series of measures should be adopted to minimize the increase in carbon emissions due to the high-speed urbanization process. In the first place, increasing urban populations mean more demands for urban housing and infrastructure, resulting in a large demand for energy-intensive products such as steel, cement machinery, and other manufactured products. Therefore, the government should encourage the use of energy-efficient building materials and low carbon chemical materials. In addition, the large-scale use of motor vehicles in urban areas consumes a large amount of fossil fuels. Thus, in order to control the emissions from transport at source, R&D and use of bio-fuels, waste oil, and pure electric vehicles must be supported and encouraged. Moreover, residents should be directed to low-carbon consumption patterns in order to reduce the energy consumption intensity of family life. Keeping in line with the "three Es" (economic, ecological, and equitable) and "three Rs"(reduce, reuse, and recycle) makes great sense in realizing green consumption.

Finally, reduce the proportion of the second industry and vigorously develop the tertiary industry to optimize the industrial structure. On the one hand, efforts should be made to integrate resources of high-emission heavy industries. Corresponding government authorities are supposed to take decisive measures to adjust industrial structure by shutting off or combining energy-intensive, high-polluting small steel mill, oil refineries, and chemical plants. On the other hand, carbon emission of the tertiary industry is much lower than that of the secondary industry. Therefore, industrial structure optimization, especially the restructuring of the tertiary industry, is key for CO_2 emissions reduction. Thus, governments at all levels should intensify nurturing tertiary industry such as the financial services and information technology services industries, and increase its proportion in the industrial structure. Policy makers have to keep an eye on accelerating the optimization and upgrading of industrial structure as well as investing more in high-tech industries instead of traditional industries.

Conflict of Interest

The authors declare no conflict of interest.

References

1. CETIN M., SEVIK H. Measuring the Impact of Selected Plants on Indoor CO_2 Concentrations. Pol. J. Environ. Stud. **25**, 973, **2016**.
2. CETIN M. A Change in the Amount of CO_2 at the Center of the Examination Halls: Case Study of Turkey. Stud. Ethno-Medicine. **10**, 146, **2016**.
3. HASEEB M., HASSAN S., AZAM M. Rural-Urban Transformation, Energy Consumption, Economic Growth, and CO2 Emissions Using STRIPAT Model for BRICS Countries. Environ. Prog. Sustain. **36** (2), 523, **2017**.
4. WEN L., LIU Y.J. A Research About Beijing's Carbon Emissions Based on the IPSO-BP Model. Environ. Prog. Sustain. **36**, 428, **2017**.
5. SHAHIDUZZAMAN M.D., LAYTON A. Changes in CO_2 emissions over business cycle recessions and expansions in the United States: A decomposition analysis. Appl. Energ. **150**, 25, **2015**.
6. REMUZGO L., MARIA S.J. International inequality in CO_2 emissions: A new factorial decomposition based on Kaya factors. Environ. Sci. Policy. **54**, 15, **2015**.
7. MOUTINHO V., MOREIRA A.C., SILVA P.M.. The driving forces of change in energy-related CO_2 emissions in Eastern, Western, Northern and Southern Europe: The LMDI approach to decomposition analysis. Renew. Sust. Energ. Rev. **50**, 1485, **2015**.
8. CHEN, L., YANG, Z.F. A spatio-temporal decomposition analysis of energy-related CO_2 emission growth in China. J. Clean. Prod. **103**, 49, **2015.**
9. CHANG N., LAHR M.L. Changes in China's production-source CO_2 emissions: insights from structural decomposition analysis and linkage analysis. Econ. Syst. Res. **28**, 224, **2016**.
10. Di COSMO V., HYLAND M. Decomposing patterns of emission intensity in the EU and China: how much does trade matter? J. Environ. Plan. Manag., **58** (12) 2176, **2015**.
11. ZHAO L., LI L., ZHANG Y.J. Investigating the CO_2 emission differences among China's transport sectors and their influencing factors. Nat. Hazards. **77**, 1323, **2015**.
12. MI Z.F., PAN S.Y., YU H. Potential impacts of industrial structure on energy consumption and CO_2 emission: a case study of Beijing. J. Clean. Prod. **103**, 455, **2015**.
13. JIANG X.M., LIU Y.F., ZHANG J. Evaluating the role of international trade in the growth of china's CO_2 emissions. J. Syst. Sci. Complex. **28**, 907, **2015**.
14. ZHANG W.J., Li H.Q., CHEN B. CO_2 emission and mitigation potential estimations of China's primary aluminum industry. J. Clean. Prod. **103**, 863, **2015**.
15. KANG L.X., LIU Y.Z. Multi-bjective optimization on a heat exchanger network retrofit with a heat pump and analysis of CO_2 emissions control. Appl. Energ. **154**, 696, **2015**.
16. YANG W.Y., LI T., CAO X.S. Examining the impacts of social-economic factors, urban form and transportation development on CO_2 emissions from transportation in China: A panel data analysis of China's provinces. Habitat Int. **49**, 212, **2015**.
17. JOCHEM P., BABROWSKI S.J., FICHTNER W. Assessing CO_2 emissions of electric vehicles in Germany in 2030. Transp. Res. Part A-Policy. Prac. **78**, 68, **2015.**
18. ZHAO X.L., YIN H.T., ZHAO Y. Impact of environmental regulations on the efficiency and CO_2 emissions of power plants in China. Appl. Energ. **149**, 238, **2015**.
19. SOHAG K.Z., BEGUM R.A., ABDULLAH S.M.S. Dynamic impact of household consumption on its CO_2 emissions in Malaysia. Environ. Dev. Sust. **17**, 1031, **2015**.
20. MARIMOUTOU V., SOURY M. Energy markets and CO_2 emissions: Analysis by stochastic copula autoregressive model. Energy. **88**, 417, **2015**.
21. PABLO-ROMERO M.P., POZO-BARAJAS R., SANCHEZ-BRAZA A. Understanding local CO_2 emissions reduction targets. Renew. Sust. Energ. Rev. **48**, 347, **2015**.
22. EBRAHIMI R., SALEHI M. Investigation of CO_2 emission reduction and improving energy use efficiency of button mushroom production using Data Envelopment Analysis. J. Clean. Prod. **103**, 112, **2015**.
23. LIN B.Q., FEI R.L. Regional differences of CO_2 emissions performance in China's agricultural sector: A Malmquist index approach. Eur. J. Agron. **70**, 3, **2015**.
24. YUAN R., ZHAO T., XU X.S. Regional Characteristics of Impact Factors for Energy-Related CO_2 Emissions in China, 1997-2010: Evidence from Tests for Threshold Effects Based on the STIRPAT Model. Environ. Model. Assess. **20**, 129, **2015**.
25. WANG Y.N., ZHAO T. Impacts of energy-related CO_2 emissions: Evidence from under developed, developing and highly developed regions in China. Ecol. Indic. **50**, 186, **2015**.

26. XU B., LIN B.Q. Assessing CO_2 emissions in China's iron and steel industry: A dynamic vector autoregression model. Appl. Energ. **161**, 375, **2016**.
27. XU B., LIN B.Q. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. J. Clean. Prod. **131**, 594, **2016**.
28. SIMS C.A. Macroeconomics and Reality. Econometrica. **48** (1), 1, **1980**.
29. DIETZ T., ROSA E.A. Effects of population and affluence on CO_2 emissions. Proc. Natl. Acad. Sci. USA. **94**(1), 175, **1997**.
30. SEVIK H., CETIN M. Effects of Water Stress on Seed Germination for Select Landscape Plants. Pol. J. Environ. Stud. **24** (2), 689, **2015**.
31. CETIN M., SEVIK H. Indoor quality analysis of CO_2 for Kastamonu University", Conference of the International Journal of Arts & Sciences, **09** (03), 71, **2016**.
32. KRAVKAZ KUSCU I.S., CETIN M., YIGIT N., SAVACI G., SEVIK H. The Relationship of Enzyme Activity (Urease-Catalase) and Nutrient Element Related to the Use of Soil. Pol. J. Environ. Stud. **2018**.