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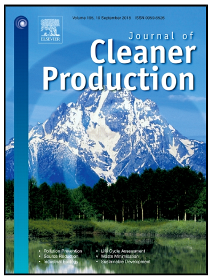

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Investigating Factors Affecting Carbon Emission in China and the USA: A Perspective of Stratified Heterogeneity

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Abstract:

As world's top two carbon emitters, driver analysis of China and the USA helped the governments to develop policies to cut or slow down carbon emission. Many studies identified the factors affecting carbon emission in China and the USA (emitting more than 40% of the global CO_2 emission), however, few studies considered stratified heterogeneity or the interactions of factors. Here, we adopted the modified Geographical Detector tool to investigate the main drivers of carbon emission from the perspective of stratified heterogeneity. The results of this analysis showed that human economic activities in China were the dominant effect of carbon emission changes, while energy intensity contributed toward controlling the carbon emission in China. Furthermore, population growth was the most significant driving force followed by energy intensity toward controlling the carbon emission of the USA. All these factors are mutually enhancing in changing carbon emissions, while oil share with energy intensity and coal share were more significantly enhanced in China's carbon emission than other interactions. The factors of human activities and energy mix posed a more powerful effect when they mutually enhanced each other to change carbon emission compared to other enhancing interactions. This work represents a pilot scheme for a carbon dioxide emission analysis from the categorical stratified heterogeneity based on statistical methods.

Keywords: CO_2 emission; geographical detector; China; USA;

1. Introduction

China is the largest CO_2 emitter and the top developing country worldwide and contributes 27.3% of the world energy-related carbon dioxide emission (BP, 2017). Furthermore, the United States of America (USA) is the world's second-largest carbon dioxide emitter as well as the world's top developed country and causes 16% of the global overall energy-related CO_2 emissions (BP, 2017). This significant share (43.3%) of carbon emission should be limited. Identifying the main drivers of these two largest carbon dioxide emitters helped to develop further carbon emission mitigation strategies.

In general, various drivers account for the energy-related carbon dioxide emission; however, a wide regional variation exists in its significance. The different economic stages, developmental patterns of the economies, and uses of energy causes a distinction in the underlying drivers of carbon emissions. Therefore, the main possible factors and the influencing mechanisms were investigated for these two top carbon emitters and energy consumers (USA and China). Furthermore, the investigation in these two typical samples, can offer new information towards the development and adjustment of more effective strategies to control the increase of energy-related carbon dioxide emissions for the rest of the world.

As is stated in Intergovernmental Panel on Climate Change (IPCC) ((Blanco et al., 2018), many drivers of Greenhouse Gas (GHG) emissions are interlinked with each other. Consequently, the problems caused by this interlinking effect need to be considered. Will the driving factors affect each other and change the total carbon emission? How do they influence each other when they work together? The interaction detector of the Geographical Detector tool can address these problems and in this case, applying the model to analyze the CO_2 emission is of vital importance.

Before their withdrawal from the Paris agreement, the USA had been actively facing the responsibility to reduce their carbon dioxide emissions (EPA, 2014). China has also been actively working toward a carbon emission reduction and introduced corresponding policy prescriptions. The energy-related carbon emission trends of both countries have changed due to the combining and interacting systems of economic development, technology improvement, and policy adjustment. Consequently, the main drivers for the CO_2 emission changes were detected, highlighting the differences in the influencing mechanisms of both countries from the perspectives of spatial differences and stratified heterogeneity.

1.1. Literature review

Overview of the CO_2 emission analysis

Detecting the main drivers of carbon dioxide emission has become a focus of socioeconomic and environmental research. Previous studies were mostly conducted using the decomposition technique, which primarily consists of two main techniques: the Structural Decomposition Analysis (SDA) and the Index Decomposition Analysis (IDA). The SDA approach was developed from an input-output (I-O) table. Of the seminal studies, Rose and Chen (Rose and Chen, 1991) applied the SDA method to analyze sectoral energy consumption changes in the USA. Later, Rose and Casler (Rose and Casler, 1996) reviewed the SDA evolution and highlighted the main fundamental principles when applying the structure decomposition tool. Recently, several studies applied the structure decomposition method to investigate the carbon emission from a sectoral perspective. Yuan et al. (Yuan et al., 2015) used the SDA method to compare the residential indirect carbon emission differences from the effects of urbanization, consumption ratio, and consumption structure in China and discussed the region differentiation. Wei et al. (Wei et al., 2016) analyzed both the direct and indirect carbon emission in Beijing between 2000 and 2010 to investigate the drivers by comparing the factors from sectoral connection, technology, economic scale, and economic structure.

The IDA was also widely used because it is easier to use for the specific analysis, and the most popular technique is the Logarithmic Mean Divisia Index (LMDI). The LMDI was first introduced by Ang (Ang et al., 1998) to identify the energy demand or emission changes during a specific timespan . Ang and Liu developed the technique to solve the zero values problem (Ang and Liu, 2007). The LMDI was mainly used to analyze the energy consumption and corresponding carbon emission (Ma et al., 2017; Mousavi et al., 2017). Diakoulaki and Mandaraka analyzed the drivers of the fourteen European Union countries (Diakoulaki and Mandaraka, 2007). Mahony combined an extended Kaya identity with the log mean Divisia index (LMDI I) to analyze carbon dioxide emission changes (Mahony, 2013).

Generally, when applying decomposition methods, all possible determinants are assumed to be independent. However, full dependence (changes in one determinant cannot occur without corresponding changes in another determinant) do not exist between separate determinants in most empirical cases (Dietzenbacher and Los, 2000). Furthermore, the decomposition methods cannot reveal the possible interaction relationship of each factor; however, analyses that focus on the interaction relationship between different potential factors are required (Blanco et al., 2018). Hence, we applied the Geo-detector tool to fill this gap.

Moreover, most studies analyzed the carbon emission on a country or region scale only. However, the characteristics of influencing factors may impact the whole carbon emission changes differently. Thus, we conducted a study to investigate the relevant effects while considering the stratified heterogeneity of these factors.

Based on this, we applied the modified Geo-detector model to identify the interactions and find the drivers that focused on the spatial differences from the perspective of spatial differences in consideration of the stratified heterogeneity.

Overview of the Geographical Detector Model

Wang et al. (Wang et al., 2010; Wang et al., 2016) proposed the Geographical Detector Model to assess health and environmental risks. The Geographical Detector model can address the spatial stratified heterogeneity phenomenon, which is an important portion of the spatial heterogeneity. However, the other kind of spatial heterogeneity phenomenon, spatial local heterogeneity, has been discussed in many ecology studies. Even though quantities of measures have been applied to tackle the issue, in general, three useful tools: Getis G_i (Arthur Getis, 1992), local indicators of spatial association (LISA) (Anselin, 2010) and spatial scan statistics (Kulldorff, 1997) are most widely used. However, the scopes and scales of the two spatial heterogeneity phenomena differed in the practical studies. In view of the characteristics of carbon emission changes in China and the USA, we apply the Geographical Detector Model to figure out the key drivers of CO_2 emission from the perspective of stratified heterogeneity. The Geographical Detector model primarily aimed to resolve the following four questions: (1) What are the domains of a potential risk variable? (2) Which factors should be responsible for the detected risk? (3) Which factor contributed more to the risk changes? (4) Do these factors operate independently or do they have an accessory effect? (FengCao et al., 2013) Therefore, the Geographical Detector Model was considered. Generally, four different detectors were performed when applying the model: the factor detector, the interaction detector, the ecological detector, and the risk detector. Wang and Hu developed the software GeoDetector to perform the tasks of geographical detectors (Wang and Hu, 2012). Currently, GeoDetector has been applied to different fields of research. Luo et al. analyzed land dissection density of the USA and reported that the most significant factors vary in different regions due to the differences of the geological and regional characteristics among the regions (Luo et al., 2016). Wang et al. analyzed anthropic pollution and nature and also detected their interaction relationships. The risk and factor detector was used to find risk spots and clarify the main influencing factor. Moreover, the ecological and interaction detectors were applied to further detect the influencing system (Wang et al., 2010).

Most of the studies on the Geographical Detector Model were used to analyze geographical distribution differences during one single year or the change between a final year and a base year in a specific area. However, since the changing trend of carbon emissions is a long-term process, all the years during a period should be considered. Thus, it is necessary to conduct year-to-year stratified sampling of the changes in carbon emissions in different years with a focus on the characteristic differences. Hence, we modified the original Geographical Detector Model to improve the pertinence in discussing the CO_2 emission issues by taking the changing process of carbon emission and the possible factors characteristics differences in various years into account. Based on the modified Geographical Detector Model, we comparatively analyzed the energy-related CO_2 emission in China and the USA and detected the differences in dominant drivers.

2 Methods and data

2.1 Materials and Methods

The geographical detector tool was mainly used to test the spatial stratified heterogeneity and the influencing drivers of a variable. It has four components: factor detector, ecological detector, risk factors, and interaction detector.

When selecting potential drivers, previous studies on the driver detection analysis of carbon emission have been considered. The decomposition method is an important subject area in energy policy making (Ang, 2004). Among the decomposition studies that addressed carbon emission, Guan et al. averaged all potential first-order decompositions and built five scenarios (economic growth, population dynamics and urbanization, changing consumption patterns, technical and structural change, and energy demand and fuel mix) based on a historical analysis (Guan et al., 2008).

Raupach et al. investigated the main drivers by decomposing carbon emission into population, Gross Domestic Product (GDP) per capita, energy intensity of GDP, and carbon intensity of energy factors on both global and regional scales (Raupach et al., 2007).

Since the carbon intensity factor is affected by the economic development level, energy consumption mix, and other factors (Zhu et al., 2014), based on this state-of-the-art work, we selected six factors to investigate the main drivers: population, GDP per capita, energy intensity (energy consumption gains per GDP added), coal share, oil share, and gas share of both China and the USA.

To better show the structure of the technique, we drew a proxy diagram to clarify the detected potential determinants and the mechanism of the model (Figure 1).

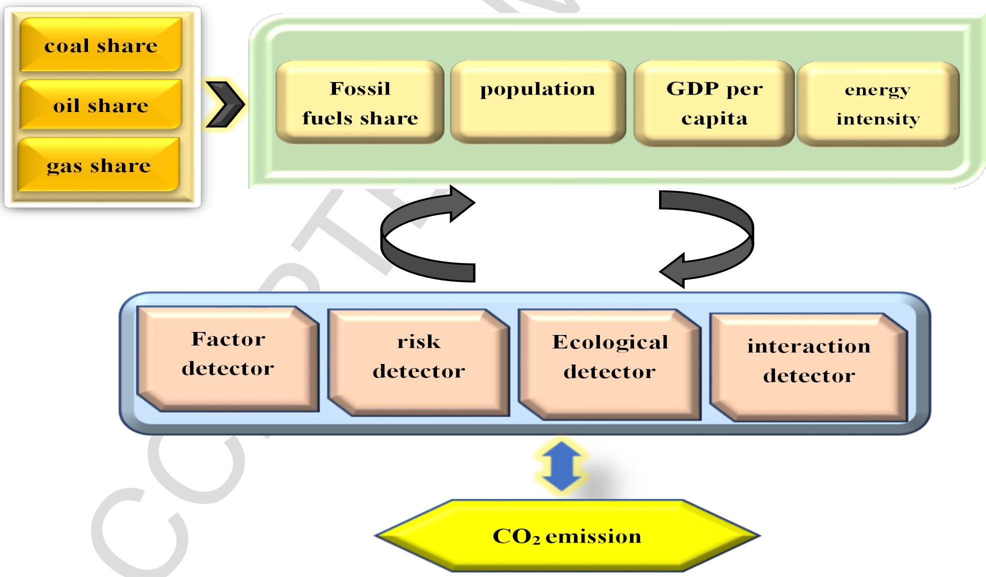

Figure 1 Diagram of the detected determinants and the model working mechanism

2.1.1 Factor detector

The factor detector identifies the degree with which a potential determinant accounted for changes in CO_2 emission, indicating the power of the determinant in different regions. Moreover, q-statistic (see Figure 2) was used to show the relationship between and Y (dependent variable) and X (explanatory variable). In general, the stratified differences of each determinant contributed to the CO_2 emission changes during various years and strata. Figure 2 clarifies the mechanism of stratified heterogeneity from different categorical variables.

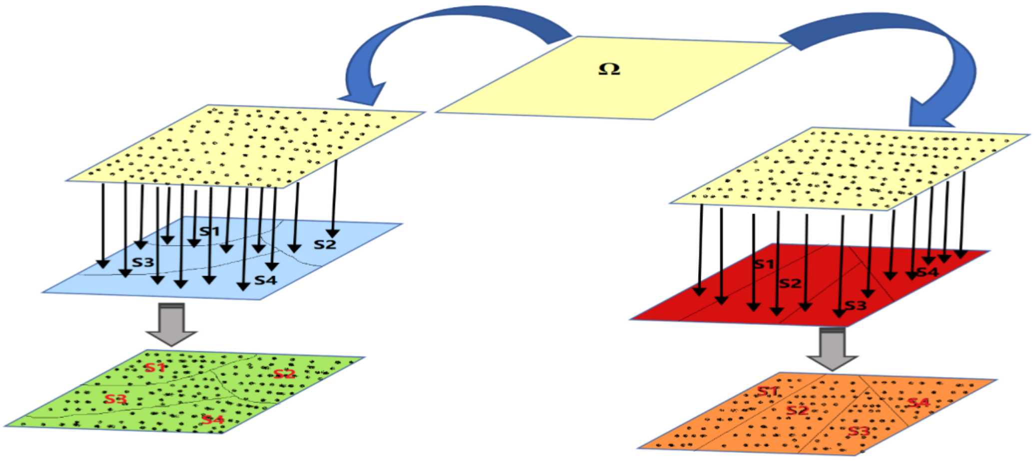

Figure 2 Schematics of the q-statistic in the factor detector

The power of determinants can be identified via the q-statistic, as shown in Eq. (1):

$$q = 1 - \sum_{h=1}^{L} N_h {\sigma_h}^2 / N\sigma^2 = 1 - SSW/SST \qquad (1)$$

Here, N represents the populations of the samples and σ^2 represents the variance of a specific area during a given phase. The analyzed target can then be divided into different strata (h) based on the characteristic differences of each potential influencing factor. The q-statistic can disclose the stratified heterogeneity level. Particularly, when q = 1, Y (the dependent variable) has perfectly stratified heterogeneity, and the dependent variable is completely determined by the detected potential driver (one explanatory variable). In contrast, when q = 0, no relationship between the stated variables can be detected; furthermore, no stratified heterogeneity was found. With regard to the comparative analysis of the energy-related carbon dioxide emissions of China and the USA, the q statistic offers a practical tool to compare the main drivers of the carbon dioxide emission changes of both countries in each timespan from the perspective of stratified heterogeneity.

2.1.2 Risk detector

The risk detector was originally used to detect areas of potential health hazard. In this paper, the risk detector was applied to compare the difference of average carbon dioxide emissions between various years. The greater the differences, the more danger exists for environmental damage during the studied phase.

The mechanism of the risk detector is based on statistical methods. The difference between the means of two divisional strata can be obtained via the means of the statistics for measuring the significance of the difference between the means of two strata with unequal variance (Wang et al., 2010):

$$\mathbf{t}' = (\overline{\boldsymbol{R}_{h=m,Xi}} - \overline{\boldsymbol{R}_{h=k,Xi}}) \Big/ \sqrt{\boldsymbol{\sigma}^{2}_{\overline{\boldsymbol{R}_{h=m,Xi}}}/\boldsymbol{N}_{h=m,Xi} - \boldsymbol{\sigma}^{2}_{\overline{\boldsymbol{R}_{h=k,Xi}}}/\boldsymbol{N}_{h=k,Xi}} \quad (2)$$

The certain forms of reasonable high level of carbon dioxide emission risk measure, defined as R, $\overline{R_{h=m,Xi}}$, and $\overline{R_{h=k,Xi}}$ represent the average carbon emission changes caused by a risk factor from stratum m and stratum k, respectively; accordingly, $\sigma^{2}_{\overline{R_{h=m,Xi}}}$ and $\sigma^{2}_{\overline{R_{h=k,Xi}}}$ represent the division variance of strata m and k. The null hypothesis H_0: $\overline{R_{h=m}} = \overline{R_{h=k}}$ is made at a confidence level of 95%.

2.1.3 Ecological detector

The impacts detection of two influencing factors on the annual carbon dioxide emissions are significantly different. F-tests can be used to compare the variance calculated in specific strata attributed to one risk factor with the variance attributed to the other risk factor. As a result, the most significant factors could be distinguished and the method is shown in Eq. (3):

$$\mathbf{F} = \left[\boldsymbol{N_{Xi}}(\boldsymbol{N_{Xj}} - \mathbf{1})\boldsymbol{SSW_{Xi}} \right] / \left[\boldsymbol{N_{Xj}}(\boldsymbol{N_{Xi}} - \mathbf{1})\boldsymbol{SSW_{Xj}} \right] \tag{3}$$

Where N_{Xi} and N_{Xj} represent the populations of units i and j, SSW_{Xi} and SSW_{Xj} represent the within variance sum of each sample. Moreover, the following null hypothesis (H_0) was proposed: $SSW_{Xi} = SSW_{Xj}$; also, the alternative hypothesis was given: $SSW_{Xi} \neq SSW_{Xj}$ (at a confidence level of 95%), after comparison with p value or the value in the distribution table. The null hypothesis will be rejected when $\mathrm{F(m-1, n-1)} > (\mathrm{f}_{\alpha})_{max}$ or if the p value is smaller than 0.05. Then, the alternative hypothesis can be considered. In this situation, the determinant power exerted a distinct effect on the dependent variable. Otherwise, the null hypothesis will not be rejected. No significant differences of the determinant power were found.

2.1.4 Interaction detector

The interaction detector can uncover the interaction effect between factor X_i and factor X_j. Although many articles have addressed the possible factors, whether these are independent or have impact each other needs to be disclosed. When launching an interaction analysis, the q statistic from different influencing factors q (X_i) and q (X_j) should first be calculated. Then, the combining index can be obtained. After comparing the values, the interaction relationship between these and their degree of interaction can be identified. Different types of possible interactions between various covariates are shown in Table 1. "∩" represents the intersection between X_i and X_j.

The interaction between two given determinants can be identified by comparing the sum of carbon dioxide emissions in different areas of two individual attributes with the contribution of both attributes when they are combined.

Table 1 Interactions between two covariates

State	Interaction	Graphical representation
q (Xi∩Xj) < Min (q (Xi∩Xj))	Weaken, nonlinear	
Min (q (Xi∩Xj)) <q (Xi∩Xj) < Max (q (Xi∩Xj))	Weaken, univariate, nonlinear	
q (Xi∩Xj) > Max (q (Xi∩Xj))	Enhance, linear, binear	
q (Xi∩Xj) = q (Xi)+ q (Xj)	Independent	
q (Xi∩Xj) > q (Xi)+ q (Xj)	Enhance, nonlinear	

Note: means Min (q (X_i∩X_j)), denotes Max (q (X_i∩X_j)), is q (X_i) + q (X_j) and reveals q (X_i∩X_j).

2.2 Data Source and Processing

The data on energy-related CO_2 emission, population, energy consumption, and GDP in China and the USA between 1990 and 2016 used in this study were primarily obtained from the World Bank (WorldBank, 2017) and the BP Statistical Review of World Energy (BP, 2017). It should be noted that the GDP indicator was a constant US dollar rate (of 2010) to eliminate the influence of inflation. The total and the proportion of each fuel consumption (coal, oil, and gas) were converted to Million tons oil equivalent (Mtoe).

In this study, carbon dioxide emission can be decomposed into population, GDP per capita, energy intensity, and energy consumption mix (coal, oil, and gas). To be more specific, X1, X2, and X3 represent population, GDP per capita, and energy intensity, respectively; X4, X5, and X6 represent the proportion of coal, oil, and gas during the primary energy combustion process, respectively. More detailed information on the detected factors is listed in the following:

* Per capita GDP (G): is calculated as GDP (in 2010 USD) divided by the population per capita. GDP per capita is an indicator of the standard of living of a region and one of the drivers of energy consumption.
* Energy intensity (EI): energy consumption divided by GDP, which indicates the energy efficiency level.

3 Results and Discussion

3.1 Factor Detection analysis

As shown in Table 2, the influence of tested factors to carbon dioxide emission changes in China can be ranked by their influence occurrence in the following order: GDP per capita > population > gas share > energy intensity > coal share > oil share. To be more specific, the most significant determinant accounting for the carbon dioxide emission changes were human economic activities effect (X2) in China, followed by X1 (population). However, China has taken positive measures to counteract the high energy consumption development pattern (BBC, 2013; ChinaDaily, 2017). X6 (the share of gas) and X3 (energy intensity) also greatly contributed to the total carbon emission changes. X4 (the proportion of coal) caused strong changes to the total carbon emission even though the annual changes were not significant. X5 (the proportion of oil) had a comparatively minor effect on CO_2 emission change, which was consistent with small proportional changes of oil.

However, as shown in Table 2, the order of contribution to the carbon dioxide emission in the USA is population > energy intensity > GDP per capita > oil share > gas share > coal share. Unlike the booming economic development pattern, the relatively stable increase of the USA led to a more significant role of the average determinant power of population growth (X1) compared to the GDP per capita. Moreover, the economic turmoil, especially the outbreak of the economic crisis in 1990-1991 and 2007-2012, caused the demographic effect to contribute more than the pure human economic activities effect during the studied period. In general, the population factor was the most significant driving force of the carbon dioxide emission of the USA, which was consistent with previously reported findings (Feng et al., 2015). Furthermore, the USA energy intensity effect (X3) was the next main determinant of the CO_2 emission and the most important factor to control the carbon emission; relative small decreases of changes of energy intensity indicated a slow improvement of energy efficiency. The decrease was mainly related to technology, changes in the economic structure, the mix of energy sources, and changes in the participation of inputs such as capital and required labor (Blanco et al., 2018). Human economic activities (X2) also contributed greatly to carbon dioxide emission change, even though the annual per capita income remained stable in the USA. The proportion of each fossil fuel exerted a relatively small effect on the total carbon dioxide emission; to be more specific, among these, the oil share change (X5) had comparatively the greatest impact, followed by the gas share (X6) and coal proportion (X4) changes.

Since the factor detector identified the average determinant power of each factor, being in a different the economic stage and with a distinct development pattern, the economic factor in the USA did not show the powerful determinant force than that in China. Moreover, the financial recession of the US in the 1990s and 2008-2012 also deprived of the average dominating power of the carbon emission in the USA during the observed years. During the financial recession, the carbon emission decreased by 726.43 Mt (BP, 2017) between 2008 and 2012. However, the population grew by 29.45% between 1990 and 2016, played a positive role of increasing carbon emission during the period in the USA.

Moreover, the energy efficiency improvement and fuel switch from carbon-extensive fuels to less extensive fuels decrease the energy intensity in the USA at an annual rate of 1.82%. The replacement of coal with oil and natural gas in the USA led to a decrease of the total carbon dioxide emission. (Feng et al., 2015) Even though these did not cause the most pronounced carbon emission reductions, the adjustment of the fuel share, especially the substitution of coal with natural gas, can further decrease emissions, a further decarbonization of the energy system, and an energy efficiency improvement. Since energy efficiency changes reveal the changes of energy intensity. This made energy intensity became the second significant driver of the USA.

Table 2. Contribution of each factor and the determinant power

Region	X1	X2	X3	X4	X5	X6
China	0.8885	0.9543	0.5673	0.5172	0.1924	0.8545
p_{China}	0.0000	0.0000	0.0000	0.1588	0.2595	0.0000

US	0.8636	0.4906	0.7167	0.1021	0.2450	0.1554
p-$_{US}$	0.0000	0.9994	0.3489	1.0000	0.9928	1.0000

Note: p-$_{China}$ and p-$_{US}$ denote the p values of China and the US.

3.2 Risk detector analysis

As shown in Figure 3, X1 (population) contributed to the carbon dioxide emission increase and a difference was found between every two strata of CO_2 emission from four population stages at the 95% confidence interval during the studied span in China. X2 (GDP per capita) also accounted for an increase in carbon emissions, except for type III and type IV, where a significant difference at the 95% confidence level was found between other strata. Energy intensity decelerated the carbon dioxide emissions and the difference between two strata was significant at the confidence level of 95%. According to Figure 3, the coal share helped to accelerate the carbon emission growth. Apart from stratum I (with an average CO_2 emission of 9143.75 Mt) and stratum II (with an average CO_2 emission of 9140.75 Mt), stratum III (with an average CO_2 emission of 5179.92 Mt) and stratum IV (with an average CO_2 emission of 3928.37 Mt), the difference between two distinct strata was significant at the confidence level of 95%. After 2011, the coal consumption shares of the total energy consumption steadily decreased at an annual rate of 2.66%. For stratum I (with an average CO_2 emission of 6020.97 Mt), stratum IV (with an average CO_2 emission of 3432.87 Mt), stratum II (with an average CO_2 emission of 6450.19 Mt), and stratum IV, the differences between two distinct strata were significant at the confidence level of 95%. With regard to the gas proportion, except for stratum III (with an average

CO_2 emission of 8893.05 Mt) and stratum IV (with an average CO_2 emission of 9182.59 Mt), other strata showed significant differences at the confidence level of 95%. Furthermore, it should be noted that the error bars represent the standard error of each stratum.

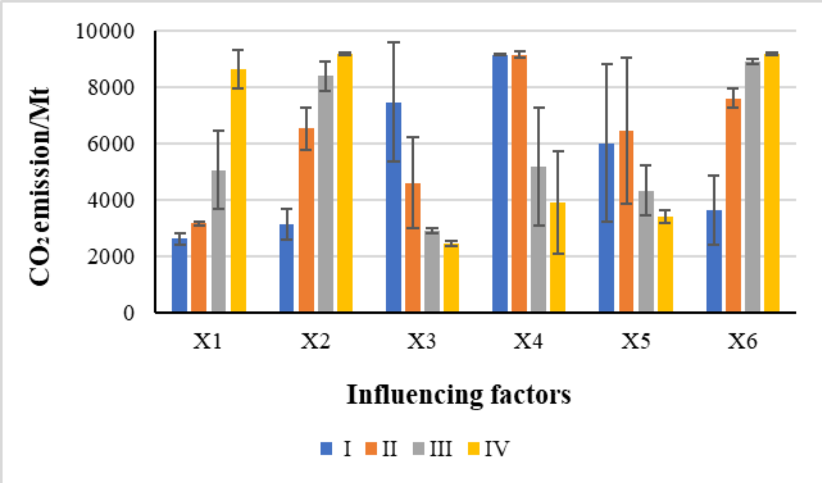

Figure 3 Risk detector results of CO_2 emissions in China

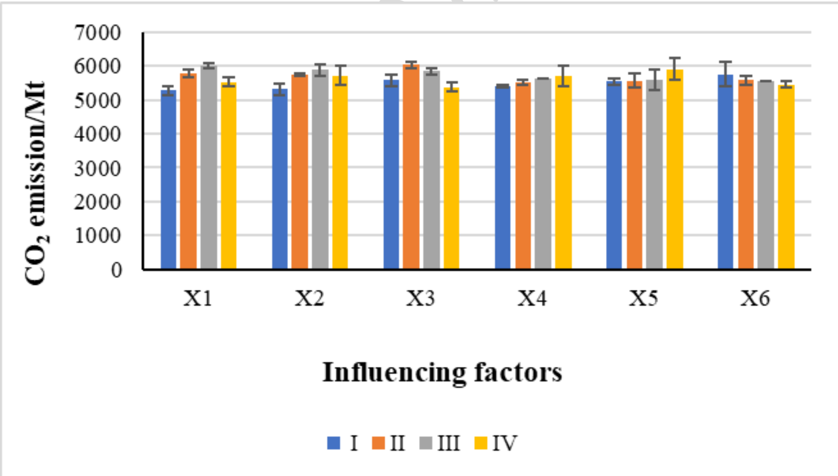

Figure 4 Risk detector results of CO_2 emissions in the USA

With regard to the US, a significant difference exists between every two strata of demographic effect and population variation contributed to the carbon dioxide emission growth in the USA. As shown in Figure 4, for the demographic effect, a significant difference was found between every two strata and population variation contributed to the carbon dioxide emission growth in the USA. X1 (population) accounted for a carbon dioxide emission increase and a difference was found between every two strata of CO_2 emission from four population stages at the 95% confidence interval in the US. X2 (GDP per capita) also accounted for carbon emission increase, except for type II (with an average CO_2 emission of 5752.05 Mt) with type II (with an average CO_2 emission of 5752.05 Mt), type IV (with an average CO_2 emission of 5721.93 Mt) with type II, and type III, significant differences were found at the at the 95% confidence level between other strata. X2 (GDP per capita) also accounted for an increase in carbon emissions, type I (with an average CO_2 emission of 5322.51 Mt) had differences between other strata, type II (with an average CO_2 emission of 5752.05 Mt), type III (with an average CO_2 emission of 5884.36 Mt), type IV (with an average CO_2 emission of 5721.93 Mt) with type II and type III, a significant difference was found at the at the 95% confidence level between other strata. Energy intensity decelerated carbon dioxide emissions in the USA and except for X1 and X4, the difference between two given strata was significantly different at a confidence level of 95%. According to Figure 3, coal share decreases also slowed the increase of CO_2 emissions in the USA. The difference between stratum I (with an average CO_2 emission of 5397.69 Mt) and stratum IV (with an average CO_2 emission of 5704.68 Mt) was significant at the confidence level of 95%. No differences were found between stratum I and stratum II as well as between stratum II and stratum IV. For the oil share effect, stratum I (with an average CO_2 emission of 5541.85 Mt) and stratum IV (with an average CO_2 emission of 5904.86 Mt), stratum II (with an average CO_2

emission of 5569.72 Mt) and stratum IV, differences between two distinct strata were significant at the confidence level of 95%.

With regard to the gas proportion of the USA, stratum I (with an average CO_2 emission of 5755.98 Mt) and stratum IV (with an average CO_2 emission of 5450.31 Mt) showed a significant difference at the confidence level of 95%. The gas share increased from 25.13% in 1990 (in stratum I) to 31.52% in 2016 (in stratum IV), while the average 2 emission decreased during the same time. The switch from coal or oil to natural gas strongly affected the carbon mitigation since the dramatic carbon emission drop of the USA during recent years was closely connected to the gas boom (WALL STREET JOURNAL, 2013).

3.3 Ecological detector analysis

The ecological detection focused on whether significant differences existed among the effects of detected factors in China and the USA. The results showed that for China, the incidence of carbon dioxide emission increased between X1 and X2, X3 and X6, X4 and X6, as well as X5 and X6 which were significantly different at the 95% confidence level, while the others were not. However, for the USA, the CO_2 emission increase between X2 and X3 was significantly different. Apart from CO_2 emission increase incidence differences due to human economic activities and population, the incidence of carbon emission increase caused by other influencing factors were not significantly different.

3.4 Interaction Detector analysis

As shown in Table 3, the factors X1 and X2 were found to enhance each other, thus increasing energy-related carbon dioxide emissions in China, following a bilinear relationship. The interactions of factor X1 ∩ X3, X1 ∩ X4, X1 ∩ X5, X1 ∩ X6, and X5 ∩ X6 showed a similar effect. The relationships between X3 and X5 (X3 ∩ X5 (0.942) > 0.759 = X3 (0.567) + X5 (0.192)), X4 and X5 (X4 ∩ X5 (0.801) > 0.709 = X4 (0.517) + X5 (0.192)) were nonlinear and enhanced each other while the remaining factors enhanced each other, thus increasing the decisive power of factors to energy-related CO_2 emission growth, exerting synergistic effect on the CO_2 emission in China with a bilinear relationship.

Both the coal share effect and oil share effect enhanced each other in a nonlinear relationship; in other words, they more significantly impacted each other for changing the carbon emission. Due to the low price of coal and the rigid energy consumption behavior of many years, China still relies heavily on coal:61.83% of the total primary energy use originated from coal consumption (BP). Even though the annual rate declines at 0.85% yr^{-1}, the Chinese coal consumption accounts for 50.58% of the whole world coal consumption. Moreover, excessive use of coal and oil (two carbon-intensive fuels (Yang et al., 2016)) will lead to more carbon emissions in China. Therefore, the dependence on these two types of fuels should be further reduced in China.

The combined impact of oil share and energy intensity significantly enhances the sum of the two separate factors. This shows that the adjustment of China's oil share can strengthen the impact of energy intensity on carbon emissions. Energy intensity decreased at an average annual rate of 2.83%, which is mainly due to the improvement of energy efficiency. However, as the second-largest oil importing country, China's oil import growth in the year 2016 was 10.6%, which exceeded the annual growth rate of 9.3% of 2005-2015. Therefore, the oil consumption share in China is likely affected by oil prices; moreover, the oil price was a significant factor for reducing the energy intensity in China (Herrerias et al., 2013). The changes of the oil share effect and the energy intensity effect enhanced each other toward influencing the carbon emission.

Although the energy intensity and proportion of oil significantly promote each other, the effect of the energy mix on carbon emissions is less than the effect of energy intensity on reducing carbon emissions (Schipper et al., 2001; Zhu et al., 2014). Therefore, more attention should be paid to improving the energy efficiency in the process of policy formulation.

Table 3. Interaction relationship of each factor on CO_2 emission in China

Factor combination	Graphical representation	Interaction relationship
X1 ∩ X2		Enhance, bi-
X1 ∩ X3		Enhance, bi-
X1 ∩ X4		Enhance, bi-
X1 ∩ X5		Enhance, bi-
X1 ∩ X6		Enhance, bi-
X2 ∩ X3		Enhance, bi-
X2 ∩ X4		Enhance, bi-
X2 ∩ X5		Enhance, bi-
X2 ∩ X6		Enhance, bi-

X3 ∩ X4		Enhance, bi-
X3 ∩ X5		Enhance, nonlinear
X3 ∩ X6		Enhance, bi-
X4 ∩ X5		Enhance, nonlinear
X4 ∩ X6		Enhance, bi-
X5 ∩ X6		Enhance, bi-

As for the USA (table 4), the relationship between X2 and X4 is nonlinear and they also enhance each other thus increasing the total carbon dioxide emission, which is the same as X2 ∩ X5 and X2 ∩ X6. In other words, the effect of human activities and the energy mix effect enhanced each other in a nonlinear relationship. However, the interactions between the remaining influencing factors is bilinear, indicating a synergistic impact on the carbon dioxide emission in the USA. They also enhanced each other but did not have an as pronounced strengthening effect as the human activities effect and the energy mix effect.

Since the carbon emission coefficients of oil and gas are smaller than that of coal (approximately 0.83 and 0.63 of coal emission coefficient, respectively) (Zhu et al., 2014), the carbon emissions from oil and natural gas are less than those of coal. The massive switch from coal consumption to oil or gas in the USA slowed the carbon emission increase. Furthermore, this shift helped to lower the energy intensity because plants improved the energy efficiency by approximately 20% in the fuels converting process when using natural gases compared to traditional coal-fired power plants (Feng et al., 2015). According to Voigt et al. (Voigt et al., 2014), the industry structure change was the main driver of energy intensity in the USA. Furthermore, the gas price adjustment of the USA stimulated the gas consumption and the shift from more carbon-intensive coal. Moreover, the carbon emissions (BP) in the USA achieved a decoupling state from economic growth (WorldBank, 2017) in 2013, when CO_2 emission decreased with the persistent economic growth. Thus, the interaction between energy mix and the economic factor were mutually enhancing in influencing the carbon emission in the USA.

Table 4. Interaction relationship of each factor on the CO_2 emission in the USA.

Factor combination	Graphical representation	Interaction relationship
X1 ∩ X2		Enhance, bi-
X1 ∩ X3		Enhance, bi-
X1 ∩ X4		Enhance, bi-
X1 ∩ X5		Enhance, bi-
X1 ∩ X6		Enhance, bi-
X2 ∩ X3		Enhance, bi-
X2 ∩ X4		Enhance, nonlinear
X2 ∩ X5		Enhance, nonlinear
X2 ∩ X6		Enhance, nonlinear
X3 ∩ X4		Enhance, bi-
X3 ∩ X5		Enhance, bi-
X3 ∩ X6		Enhance, bi-
X4 ∩ X5		Enhance, bi-

X4 ∩ X6		Enhance, bi-
X5 ∩ X6		Enhance, bi-

4 Conclusions and Policy Implications

4.1 Conclusions

This study examined the driving factors of energy-related CO_2 emission by applying the geographical detector methods for China and the USA. Furthermore, a comparative analysis of two typical countries was conducted from the perspective of stratified heterogeneity and spatial differences; several conclusions are proposed:

(1) The effect of human economic activities was the most significant determinant of the carbon emission in China followed by population effect. High speed economic development and population gains during the last decades increased corresponding to energy-related CO_2 emissions. Energy intensity was the significant factor that helped to decelerate the CO_2 emission. In addition, all factors were found to enhance each other to change the CO_2 emission. Most interactions followed a nonlinear relationship while oil share with energy intensity and coal share had more significant enhanced power in China.

(2) In general, population growth was the most significant driving factor for the CO_2 in the USA. The energy intensity effect was the next main determinant of CO_2 emission and contributed to slowing down the growth of CO_2 emissions. Both the human activities factor and the energy mix factor had a more powerful effect when they enhanced each other to change carbon emission than other

enhancing interactions in the USA.

4.2 Policy Implications

After the Paris Agreement (2016), the massive consumption of fossil fuels will be further reduced via rapid replacement with renewable fuels. Since the driving factors of total CO_2 emission vary from country to country, corresponding adjustments on CO_2 emission mitigation and energy consumption must be made. For China, developing a low-carbon economy and adjusting the industrial structure helps to change the rigid development that relied heavily on fossil fuels (especially on coal consumption). The replacement of traditional high-emission fuels with renewable fuels should be initiated; furthermore, price and technology issues should be considered. The improvement of energy efficiency and the conversion technology also played a significant role in China to decelerate carbon dioxide emissions. In the USA, coal replacement seemed to help to decrease carbon emissions; however, with regard to other pollution of mercury, arsenic, chlorine or some heavy metals, additional energy efficiency improvement and decarbonation of the energy system strategies should be considered and further developed.

Appendix A

Factor detector

A F-test is applied to check whether a significant difference exists between the two variances.

$$F = {SST}/{SSW} = \left[ms_1^2(n-1)\right]/\left[ns_2^2(m-1)\right] \tag{A.1}$$

Where SST denote dispersion variance or the total sum of the squares; SSW means the stratified population dispersion variance, which can also be called as the within sum of squares. Also, since the statistic is approximately distributed as $F(m-1, n-1)$, the degree of freedom can be considered as $df = (m-1, n-1)$ (Grimmett and Stirzaker, 2001). As a result, we made the null hypothesis H_0: $SST = SSW$ (the significant level 95%). After comparing the result with the value in distribution table or analyzing the p value, conclusions can be made. When $F(m-1, n-1) > (f_\alpha)_{max}$, the null hypothesis can be rejected at the 95% confidence level. Then an alternative hypothesis: H_a: $SST \neq SSW$ is taken instead. In other words, there was a significant difference between the tested variances. Otherwise, the null hypothesis cannot be rejected. No significant differences between the two variances can be detected. In general, the stratified differences of each determinant contributed to CO_2 emission changes in various years and strata.

Where the total sum of the squares:

$$SST = \sum_{h}^{N}(Y_i - \bar{Y}) = N\sigma^2 \tag{A.2}$$

the within sum of squares:

$$SSW = \sum_{h=1}^{L}\sum_{h}^{N}(Y_{hi} - \overline{Y_h}) = \sum_{h=1}^{L} N_h {\sigma_h}^2 \tag{A.3}$$

$\overline{Y_h}$ is the mean of stratum h and $\overline{\mathrm{Y}}$ is the population variance.

$$q = 1 - {}^{SSW}/_{SST} \tag{A.4}$$

If the variance within every single stratum is relatively small, meanwhile, the between variance of different strata is much bigger, indicating the division method explains most of the change trends brought from the influencing factors.

Risk detector

This statistic is distributed approximately as Student's t in paired regions with the value of degrees of freedom equal to:

$$df = \frac{\sigma^2_{\overline{R_{h=m,Xi}}}/N_{h=m} + \sigma^2_{\overline{R_{h=k,Xi}}}/N_{h=k}}{{}^{1}/{N_{h=m,Xi}}^{-1} * \left(\sigma^2_{\overline{R_{h=m,Xi}}}/N_{h=m,Xi}\right)^2 + {}^{1}/{N_{h=k,Xi}}^{-1} * \left(\sigma^2_{\overline{R_{h=k,Xi}}}/N_{h=k,Xi}\right)^2} \tag{A.5}$$

The null hypothesis H_0: $\overline{R_{h=m}} = \overline{R_{h=k}}$ is made, also, a significant level α (0.05) is given. If $|t'| > t'_{\frac{\alpha}{2}}$ in the student-t distribution table, the null hypothesis is rejected, then it comes to the alternative hypothesis: H_a: $\overline{R_{h=m}} \neq \overline{R_{h=k}}$. Otherwise, the null hypothesis cannot be rejected.

Interaction detector

When q ($X_i \cap X_j$) > Max (q ($X_i \cap X_j$)), the interaction relationship between factor X_i and X_j is the bilinear relation, moreover, they had a strengthening effect working together. The interaction between factor X_i and X_j is defined as weaken and nonlinear when q ($X_i \cap X_j$) < Min (q ($X_i \cap X_j$)). In addition, when q ($X_i \cap X_j$) distributes between the minimum and maximum of q ($X_i \cap X_j$), the uni-directionally and weakened status is defined. When q ($X_i \cap X_j$) > q (X_i)+ q (X_j), the relationship is nonlinear, and they enhanced each other in increasing the carbon dioxide emission. However, when they equal, they are independent from each other.

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Highlights:

- China and United States produce 2/5 of global carbon emission.
- Investigating the drivers of carbon emission in China and US from a perspective of spatial heterogeneity.
- Using geographic technique to analyze carbon emission.
- Policy implications are offered.