An Empirical Study of Carbon Emissions and Energy Consumption in China

Liu Fangjun

School of Economics and Finance, Zhanjiang Institute of Science and Technology, Zhanjiang, China

Email address:

1259426079@qq.com

Abstract: This paper obtains the data of China's total energy consumption and consumption structure from 1990 to 2021 from the Statistical Yearbook of China 2022. And use it to calculate the total coal consumption, oil consumption, natural gas consumption and primary electricity and other energy consumption in the same period. The carbon emission coefficients of coal, oil and gas from various institutions in Dr Danyang's thesis (2020) were used to calculate the total carbon emissions for the same period. Using these data and using unit root test, co-integration analysis, step-up regression method and generalized difference method, this paper empirically studies the relationship between total carbon emission and total coal consumption, total oil consumption, total natural gas consumption, total primary power consumption and other energy consumption in China. The results show that the total consumption of primary power and other energy has no significant effect on China's total carbon emissions. Coal consumption, oil consumption and natural gas consumption have a significant impact on China's total carbon emissions. In addition, when the total consumption of coal, oil and natural gas increases by 1%, on average, China's total carbon emissions increase by 0.82%, 0.16% and 0.03%, respectively. Policy recommendations are put forward accordingly.

Keywords: China's Carbon Emissions, Energy Consumption, Cointegration Analysis, Stepwise Regression Method, Generalized Difference Method

1. Introduction

The Chinese government has pledged to peak carbon dioxide emissions by around 2030 and strive for carbon neutrality by 2060. In this paper, China's carbon emissions and energy consumption are selected as research objects, with the purpose of reducing high-carbon emissions, so as to reduce carbon dioxide emissions.

China is in the middle stage of industrialization and urbanization, and its high energy demand leads to serious environmental pollution, especially the pressure of carbon emission. Therefore, to actively study the influencing factors of China's energy carbon emissions is helpful to optimize the structure of energy consumption, transition and development towards low-carbon and clean direction, and is of great significance to achieve the goal of carbon peak and carbon neutrality.

There is an objective internal connection between carbon emissions and energy consumption. Too high energy consumption will inevitably lead to too high carbon emissions, which cannot achieve the "dual carbon" goal. On the contrary, too low energy consumption, although it can reduce carbon emissions, may cause a series of social problems, such as slowing economic development and increasing unemployment. At the same time, carbon emissions are closely linked to energy consumption structure. Only by understanding the accurate quantitative relationship between carbon emissions and energy consumption can we make the reduction of carbon emissions targeted. This is the theoretical and practical significance of this paper.

2. Literature Review

Hu Mengran (2021) proposed that the total carbon emission in Chinese counties would show a rapid growth trend between 1997 and 2017, and the carbon emission would mainly come from the secondary industry [1]. Qu Huimin (2021) makes an empirical analysis of the current situation of global primary energy consumption and finds that the growth of primary energy consumption is inversely proportional to the degree of

economic development, there is regional imbalance in energy consumption types, and new energy consumption keeps increasing [2]. When researching Chinese carbon emissions, Pan Dong (2020) proposes that population has the greatest impact on carbon emissions, while energy intensity comes last. He also predicts that the possibility of reaching the peak before 2030 is low by using the extended STIRPAT model [3]. Chen Ruimin (2019) analyzed the driving factors of China's industrial carbon emissions from 2000 to 2016 by using the generalized Di Exponential decomposition method (GDIM) and built a decoupling effort model with DPSIR framework to measure the decoupling effect of industrial carbon emissions. It is found that the decoupling effect of China's industrial carbon emissions presents a phased feature of "non-decoupling - weak decoupling - strong decoupling", and the output carbon intensity and technological progress are the key factors to promote the decoupling of industrial carbon emissions [4]. Engle-Granger (1987) proposed the concept of co-integration, proposed the two-step method of co-integration test and Granger's expression theorem, and conducted strict demonstration of the theorem [5]. Dickey-Fuller (1979) proposed ADF (Augment Dickey-Fuller) test and then solved the problem of false regression [6].

Peng Jingxiao et al. (2019) adopted the system dynamics method to build and simulate the carbon emission model of energy consumption in Hunan Province from 2017 to 2030, and the results showed that industrial structure optimization was needed to reduce carbon emissions [7]. Wang Duo (2021) studied the carbon emissions of Anhui Province based on the S-D model and found that increasing scientific and technological input per unit of GDP could reduce coal consumption and thus reduce carbon emissions [8]. Shao Shuai et al. (2017) believe that the manufacturing industry is a pillar industry and a major carbon emitter in China. In order to achieve the carbon emission reduction target, the government should further guide the manufacturing enterprises to carry out energy conservation and emission reduction [9]. Wang Yixuan (2020) uses grey correlation analysis method to study and find that coke and electricity are the energy sources that are most closely related to economic growth in Liaoning Province [10]. Xu Chengbin (2020) believes that in the face of the difficulty of low energy economic efficiency, efforts should be made from the aspects of industrial transformation, energy-saving technology innovation and clean and low-carbon energy [11]. Lin Boqiang (2001) found a long-term equilibrium relationship among total energy consumption, GDP, energy price and structural changes [12]. Lin Boqiang (2018) proposed that the clean and low-carbon transition should take into account energy costs, improve energy efficiency and accelerate energy system reform by seeking truth from facts [13]. Lin Boqiang (2021) found that fossil energy plays a dominant role in the energy consumption structure, so clean replacement of coal by electricity is the key, and both sides of supply and demand will affect the goal of carbon neutrality [14]. Liu Danyang (2020) proposed the calculation formula of carbon emission in his doctoral dissertation [15].

3. Current Situation of Carbon Emission and Energy Consumption in China

3.1. China's Carbon Emissions Continue to Grow in Most of the Time

China's total carbon emissions increased from 651,314,200 tons in 1990 to 2888,049,000 tons in 2021, an increase of 3.434 times in 32 years, with an average annual increase of 11.08%. With the exception of two years, 1997 and 1998, when China's total carbon emissions fell slightly, the rest of the years have seen an increase.
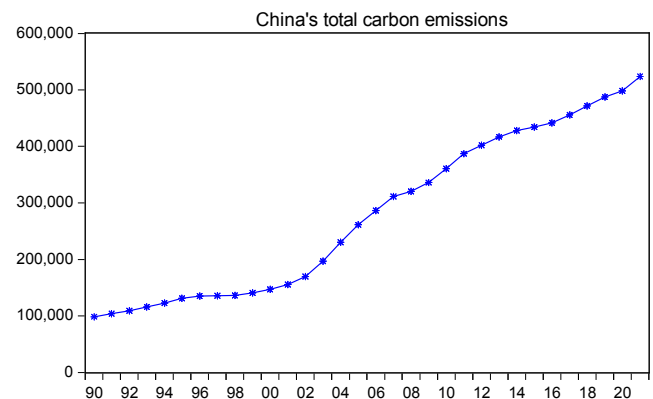

Figure 1. *Time sequence chart of China's total carbon emissions from 1990 to 2021.*

3.2. China's Total Energy Consumption Keeps Growing

China's total energy consumption increased from 98,703 million tons of standard coal in 1990 to 524,000 million tons of standard coal in 2021, an increase of 4.309 times in 32 years, or an average annual growth of 17.13 percent.
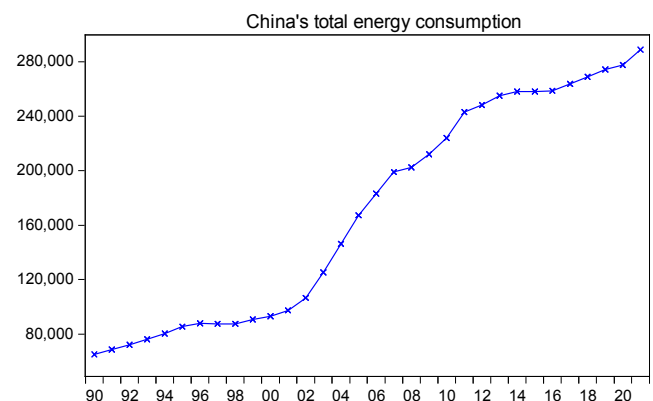

Figure 2. *Time sequence chart of China's total energy consumption from 1990 to 2021.*

3.3. All Components of China's Energy Consumption Have Increased to Varying Degrees

The total coal consumption increased from 75,211.7 million tons of standard coal in 1990 to 293,440 million tons of standard coal in 2021, an increase of 2.902 times in 32 years, with an average annual growth of 9.36 percent. The total oil consumption increased from 16,384.7 million tons of standard

coal in 1990 to 96,940 million tons of standard coal in 2021, an increase of 4.916 times in 32 years, with an average annual growth of 15.86 percent. The total consumption of natural gas increased from 2,072.8 million tons of standard coal in 1990 to 46,636 million tons of standard coal in 2021, an increase of 21.499 times in 32 years, or an average annual increase of 69.35 percent. The total consumption of primary power and other energy sources increased from 5,033.9 million tons of standard coal in 1990 to 86,984 million tons of standard coal in 2021, a 16.280 times increase in 32 years, with an average annual growth of 52.51 percent.
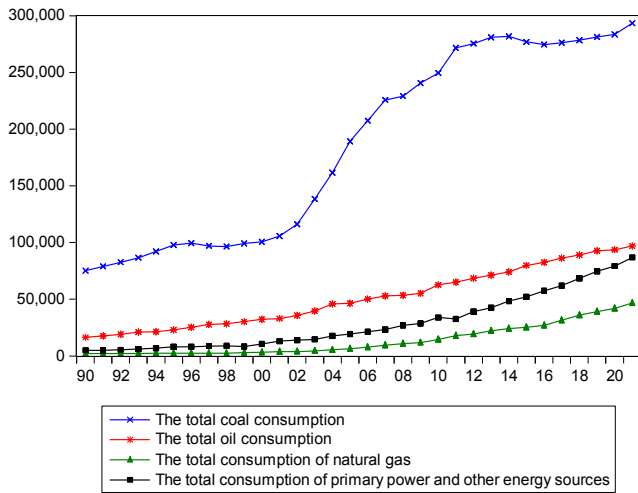

Figure 3. *Time sequence diagram of each component of China's energy consumption from 1990 to 2021.*

3.4. China's Energy Consumption Structure Has Been Continuously Optimized
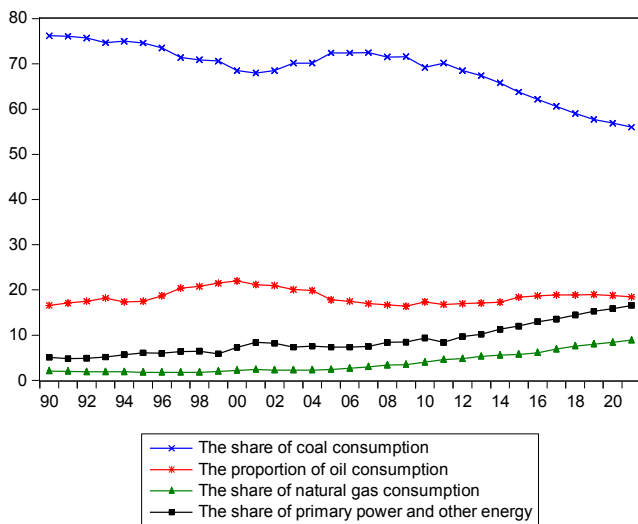

Figure 4. *Time series chart of the proportion of each component of China's energy consumption during 1990-2021.*

The share of coal consumption in consumption dropped from 76.2 percent in 1990 to 56 percent in 2021, an average annual decline of 0.652 percentage points over the 32 years. The proportion of oil consumption in consumption first increased and then decreased, from 16.6 percent in 1990 to 22

percent in 2000 and then to 18.5 percent in 2021, an average annual increase of 0.061 percentage points for 32 years. The share of natural gas consumption in consumption increased from 2.1 percent in 1990 to 8.9 percent in 2021, an average annual increase of 0.219 percentage points over the past 32 years. The share of primary power and other energy in consumption increased from 5.1 percent in 1990 to 16.6 percent in 2021, an average annual increase of 0.371 percentage points over the past 32 years.

4. Data Sources and Processing, Explained Variables and Explained Variables

4.1. Data Sources

Data on China's total energy consumption (10,000 tons of standard coal) and the proportion of energy in consumption (%) during 1990-2020 are obtained from the Statistical Yearbook of the National Bureau of Statistics, PRC (2022); Carbon emission coefficients of coal, oil and Gas in various institutions from Liu Danyang's PhD thesis (2020); From 1990 to 2021, China's total carbon emissions (10,000 tons) and energy consumption (10,000 tons of standard coal) are calculated.

4.2. Measurement of Carbon Emissions

The main types of energy used to calculate the total amount of carbon emissions are coal, oil and natural gas, three primary fossil energy sources. After searching the literature, the calculation formula of carbon emissions is as follows:

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} E_i \times F_i \qquad (1)$$

In formula (1), C is the total carbon emission (unit: 10,000 tons); C_i is the carbon emission of a certain energy i, and the unit is 10,000 tons; E_i is the consumption of a certain energy i, and the unit is 10,000 tons of standard coal; F_i is the carbon emission coefficient of a certain energy i. The carbon emission coefficient is a constant selected from the average carbon emission coefficient of four institutions: Department of Energy of the United States, Institute of Energy Economics of Japan, Climate Change Project of the National Science and Technology Commission and Energy Research Institute of the National Development and Reform Commission, as shown in Table 1.

Table 1. *Carbon emission coefficients of coal, oil and gas by institution.*

Data source organization	Coal	Oil	Gas
The United States Department of Energy	0.702	0.478	0.389
Japan Institute of Energy Economics	0.756	0.586	0.449
State Science and Technology	0.726	0.583	0.409
Energy Research Institute, National Development and Reform Commission	0.7476	0.5825	0.4435
Mean value	0.7329	0.5574	0.4226

Data source: Liu Danyang. Empirical analysis of Influencing Factors of carbon emission in China [D]. North China University of Technology, 2020.

4.3. Explained Variables and Explanatory Variables

In this paper, China's total carbon emissions are selected as the explained variable Y, and China's total carbon emissions from 1990 to 2021 are calculated by using the carbon emission measurement formula (1) above and carbon emission coefficients of all energy sources in Table 2. Since the influence of heteroscedasticity can be mitigated by taking logarithm, lnY can be obtained by taking logarithm of explained variable Y.

The paper selects total coal consumption as explanatory variable X1. Total oil consumption as explanatory variable X2; Total natural gas consumption as explanatory variable X3;

Total primary power and other energy consumption as explanatory variable X4. Logarithmic transformation of these explanatory variables gives lnX1, lnX2, lnX3, and lnX4.

5. Empirical Research

5.1. Unit Root Test

In order to prevent the phenomenon of "pseudo-regression", the stationarity test of all variables was conducted first. Here, ADF test was used to conduct stationarity test, and the test results were shown in Table 2.

Table 2. *Test results of ADF test of each variable.*

Test variable	Inspection form	ADF statistics	1% significance level threshold	D.W value	p value	conclusion
lnX1	(C,T,1)	-2.484242	-4.296729	2.311712	0.3329	unstable
lnX2	(C,0,0)	-2.206672	-3.661661	2.286513	0.2080	unstable
lnX3	(C,T,7)	-5.961987	-4.394309	2.197312	0.0003	stable
lnX4	(C,T,0)	-3.575363	-4.284580	1.846494	0.0487	unstable
lnY	(C,T,1)	-2.633286	-4.296729	2.007968	0.2694	unstable
ΔlnX1	(0,0,0)	-1.477348	-2.644302	1.967212	0.1280	unstable
ΔlnX2	(C,0,0)	-5.384175	-3.670170	2.002789	0.0001	stable
ΔlnX3	(C,0,0)	-3.039024	-3.670170	2.085358	0.0426	unstable
ΔlnX4	(C,0,0)	-6.567921	-3.670170	2.123131	0.0000	stable
ΔlnY	(0,0,0)	-1.286049	-2.644302	1.714422	0.1785	unstable
Δ^2lnX1	(0,0,2)	-3.605035	-2.653401	1.860804	0.0008	stable
Δ^2lnX2	(0,0,1)	-6.928746	-2.650145	2.124552	0.0000	stable
Δ^2lnX3	(0,0,0)	-6.774116	-2.647120	2.125652	0.0000	stable
Δ^2lnX4	(C,T,7)	-5.542626	-4.440739	1.910498	0.0010	stable
Δ^2lnY	(0,0,0)	-4.758410	-2.647120	1.979125	0.0000	stable

From the test results, the original logarithmic sequence lnX1, lnX2, lnX3, lnX4 and lnY was only lnX3 stable in their respective test forms and at the 1% significance level, The logarithmic first-order difference sequences ΔlnX1, ΔlnX2, ΔlnX3, ΔlnX4 and ΔlnY are both stable in their respective test forms and at the 1% significance level; The logarithmic second-order difference sequences Δ^2lnX1, Δ^2lnX2, Δ^2lnX3, Δ^2lnX4 and Δ^2lnY are all stationary in their respective test forms and at the 1% significance level.

5.2. Model Construction

If the explanatory variable and the explained variable have the same stationary order, then the conditions for integral modeling are satisfied. lnX1, lnX2, lnX3, lnX4 and lnY are all second-order single integral sequences. Therefore, lnY is selected as explained variable, and X1, X2, X3, X4 and X5 are selected as explained variables. The co-integration model is constructed as follows:

$$lnY = C + \beta_1 lnX1 + \beta_2 lnX2 + \beta_3 lnX3 + \beta_4 lnX4 + \varepsilon$$

Where, C is the constant term, and β_1 to β_4 are the parameters to be estimated; Y represents total carbon emissions, while X1, X2, X3 and X4 respectively represent coal consumption, oil consumption, natural gas consumption, primary power consumption and other energy consumption. ε is a random perturbation term, which represents the sum of all factors not enumerated in the model.

5.3. E-G Co-integration Analysis

The E-G two - step method was used for co-integration analysis.

First, estimate the parameters of the model. Using the ordinary least squares (OLS) estimation method and the time series data of China's total carbon emission, coal consumption, oil consumption, natural gas consumption, primary power consumption and other energy consumption from 1990 to 2021, the parameters of the estimation model are as follows:

$$lnY = 0.432 + 0.783 lnX1 + 0.155 lnX2 + 0.034 lnX3 + 0.013 lnX4$$

$$T = (12.04) \quad (157.08) \quad (15.51) \quad (8.09) \quad (1.51)$$

$$R^2 = 0.999975, F = 266228.4, DW = 0.484534, N = 32.$$

The second step is to check the stationarity of the residual sequence. Extract resid of the above equation, denoted as e. For the ADF unit root test of residual e, the test results are shown in Table 3.

Table 3. *ADF unit root test results of residual e.*

Test variable	Inspection form	ADF statistics	1% significance level threshold	D.W value	P value	conclusion
e	(0,0,2)	-2.858384	-2.647120	1.868127	0.0059	stable

As can be seen from Table 3, the statistical value of ADF is less than the critical value of 1% significance level, and the P value is less than 0.01. Therefore, the residual series e is stable at the significance level of 1%. Thus, the explained variable lnY has a long-term stable relationship with explanatory variables lnX1, lnX2, lnX3 and lnX4, which passes the co-integration test.

5.4. Multicollinearity Test and Correction

It can be seen from the estimated cointegration equation that the T statistics of lnx1, lnx2 and lnx3 are 157.08, 15.51 and 8.09, respectively, and they can all pass the significance test of variables. While the T statistic of lnX4 is 1.51, their absolute values are less than 2, and they cannot pass the significance test of the variables. In other words, the co-integration equation has multicollinearity.

The stepwise regression method is used to eliminate the multicollinearity of the co-integration model.

With lnY as the explained variable and lnX1, lnX2, lnX3 and lnX4 as explanatory variables, four unary linear regression models can be obtained, and their corresponding R^2 values are 0.996670, 0.967129, 0.948308 and 0.955056, respectively. Choose the one with the largest R^2 as the basic equation, and we get the basic equation lnY=f(lnX1).

By adding explanatory variable lnX2 to the basic equation, the model becomes a binary linear regression model lnY=f(lnX1, lnX2). Because the correction R^2 has changed from 0.996559 to 0.999649, it has become larger; Meanwhile, the absolute values of T statistics corresponding to all explanatory variables are greater than 2, which can pass the significance test of variables. Therefore, the explanatory variable lnX2 is retained.

By adding explanatory variable lnX3 to model lnY=f(lnX1, lnX2), the model becomes a three-way linear regression model lnY=f(lnX1, lnX2, lnX3). As the corrected R^2 changes from 0.999649 to 0.999970, it becomes larger. Meanwhile, the T statistics corresponding to explanatory variables lnX1, lnX2 and lnX3 are 169.2135, 33.16125 and 17.49155, respectively, which can all pass the significance test of variables. Therefore, the explanatory variable lnX3 is retained.

Finally, the regression equation after eliminating multicollinearity is as follows:

$$lnY = 0.40789 + 0.77939lnX1 + 0.16800lnX2 + 0.03887lnX3$$

$$T = (12.44) \quad (169.21) \quad (33.16) \quad (17.49)$$

$$R^2 = 0.999973, F = 339448.3, DW = 0.355543, N = 32.$$

5.5. Test and Correction of Sequence Correlation

Since DW=0.355543, it indicates that the model has a first-order positive correlation. According to the LM multiplier method, the results shown in Table 4 are obtained. At the significance level of 1%, the model has a continuous order of 15 autocorrelation, while the order of 16 is uncorrelated. Therefore, the model has a maximum of 15 orders of autocorrelation at the significance level of 1%.

Table 4. *LM test results.*

Obs*R-squared	30.69393	Prob. Chi-Square (15)	0.0097
Obs*R-squared	30.82074	Prob. Chi-Square (16)	0.0142

According to whether the adjoint probability of AR (i) is less than 1% significance level, both AR(1) and AR(3) are significant.

Thirdly, the sequence correlation is corrected. The generalized difference method is used to eliminate the autocorrelation of the model, and the following results are obtained:

$$lnY = 0.14 + 0.82lnX1 + 0.16lnX2 + 0.03lnX3 + 1.40AR(1) - 0.48AR(3)$$

$$T = (3.2) \quad (189) \quad (50) \quad (11) \quad (31) \quad (-8)$$

$$R^2 = 0.999998, F = 2082810, DW = 2.242092, N = 32.$$

As can be seen from the above results, since F=2082810, it can pass the F test; Since the absolute values of T statistics of lnX1, lnX2 and lnX3 are all greater than 2, and the absolute values of T statistics of AR(1) and AR(3) are all greater than 2, they can all pass the significance test of variables at the significance level of 5%, that is, lnX1, lnX2, lnX3, AR(1) and AR(3) are all independent variables, thus passing the multicollinearity test. DW=2.242092, which is near 2, so there is no sequence correlation in this model, which passes the sequence correlation test. The sample can explain 99.9998% of the whole; Therefore, the optimized model is the optimal model.

6. Conclude the Sentence

6.1. Conclusion

The following conclusions can be drawn from the above optimal model:

(1) At the significance level of 5%, the logarithm of primary power and other energy consumption (lnX4) of the explanatory variable has no significant effect on the logarithm of total carbon emissions (lnY) of the explained variable;

(2) At the significance level of 5%, the logarithm of coal

consumption (lnX1), the logarithm of oil consumption (lnX2) and the logarithm of natural gas consumption (lnX3) of explanatory variables had a significant effect on the logarithm (lnY) of total carbon emissions of explained variables; In addition, when coal consumption, oil consumption and natural gas consumption increase by 1%, on average, the total carbon emission can increase by 0.82%, 0.16% and 0.03% respectively.

(3) Although the logarithm of primary electricity and other energy consumption (lnX4) of the explanatory variable has no significant effect on the logarithm of total carbon emissions (lnY) of the explained variable, it is removed from the model and has a significant effect with a lag of up to 3 years, in which the effect with a lag of 1 year is positive and that with a lag of 3 years is negative.

6.2. Policy Suggestions

According to the conclusions obtained from the optimal model, the following policy recommendations are put forward:

First, increase primary electricity and other energy consumption without significantly increasing total carbon emissions; In particular, we will vigorously develop non-fossil energy sources such as wind power, hydropower, nuclear power, solar energy, geothermal energy and biomass energy.

Secondly, improve the technical level, improve the efficiency of energy utilization. Increased energy efficiency will reduce the consumption of coal, oil and natural gas, thus reducing total carbon emissions.

Third, optimize the energy consumption structure, without affecting normal production, as far as possible use less coal and oil, more natural gas, primary electricity and other energy, increase the proportion of clean and efficient energy consumption.

Acknowledgements

References

[1] HU M R. Spatial pattern and influencing factors of carbon emission at county level in China [D]. Lanzhou University, 2021.

[2] QU H M. Study on spatial variation pattern and convergence of global energy consumption [D]. Shandong University of Finance and Economics, 2021.

[3] Pan D. Analysis and prediction of influencing factors of energy carbon emissions in China [D]. Beijing Forestry University, 2020.

[4] Chen R M. Factor decomposition and decoupling effect of China's industrial carbon emissions [D]. Dongbei University of Finance and Economics, 2019.

[5] R. F. Engle, C. W. J. Granger, Co-integration and error correction: representation, estimation and testing [J]. Econometrics, 1987 (55): 251-276.

[6] Dickey. D. A, W. A. Fuller. Distribution of the estimators for autoregressive time series with aunit root. Jounal of the American Statistical Association, 1979, 74: 427-431.

[7] Peng Jingxiao, Yuan Chao, Gao Minghui, Zhao Xianchao. Simulation of energy consumption carbon emission in Hunan Province based on System Dynamics [J]. Journal of Hunan University of Technology, 2019, 33 (06): 51-59.

[8] Wang D. Systematic study and simulation of energy, economy and carbon emission in Anhui Province based on SD model [D]. Jiangxi University of Finance and Economics, 2021.

[9] Shao S., Zhang X., Zhao X. Empirical decomposition and peak path of carbon emissions in China's manufacturing industry: Generalized Dili index decomposition and dynamic scenario analysis [J]. China Industrial Economics, 2017 (03): 44-63.

[10] Wang, Y. Grey correlation analysis of energy consumption and economic growth in Liaoning Province [D]. Liaoning University, 2020: 3-8.

[11] Xu, C. Research on energy development and economic efficiency in China [J]. Macroeconomic Management, 2020 (06): 51-60.

[12] Lin, B. Econometric analysis of China's energy demand [J]. Statistical Research, 2001 (10): 34-39.

[13] Lin, B. Clean and low-carbon transformation needs to take into account energy costs [J]. Environmental Economics Research, 2018 (3): 1-5.

[14] Lin, B. Problems and solutions towards carbon Neutrality [J]. Innovation World Weekly, 2021.8.

[15] LIU D Y. Empirical analysis of influencing factors of carbon emission in China [D]. North China University of Technology, 2020.

Biography

Liu Fangjun (1967-), male, born in Yongxing, Hunan Province, Master, Associate researcher; His research interests include econometrics and time series analysis.