The Impacts of Income Inequality on China's Carbon Emissions: A Longitudinal Analysis

Zijia Li[1], Ruiyi Yang[2](✉), and Zhiyang Zhong[3]

[1] School of Humanities, Tongji University, Shanghai 200092, China
[2] Business School, The University of Hong Kong, Hong Kong 999077, China
u3594623@connect.hku.hk
[3] Tabor Academy, Marion 02738, USA

Abstract. Reducing inequalities while boosting economic growth has long been a primary social policy objective for many countries. Human emissions of carbon dioxide, on the other hand, as a chief driver of global warming and other environmental issues, are becoming an increasingly important consideration for governments in formulating sustainable development policies. However, a consensus on the relationship between achieving the two goals has yet to be reached due to the interactive effects of the emission-reduction and income redistribution policies. The purpose of this study is to evaluate the impacts of income inequality on carbon emissions in China. The data of China's Gini coefficients and the emissions of carbon dioxide from 1981 to 2017 are chosen in this study to indicate the income inequality and carbon emission levels respectively. Correlation analysis and linear regression models are employed to examine the relationship, and the findings suggest a positive correlation between levels of income inequality and carbon emissions in China and that a time lag exists between the two variables. The results are analyzed from both the consumption and production perspectives with particular references to China's enhancing living standards, improving productivity and technological advances. The findings offer a perspective for understanding the synergy and conflicts between achieving both policy objectives, to preserve the environment while increasing economic welfare for sustainable growth and development of China's economy.

Keywords: Income inequality · Environmental economics · Carbon emissions · Sustainability · China

1 Introduction

Globally, the emissions of all main greenhouse gases (GHG) have been rising. The emissions of carbon dioxide, in particular, have increased by more than 50 percent between 1990 and 2018 [1]. Global warming and environmental degradation are posing long-lasting threats to humanity and the most vulnerable groups, including the poor who are the least responsible for greenhouse gas emissions, are the most seriously affected.

Z. Li, R. Yang and Z. Zhong—Contributed equally.

F. Balli et al. (Eds.): ESFCT 2022, AEBMR 226, pp. 995–1004, 2022.
https://doi.org/10.2991/978-94-6463-052-7_113

Since household consumption is one of the primary sources of global GHG emissions while income level affects households' consumption behaviours which will, in turn, affect pollution in the long run, a study on the link between individuals' economic wellbeing and carbon emission is crucial in understanding the quality of economic development (including inequalities) and formulating welfare policies, not least because CO_2 contributes to around 75% of global total GHG emissions [2].

The "Environmental Kuznets Curve" hypothesizes an inverted U-shaped relationship between the per-capita level of income and degree of environmental deterioration [3]. The link between economic growth and environmental quality has been widely studied both theoretically and empirically [4–7]. Tsurumi's study further decomposes the factors affecting environmental quality into three dimensions (the scale effect, the technique effect, and the composition effects), finding that although the technique effect was adequate to reduce SO_2 emissions, its effect was insufficient to lower energy use and the level of carbon dioxide emission, with the exception of the case of carbon emissions in higher-income countries [8].

By extension, despite that numerous studies have identified a link between inequality and consumption-based CO_2 emissions, a consensus on the link has yet to be reached. Some have found that greater inequality results in differences in consumption habits which in turn affects energy structure and carbon emissions in the long run [9–11]. The empirical regression analysis done by Torras and Boyce in which income inequality is included as an explanatory variable shows that a more equitable distribution of income can positively affect environmental quality, and such influence appears to be specifically strong in low-income countries [12]. On the other hand, a separate branch of studies suggests that greater income disparity could have a positive influence on overall environmental quality [13, 14].

According to the China National Bureau of Statistics, the national Gini coefficient of China was 0.288 in 1981. The figure reached 0.467 in 2017 and during the same period, China's carbon emission level has also been growing.

In order to understand the short-term and long-term influences of income inequality on China's emissions of carbon dioxide, this paper first creates scatterplots to visualize the variations of China's CO_2 emission and Gini coefficients during the period 1981–2017; correlation analysis and regression analysis will then be conducted to test the statistical relationship between the levels of carbon emission and income inequality. Sect. 2 evaluates the data and methodology used in this study and presents the results visually. Section 3 discussed the relationship between the two variables based on statistical results in the previous section. Section 4 concludes the findings and offers some policy suggestions regarding poverty reduction and environmental preservation.

2 Methodology

2.1 Data

The data used in this research is a fusion of statistics extracted from the China Statistical Yearbook. The Gini coefficient is utilized to measure China's income inequality and the volume of total apparent CO_2 emission is used to represent the CO_2 emission level. The panel study includes annual data points for China's 30 provinces, autonomous regions

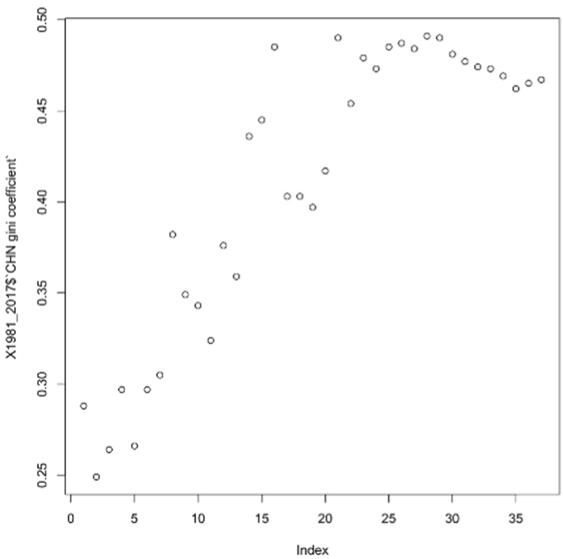

Fig. 1. China's Gini coefficient from 1981 to 2017

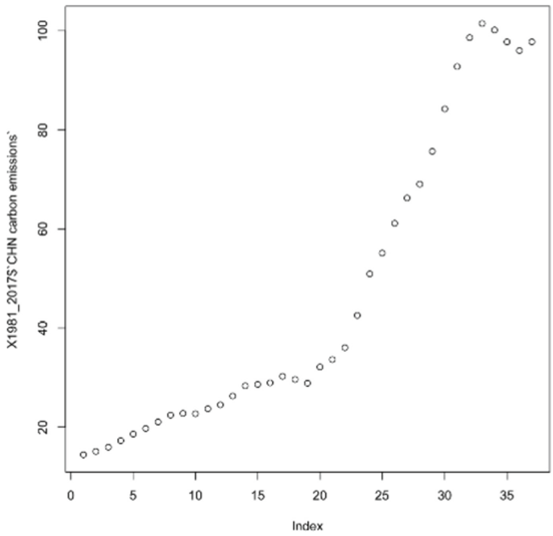

Fig. 2. China's CO_2 emissions from 1981 to 2017

and municipalities (Taiwan, Tibet, and two special administrative regions Macau and Hong Kong are excluded due to the inadequacy of reliable data sources), the national average of the Gini coefficient, and China's overall total amount of CO_2 emitted throughout the period 1981–2017. Figure 1 and Fig. 2 visualize the variations of China's Gini coefficients and CO_2 emission throughout the period 1981–2017. Graphically, it can

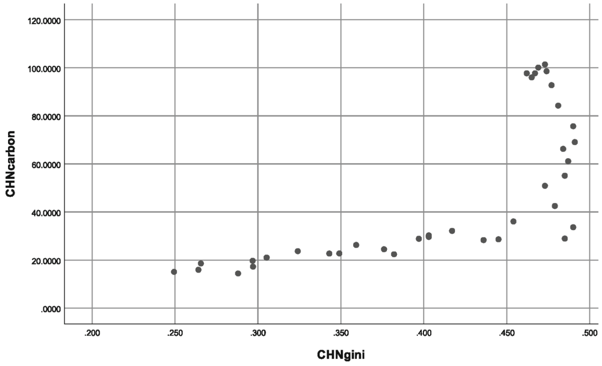

Fig. 3. The scatterplot of China's Gini coefficient and carbon emissions.

Table 1. Correlation coefficient

Correlations

		CHN carbon emissions	CHN gini coefficient	GDP per capita (current US$)
Pearson Correlation	CHN carbon emissions	1.000	.715	.960
	CHN gini coefficient	.715	1.000	.573
	GDP per capita (current US$)	.960	.573	1.000
Sig. (1-tailed)	CHN carbon emissions	.	.000	.000
	CHN gini coefficient	.000	.	.000
	GDP per capita (current US$)	.000	.000	.
N	CHN carbon emissions	37	37	37
	CHN gini coefficient	37	37	37
	GDP per capita (current US$)	37	37	37

be seen that China has reached the "turning point" of the traditional income inequality Kuznets curve, while it is still on its path to the point on the Environmental Kuznets Curve for the pollution to start decreasing.

2.2 Correlation Analysis

China's national Gini coefficient and the total amount of CO_2 emitted are used in correlation analysis to assess the overall relationship between the two variables. Figure 3 shows a non-linear relationship between the levels of the Gini coefficient and carbon emissions during the period 1981–2017. The curve estimation model therefore is first applied in this regression analysis. Due to the limited size of the data sample, we assume the normality of the distribution of the two variables. The result of the Pearson correlation analysis in Table 1 shows that the carbon emission level is in strong correlation with the Gini coefficient at a 1% significance level, where the Pearson correlation coefficient is 0.715 (> 0.7) and the p-value for the two-tailed significance test is 0.000 (< 0.01).

2.3 Regression Analysis and Results

To further explore the statistical relationship between the two variables, regression analysis of the levels of Gini coefficient and carbon emission is performed. The hypothesis proposed in this analysis is as follows:

Table 2. Curve Estimation Model Summary and Parameter Estimates

Model Summary and Parameter Estimates

Dependent Variable: CHN carbon emissions

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.511	36.543	1	35	.000	−66.253	275.336		
Logarithmic	.484	32.864	1	35	.000	137.913	100.069		
Inverse	.451	28.720	1	35	.000	135.428	−34.847		
Quadratic	.550	20.789	2	34	.000	118.174	−731.850	1311.895	
Cubic	.548	20.650	2	34	.000	57.825	−237.937	.000	1134.985
Compound	.695	79.617	1	35	.000	2.378	867.239		
Power	.672	71.606	1	35	.000	366.912	2.483		
S	.639	61.947	1	35	.000	5.868	−.874		
Growth	.695	79.617	1	35	.000	.866	6.765		
Exponential	.695	79.617	1	35	.000	2.378	6.765		
Logistic	.695	79.617	1	35	.000	.421	.001		

The independent variable is CHN gini coefficient.

H_0: Gini coefficient has a negative influence on China's CO_2 emission levels.
H_1: Gini coefficient has a positive influence on China's CO_2 emission levels.

Table 2 shows the summary of the curve estimation model. The three equations of the highest R^2 value are the compound equation, the growth equation and the exponential equation all with R^2 equal to 0.695. The low R^2 value indicates that the independent variable, the Gini coefficient value, is not explaining much of the change in China's carbon emission levels.

Table 1 shows the coefficient of correlation between China's levels of carbon emission, Gini coefficient, and per-capita GDP. Including the levels of GDP per capita which is highly correlated to the carbon emission level in the analysis, the results of the multi-linear regression analysis are shown in Table 3(3.1–3.5).

As shown in Table 3(3.2), the values of the coefficient of determination of (R^2) in Model 1 and Model 2 are 0.921 and 0.961 respectively, indicating small differences between the observed annual data and the fitted values and that the majority of variation in Carbon emission level can be explained by changes in Gini coefficient in our model.

The results of the analysis of variance (ANOVA) are visible in Table 3(3.3). The F-test statistics in the two models are 409.300 and 423.697, and the p-values are both 0.000. Therefore, there is significant evidence that a difference exists between the group means. Since the p-value is lower than 0.005, the null hypothesis of ANOVA is rejected and hence there is a statistically significant difference between the group means.

As shown in Table 3(3.4), in Model 2, the p-values of the three variables are 0.046, 0.000, and 0.000, all smaller than 0.05, and the corresponding t-values are all greater than 1.96. Both of these indicate that the three variables have statistically significant impacts on the carbon emission levels.

Equation (1) shows the results of the multi-linear regression, where X_1 and X_2 stand for China's national Gini coefficient and GDP per capita in US dollars respectively, and Y represents the overall national carbon emission volume in metric tons (mt).

$$Y = -12.565 + 94.289X_1 + 0.009X_2 \tag{1}$$

Table 3. Multi-linear regression

Table 3.1

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GDP per capita (current US$)	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	CHN gini coefficient	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: CHN carbon emissions

Table 3.2

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.960[a]	.921	.919	8.6601566	
2	.981[b]	.961	.959	6.1486395	.425

a. Predictors: (Constant), GDP per capita (current US$)

b. Predictors: (Constant), GDP per capita (current US$), CHN gini coefficient

c. Dependent Variable: CHN carbon emissions

Table 3.3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30696.807	1	30696.807	409.300	.000[b]
	Residual	2624.941	35	74.998		
	Total	33321.748	36			
2	Regression	32036.352	2	16018.176	423.697	.000[c]
	Residual	1285.396	34	37.806		
	Total	33321.748	36			

a. Dependent Variable: CHN carbon emissions

b. Predictors: (Constant), GDP per capita (current US$)

c. Predictors: (Constant), GDP per capita (current US$), CHN gini coefficient

Table 3.4

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	22.603	1.858		12.165	.000					
	GDP per capita (current US$)	.011	.001	.960	20.231	.000	.960	.960	.960	1.000	1.000
2	(Constant)	-12.565	6.053		-2.076	.046					
	GDP per capita (current US$)	.009	.000	.819	19.930	.000	.960	.960	.671	.671	1.490
	CHN gini coefficient	94.289	15.840	.245	5.953	.000	.715	.714	.201	.671	1.490

a. Dependent Variable: CHN carbon emissions

Table 3.5

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	Collinearity Statistics VIF	Collinearity Statistics Minimum Tolerance
1	CHN gini coefficient	.245[b]	5.953	.000	.714	.671	1.490	.671

a. Dependent Variable: CHN carbon emissions

b. Predictors in the Model: (Constant), GDP per capita (current US$)

3 Discussion

Several patterns have been found from the results of this empirical analysis.

3.1 Increasing Income Level and Improving Productivity

Analysis in Sect. 2 shows that reduced income inequality decreases carbon emissions in China. Such a positive correlation has also been verified by Golley and Meng [9], Zhang and Zhao [10], and Jorgenson et al. [11]. A study by Clarke-Sather et al. on China's inequality in CO_2 emissions further explains the differences between interprovincial GDP inequality and CO_2 inequality based on a sub-national scale by highlighting the critical role of carbon intensity [15]. This result is consonant with Meng et al.'s argument that reduced unbalanced cross-regional income growth may help reduce the emission level [16]. Based on a fixed-effect panel data model, these authors also show that there are significant disparities among the western, central, and eastern regions in China, as well as sub-national elasticity of per-capita income and energy intensity in carbon dioxide emissions, which reflects the differences in regional economic development and has diverse impacts on regional emission.

Economic growth has been found to be the primary driver of rising CO_2 emissions in many emerging economies. A study on the Next Eleven economies has found the link between energy consumption, economic growth, and the level of CO_2 emission levels using the time-varying Granger causality approach, showing that economic growth results in greater energy consumption in the Philippines, Vietnam, and Turkey [17]. Increasing income levels as a result of improvement in living standards and economic growth has increased household consumption, which is a major source of global GHGs emissions [2].

As the country develops, China's improving productivity and technological progress is another factor affecting carbon emission. Technology spillovers have been found to have a significant threshold effect on energy intensity and CO_2 emissions, and the impacts vary differently in different regions in China [18]. Both the consumption-led and production-led emissions as China's economy grows offer explanations for the positive correlation found in this study.

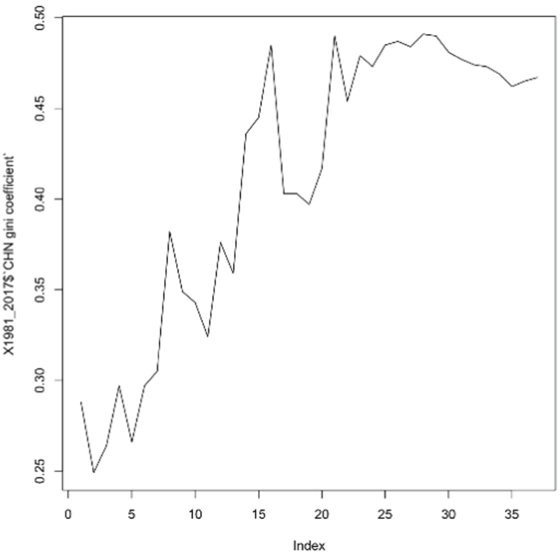

Fig. 4. China's Gini coefficient from 1981 to 2017

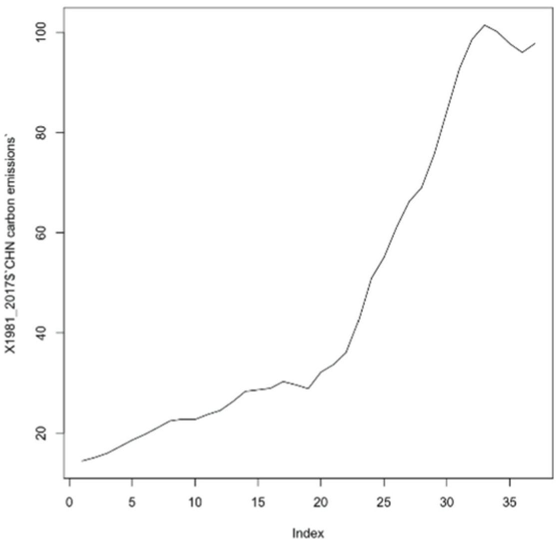

Fig. 5. China's carbon emissions from 1981 to 2017

3.2 Time Lag

A time lag is visible between the variation of China's Gini coefficients and the level of carbon emissions. As illustrated in Fig. 4 and Fig. 5, the Gini coefficient decreased gradually throughout 2008–2017; while it was not until 2013 that carbon emissions in China began to decline. The reduction in the Gini coefficient figure over the period is attributed mainly to the government's poverty reduction policies including the Development-oriented Poverty Reduction Program for China's rural regions and the Targeted Measures in Poverty Alleviation and Poverty Alleviation through Tourism. The implementation of these policies has increased the income level of the disadvantaged and narrowed the wealth gap.

4 Conclusion and Policy Implications

Through analysis of data from 1981 to 2017, this paper analyzes the influence of income inequality on China's emissions of carbon dioxide with explanations based on existing theories and research. Our results show that income inequality is positively correlated with the level of CO_2 emissions in China. The results offer potential implications for future policy-making. Firstly, environmental policies to reduce pollutant emissions should take into account regional disparities. The substantial differences in regional income levels, energy efficiencies, and availability of green production technologies between China's Eastern, Central, and Western regions generate inconsistent counterbalancing impacts on CO_2 emissions. Policies such as tradable pollution permits and green taxation could be practised in regions with limited access to clean energy and low energy efficiency. Secondly, efforts to redistribute income should be more detailedly customized to bring environmental benefits considering the positive correlation between levels of carbon emission and income inequality. The results of this paper's analysis show that reduced income disparity has a significant impact on carbon dioxide emission levels. Therefore, achieving greater equality in income distribution potentially contributes to environmental improvement. Sustainable industries could be established in poverty-stricken areas to create new job opportunities and boost the local economy, while simultaneously reducing carbon emissions by adopting new and renewable energy and greener production technologies.

The main limitations of this paper are that only a limited number of variables are included in the analysis and a specific time lag between the two variables is not identified. Future research should take in more factors that could affect regional inequality levels and carbon emissions.

References

1. Climate Watch Historical GHG Emissions. (2021). Washington, DC: World Resources Institute. https://www.climatewatchdata.org/ghg-emissions
2. J. Li, D. Zhang, B. Su, The impact of social awareness and lifestyles on household carbon emissions in China, Ecological Economics, vol. 160, 2019, pp. 145–155. DOI: https://doi.org/10.1016/j.ecolecon.2019.02.020
3. S. Kuznets, Economic Growth and Income Inequality, The American Economic Review, vol. 45, no. 1, 1955, pp. 1–28. DOI: http://www.jstor.org/stable/1811581.
4. N. L. Stokey, Are There Limits to Growth? International Economic Review, vol. 39, no. 1, 1998, pp. 1–31. DOI: https://doi.org/10.2307/2527228.
5. J. Andreoni, A. Levinson, The simple analytics of the environmental Kuznets curve, Journal of Public Economics, vol. 80, no. 2, 2001, pp. 269-286. DOI: https://doi.org/10.3386/w6739.
6. G. M. Grossman, A. B. Krueger, Economic Growth and the Environment, The Quarterly Journal of Economics, vol. 110, no. 2, 1995, pp. 353–377. DOI: https://doi.org/10.2307/2118443.
7. S. Borghesi, The Environmental Kuznets Curve: A Survey of the Literature, Fondazione Eni Enrico Mattei Working Papers, vol. 85, 1999.
8. T. Tsurumi, S. Managi, Decomposition of the environmental Kuznets curve: scale, technique, and composition effects, Environmental Economics and Policy Studies, vol. 11, 2010, pp. 19-36. DOI: https://doi.org/10.1007/s10018-009-0159-4.
9. J. Golley, X. Meng, Income inequality and carbon dioxide emissions: The case of Chinese urban households, Energy Economics, vol. 34, no. 6, 2012, pp. 1864-1872. DOI: https://doi.org/10.1016/j.eneco.2012.07.025.
10. C. Zhang, W. Zhao, Panel estimation for income inequality and CO2 emissions: A regional analysis in China, Applied energy, vol. 136, 2014, pp. 382-392. DOI: https://doi.org/10.1016/j.apenergy.2014.09.048.
11. A. Jorgenson, J. Schor, X. Huang, Income inequality and carbon emissions in the United States: a state-level analysis, 1997–2012, Ecological Economics, vol. 134, 2017, pp. 40-48. DOI: https://doi.org/10.1016/j.ecolecon.2016.12.016.
12. M. Torras, J. Boyce, Income, Inequality, and Pollution: A Reassessment of the Environmental Kuznets Curve, Ecological Economics, vol. 25, 1998, pp. 147-160. DOI: https://doi.org/10.1016/S0921-8009(97)00177-8.
13. S. Borghesi, Income inequality and the environmental Kuznets curve, Environment, inequality and collective action, vol. 33, 2006.

14. L. Charfeddine, Z. Mrabet, The impact of economic development and social-political factors on ecological footprint: A panel data analysis for 15 MENA countries, Renewable and Sustainable Energy Reviews, Elsevier, vol. 76, no. C, 2017, pp. 138-154. DOI: https://doi.org/10.1016/j.rser.2017.03.031.
15. C. Afton, J. Qu, Q. Wang, J. Zeng, Y. Li, Carbon inequality at the sub-national scale: A case study of provincial-level inequality in CO2 emissions in China 1997-2007, Energy Policy, vol. 39, no. 9, 2011, pp. 5420-5428. DOI: https://doi.org/10.1016/jenpol201105021.
16. L. Meng, J. E. Guo, J. Chai, Z. Zhang, China's regional CO2 emissions: characteristics, inter-regional transfer and emission reduction policies, Energy Policy, vol. 39, no. 10, 2011, pp. 6136-6144. DOI: https://doi.org/10.1016/j.enpol.2011.07.013.
17. M. Shahbaz, M. K. Mahalik, S. H. Shah, J. R. Sato, Time-varying analysis of CO2 emissions, energy consumption, and economic growth nexus: Statistical experience in next 11 countries, Energy Policy, vol. 98, 2016, pp. 33-48. DOI: https://doi.org/10.1016/j.enpol.2016.08.011.
18. X. Yang, Z. Yang, Z. Jia, Effects of technology spillover on CO2 emissions in China: a threshold analysis, Energy Reports, vol. 7, 2021, pp. 2233-2244. DOI: https://doi.org/10.1016/j.egyr.2021.04.028