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Does income inequality lead to more direct and indirect household CO_2 emissions in different income group? Evidence from China during 2000-2015

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Abstract: Income inequality plays as a driver of direct and indirect CO_2 emissions from the household sector. Existing literature have done extensive research on the impact of income inequality on direct carbon emissions at the national level. Few regional studies focus on the regional differences. This paper investigates the impact of income inequality on both direct and indirect carbon emissions of 30 provinces in China from 2000 to 2015 based on the STIRPAT model. Theil index is selected to measure income inequality and population, household consumption level, energy intensity, urbanization and industry structure are chose as control variables. The results indicate that income inequality is negatively correlated with CO_2 emissions in middle and high Theil regions, while positively correlated in low Theil region. Population, per capita consumption level and urbanization have positive impacts on CO_2 emissions. Among them, the effect of population on CO_2 emissions is the largest, especially on the indirect carbon emissions in three regions. Energy intensity is a significant influence factor in increasing direct CO_2 emission, while industrial structure has not significant effect on indirect CO_2 emissions in the three regions.

Key words: income inequality; CO_2 emissions; Theil index; household

1. Introduction

As the biggest contributor to global warming, increasing greenhouse gas (GHG) emissions, especially carbon dioxide (CO_2) emissions, have exerted a colossal impact on global economic and social development. According to the study of Fifth assessment report (AR5) to the intergovernmental panel on climate change (IPCC, 2013), more than half of the global warming since the 1950s has been caused by human activities, and the result has a credibility of more than 95%. Since 2006, China has surpassed the United

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States to become the world's largest emitter of CO_2 (Auffhammer et al., 2017). As the top developing country worldwide, China contributes 27.3% of the world energy-related CO_2 emissions. In the past, most energy consumption and CO_2 emissions have been attributed to the industrial sector rather than the household sector. However, research shows that in some developed countries, household energy consumption has exceeded industrial energy consumption (Wang and Yang, 2014). And in China, direct and indirect household CO_2 emissions have surpassed those of industry (Li et al., 2015). Furthermore, fifty percent of carbon emissions of Egypt come from the residential sector (Dabaieh et al., 2017). With the rapid development and increasing incomes, it is estimated that energy demands of residential sector will continue to increase and may lead to more GHG emissions (Geng et al., 2017). It has been proved that people generate a lot of direct energy consumption and CO2 emissions in their lives. Vringer and Blok (2003) found that 54% of household energy demand was direct, based on data from 350 consumer categories in the Netherlands. In the EU, residential direct energy consumption of buildings accounted for a share of 27% of final energy consumption (Laes et al., 2018). Hirano et al. (2016) estimated that direct CO_2 emissions were approximately 4.9 [kg-CO_2/person/day] in Japan. At the same time, indirect energy consumption accounted for a large proportion of total energy consumption. In Korea, more than 60% of the household energy requirement was indirect (Park and Heo, 2007). Papathanasopoulou (2010) indicated that indirect energy consumption increased 60% from 1990 to 2006 in Greece. Feng et al. (2011) found that indirect energy consumption and CO_2 emissions for urban households are much greater than the direct consumption values. The extent of future global warming depends largely on the cumulative amount of global CO_2 emissions. In response to international pressure to reduce emissions, and achieve the goal of “temperatures are no more than 2 degrees Celsius warmer than pre-industrial temperatures”, we need to pay more attention to the household sector's direct and indirect CO_2 emissions.

Many scholars have done a lot of research in the field of direct carbon emissions (York, 2008; Liddle, 2013; Wang et al., 2017). Poruschi and Ambrey (2016) used data from the Australian household energy consumption survey. Using seemingly unrelated regression (SUR) equations, it was found that capital city life was associated with higher levels of direct energy consumption. Utilizing the vehicular emission factor model, Zhang et al. (2013) detected that the black carbon (BC) emissions in China were higher in the east and lower in the west, which was corresponding to regional economic development and rural population density. Sanches-Pereira et al. (2016) assessed the residential direct energy consumption and the related carbon emissions in Brazilian. The results showed that poverty reduction of the poor affected the growth of energy demand. Levy et al. (2017) quantified the impact on direct residential fuel combustion and electricity consumption, and applied an intermediate complexity electricity dispatch model called the AVoided Emissions and geneRation Tool (AVERT) to describe marginal power plant emissions by region. A logarithmic mean Divisia index (LMDI) decomposition analysis was used to examine the factors influencing the residential direct carbon emissions (RDCE) of Shanxi province in China. Zang et al. (2017) found that the increase in RDCE was mainly due to an increase in per capita household income and an increase in the number of households. Wang et al. (2018) employed Geographical Weighted Regression (GWR) model to examine the influence factors of direct CO_2 emissions and revealed that there is an obvious spatial correlation in different provinces. Furthermore, Ye et al. (2017) explored the mechanisms by which low carbon behavior affects household direct energy use and related carbon emissions, using the path analysis method-integrated with behavior and socioeconomic factors.

Meanwhile, some studies have found that indirect effects also accounts for a large proportion (Wang and Yang, 2014; Yin et al., 2017). Using the input-output model, Zhang et al. (2017) found that indirect CO_2 emissions were on the rise, mainly driven by per capita household consumption and energy intensity. Zhu et al. (2012) also established the input-output model of residential indirect carbon emissions, and the results showed that the improvement of residential consumption level played a leading role in the growth of residential indirect emissions. Weber and Perrels (2000) made use of an enhanced input-output model to measure indirect energy and emissions in West Germany, France and the Netherlands. On the basis of an analysis of input-output energy and household expenditure data, yuan et al. (2015) figured out the indirect carbon emissions from Chinese household consumption in 2002 and 2007, and concluded that the expansion of urbanization and the upgrading of consumption structure play an important role in the increase of residential indirect emissions. Some researches, however, employed Consumer Lifestyle Assessment (CLA) to estimate indirect household carbon emissions (Shui and Dowlatabadi, 2005; Huang and Jiang, 2013; Yang et al., 2017). Feng et al. (2011) compared the carbon emissions of residents in various regions of China and at different income levels, pointing out that the indirect energy consumption and CO_2 emissions of high-income households are higher than those of low-income households. Based on CLA, Wei et al. (2007) studied the impact of changes in rural and urban household consumption behavior on terminal energy consumption and related carbon emissions in China from 1998 to 2002. The results revealed that residential lifestyles have a significant impact on energy use and related CO_2 emissions, hence one of the most effective measures for energy conservation is changes in lifestyle. Ding et al. (2017) combined input-output analysis with consumer lifestyle analysis and found that the indirect energy consumption of household consumption activities was 1.35 times that of direct energy consumption.

In the study of the factors related to income. Yang et al. (2017) assessed the relationship between carbon inequality and income and housing wealth inequality through a Heckman process. Using the semi-closed input-output model, Zhang et al. (2017) divided urban and rural household income into several groups, focusing on the impact of household consumption on CO_2 emissions of different income households. It was found that as incomes rose, so did the impact of household consumption. Wang et al. (2018) used a geographical weighted regression (GWR) model to examine the spatial effect of factors on household CO_2 emissions. The results indicated that the effect of income on household CO_2 emissions was positive and showed an increasing tendency year by year. Adopting Gini coefficient as the measure of income inequality, Hao et al. (2016) investigated the impacts of income inequality on carbon emissions per capita in China. In their study, a "u-shaped" relationship was found between per capita income and per capita carbon emissions. Jorgenson et al. (2017) examined the relationship between CO_2 emissions and income inequality in the United States using both the top 10% income and the Gini coefficient. What's more, at the regional level of studies on CO_2 emissions, Wang et al. (2015) divided China into three different levels of economic development regions according to the GDP per capita from 1997 to 2012. Besides, Zhang and Zhao (2014) divided China into eastern, central and western regions according to geographical location, and studied the impact of income and its inequality on direct carbon emissions on this basis.

To sum up, a large amount of scholars have done a lot of researches of income inequality on direct carbon emissions of households. However, more studies focus on direct carbon emissions. Though some previous studies had analyzed the impact of income inequality on indirect carbon emissions on a national perspective, few of them took the regional difference into consideration. Actually, there exist great differences in income inequality level between regions, which may lead to different impact on direct and indirect CO_2 emissions. To fill these gaps, this paper comprehensively considered the impact of income inequality on both direct and indirect CO_2 emissions, which is conducive to adopting different emission reduction measures for different type of CO_2 emissions. Moreover, in order to explore the regional difference, 30 provinces in China are divided into three regions according to Theil index, representing high, medium and low income inequality region.

The rest of the paper is structured as follows. Section 2 describes the methodology and data sources. The results of classification, chart description and regression are showed in Section 3, followed by the discussions of six explanatory variables in Section 4. In the end, Conclusion and policy implications are presented in Section 5.

2. Methodology and data

2.1 STIRPAT model

In this study, the Theil index was used as the main explanatory variable, while population, per capita consumption level, energy intensity, urbanization and industry structure were selected as control variables. The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model evolved on the basis of the

IPAT model, which is mainly used to reflect the impact of economic activities on the environment. The IPAT model ($I = PAT$), proposed by Ehrlich and Holdren (1971) is widely accepted for its concise analytical framework. In this model, I, P, A and T denote the factors of environment impact, population, affluence and technology in turn. Nevertheless, the IPAT model has the following two main defects. Primarily, it is incapable of evaluate other variables with known variables, resulting in an inability to test hypotheses (York et al., 2003). In the second place, the influencing factors studied by this model are limited and the proportion of the impacts on the environment is the same. In order to overcome the drawbacks mentioned above, Dietz and Rosa (1997) proposed the STIRPAT model on the basis of preserving the multiplication structure of the IPAT model. The improved model can increase the variables according to the factors studied, and at the same time, the non-proportional influence of the influencing factors on the environment can be obtained. To some extent, the IPAT model can be understood as a special form of STIRPAT model, if and only if $a = b = c = d = e = 1$. The STIRPAT model can be summarized as Eq. (1).

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{1}$$

Where I reports the environmental impact. P represents the population. A means affluence and T denotes technology. Moreover, a is the constant term, b, c and d are the indexes of P, A and T respectively. e is the model error, and subscript i expresses province.

For ease of estimation and hypothesis testing, all the variables on both sides of Eq.(1) are transformed to natural logarithms form. the model can be shown as follows:

$$\ln I_{it} = a + b(\ln P_{it}) + c(\ln A_{it}) + d(\ln T_{it}) + e_{it} \tag{2}$$

Where subscript i represents province and subscript t denotes year. According to the concept of elastic coefficient, every 1% change in P, A and T will cause $b\%$, $c\%$ and $d\%$ change in I respectively.

This paper employ the STIRPAT model. In order to study the impact of income inequality on direct CO_2 emissions and indirect CO_2 emissions, in addition to taking into account the three factors of population, affluence and technology, the Theil index, urbanization and industry structure are also added. The empirical models of direct and indirect CO_2 emissions can be written as below:

$$\ln DCO_{2it} = a_0 + a_1(\ln TI_{it}) + a_2(\ln P_{it}) + a_3(\ln CL_{it}) + a_4(\ln EI_{it}) + a_5(\ln URB_{it}) + a_6(\ln IS_{it}) + e_{1it} \tag{3}$$

$$\ln ICO_{2it} = b_0 + b_1(\ln TI_{it}) + b_2(\ln P_{it}) + b_3(\ln CL_{it}) + b_4(\ln EI_{it}) + b_5(\ln URB_{it}) + b_6(\ln IS_{it}) + e_{2it} \tag{4}$$

Where DCO_2 and ICO_2 refer to direct and indirect CO_2 emissions separately. TI stands for the Theil index, which is a measure of income inequality. P indicates population size. CL, which means per capita consumption level, is introduced as a measure of affluence. EI represents technology, which is evaluated by energy intensity. URB denotes urbanization, while IS denotes industry structure.

Before the regression of the model, we performed unit root test and co-integration test on the panel data. We then performed Hausman test, heterogeneity test, autocorrelation test and cross-sectional correlation test. Afterwards, we used five different assessment methods to estimate the two models of direct and indirect CO_2 emissions in low, middle and high Theil index regions, resulting in a total of 30 models. These five methods are fixed effects (FE), feasible generalized least squares (FGLS), the linear regression with panel-corrected standard errors (PCSE), the linear regression with Driscoll-Kraay standard errors (DK) and the linear regression with Newey-West standard errors (N-W).Considering the heterogeneity bias, the FE estimation was applied after the robust Hausmann test. In addition, there may be automatic aggregation and cross-sectional independence within the panel data sets, so N-W and DK models are used to determine more reliable assessment methods when classic assumptions are violated. If both heterogeneity and autocorrelation exist, NW estimation can be adopted, and DK estimation can be adopted if cross section correlation exists. FGLS and PCSE can be used as references to provide more reliable estimates. When the time dimension (T) is equal or greater than the cross section dimension (N), FGLS is used to estimation, while PCSE is applicable to the case that the cross section dimension (N) is bigger than the time dimension (T).

By the estimated results obtained (Table 1-6), our main interpretations focus on DK estimation (model 19, 24 and 29) among all indirect CO_2 emissions models. In terms of the direct CO_2 emissions models, we only focus on DK estimation (model 9) in middle Theil region, while choosing N-W estimation (model 5 and 15) as preferred models for the other two regions.

2.2 Data

This paper is based on annual panel data of 30 provinces in China on the time period from 2000 to 2015. The data of direct CO_2 emissions are calculated according to the formula of CO_2 emissions in the Intergovernmental Panel on Climate Change (IPCC 2006). Data on indirect CO_2 emissions are calculated by employing Consumer Lifestyle Assessment (CLA) (Shui and Dowlatabadi, 2005), which divide indirect CO_2 emissions into eight sectors following the definition of China Statistical Yearbook (National Bureau of Statistics of China, 2000-2015a). The data of the Theil index is calculated on the basis of formulation (Wang and Ouyang, 2007).The specific data of population and income come from China Statistical Yearbook (National Bureau of Statistics of China, 2000–2015a). In addition, population, urbanization, industry structure and per capita consumption level are collected from China Statistical Yearbook (2000-2015) (National Bureau of Statistics of China, 2000–2015a). Per capita consumption level is calculated based on 2000 constant price. Data on energy intensity is calculated from the China

Energy Statistical Yearbook (2000-2015) (National Bureau of Statistics of China, 2000-2015b).

3. Results

3.1 Classification result

In order to divide regions, K-means clustering was applied to cluster analysis. The cluster analysis was carried out using SPSS12.0 statistical software, which classifies individuals according to their characteristics, so that the individuals in the same category have as high homogeneity as possible, while the categories have as high heterogeneity as possible.

While serving as the core explanatory variable of the model, the Thiel index is also the basis for the regional division. According to the results of cluster analysis, 30 provinces are divided into high, middle and low Thiel regions. At the same time, according to the digital implications of the Thiel index, they represent a reduction in inequality in turn. This kind of classification presents certain non-correspondence with the classification result which take the geographical location and the economic development level as the classification basis spatially. As shown in Fig. 1, the three regions are: high Theil region (Guangxi, Guizhou, Yunnan, Shaanxi, Gansu and Qinghai provinces), middle Theil region (Hebei, Shanxi, Inner Mongolia, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Chongqing, Sichuan, Ningxia and Xinjiang provinces) and low Theil region (Beijing, Tianjin, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu and Zhejiang provinces) respectively. However, in general, the provinces in the low Thiel region are mainly distributed in the east, while the less developed provinces in the central and western regions are the main components of the high Thiel region.

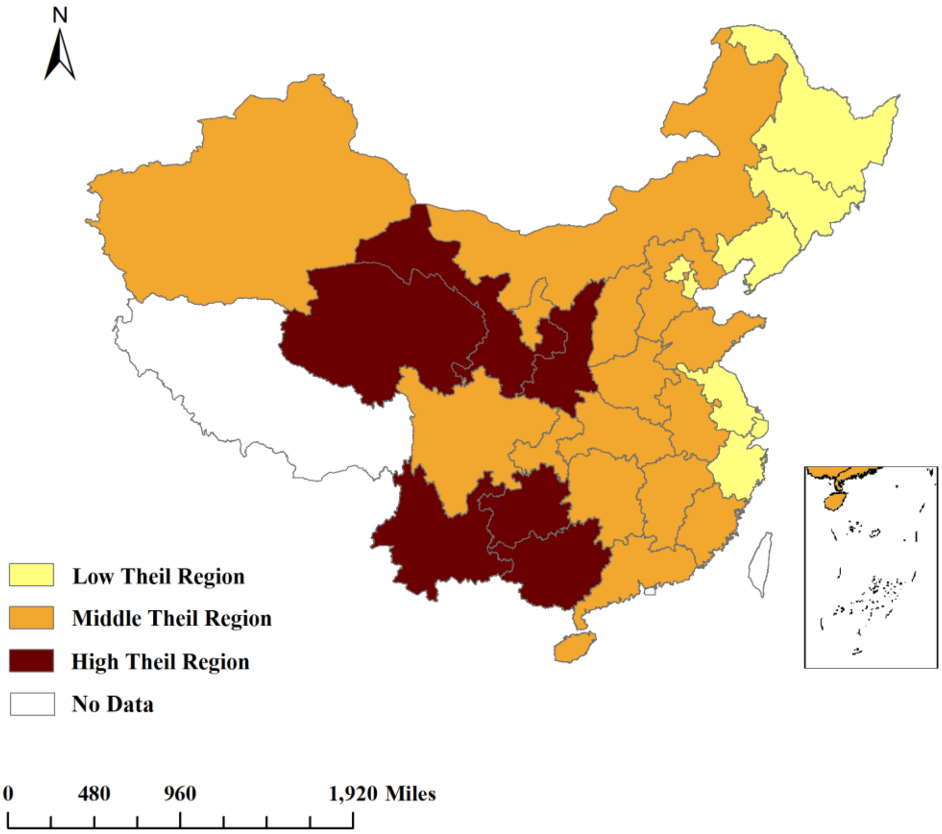

Fig.1. Classification of three Theil regions

3.2 Analysis of direct and indirect CO_2 emissions in different regions

Based on the data of Theil index we calculated in our paper, we divide 30 provinces in China into three regions: Low, Middle and High Theil regions. Fig. 2 reflects the whole CO_2 emissions of national as well as other three regions from 2000 to 2015. As shown, CO_2 emissions of the low and middle Theil regions are up to 53.5 million tons and 48.4 million tons respectively in 2000, 138.3 million tons and 153.5 million tons separately in 2015, but those of the high Theil region are only 23.2 million tons in 2000 and 80.3 million tons in 2015. Between 2000 and 2015, it clearly shows that the whole CO_2 emissions have generally increased over the past 16 years, only a minuscule drop in the national, low and middle Thiel regions in 2015. The whole CO_2 emissions of national case were 4 billion tons in 2015, three times as much as in 2000. During this period, indirect CO_2 emissions increased by 278.38%, 195.61% and 212.96% respectively in the low, middle and high Theil regions, while direct CO_2 emissions increased by 119.46%, 226.90% and 259.52% separately. Among them indirect carbon dioxide emissions increased the most in 2014.

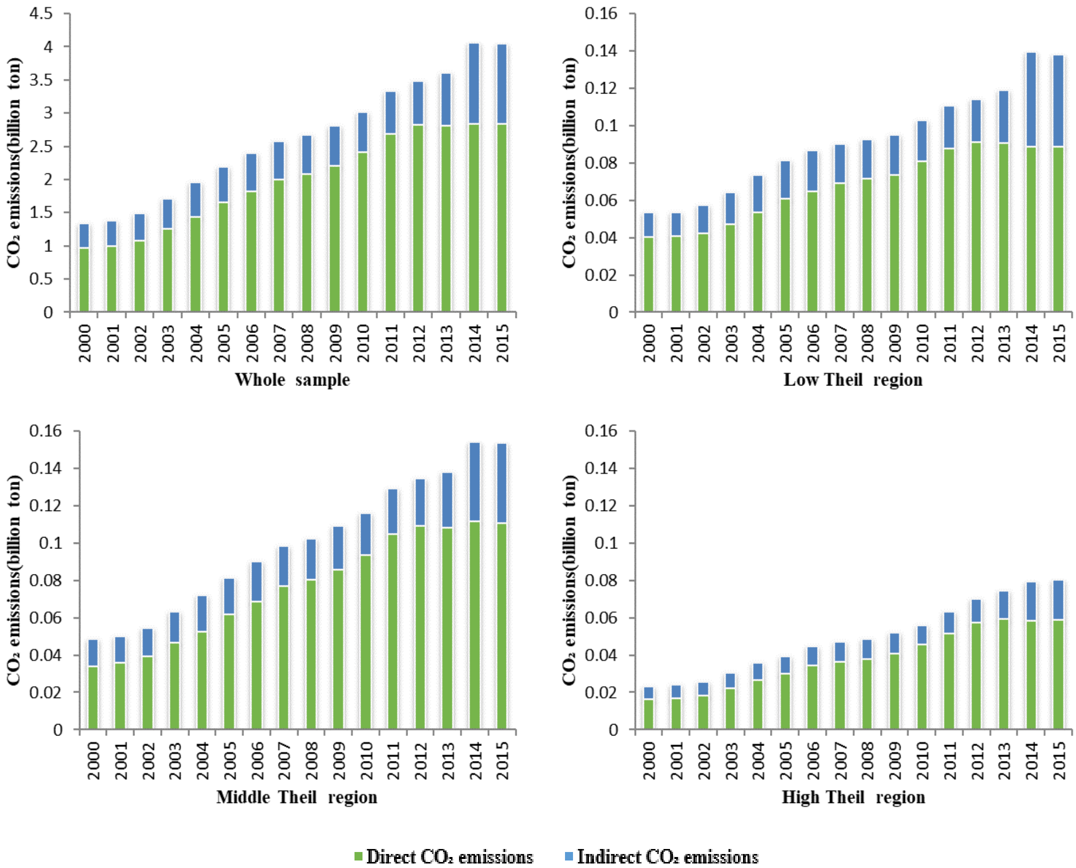

Fig.2. Direct and indirect CO_2 emissions in the nation and three regions from 2000 to 2015

To further understand the composition of indirect carbon emissions, we mapped Fig. 3. As shown in this composite pie chart, indirect carbon emissions consist of eight components (food, clothes, residence, housing facilities and services, health care and medical services, transport and communication, education, culture and recreation, and miscellaneous goods and services). Owing to the differences in consumption expenditures and carbon intensity for the eight categories, the situation of indirect emissions in the eight sectors all vary significantly.

As can be seen from the proportion of emissions, direct CO_2 emissions are significantly higher than indirect CO_2 emissions in these four graphs. which is 3.14 times in the whole sample, 2.86 times in low Theil region, 3.25 times in middle Theil region and 3.33 times in high Theil region. In terms of the components of indirect CO_2 emissions, the largest emissions sector of the three regions are all residence, which is 18.03%, 16.85% and 16.66% of the total indirect CO_2 emissions in low, middle and high Theil regions respectively. The reason for this result, on the one hand, comes from the household's large expenditure in the residence sector, on the other hand, it is also affected by the residence sector's maximum carbon intensity. The second biggest indirect CO_2 emissions sector is education, culture and recreation. In high, meddle and low Theil regions, the proportion is 4.44 percent, 3.54 percent and 3.42 percent, separately. Besides the indirect CO_2 emissions of residence and education sectors, culture and recreation, food, clothes, health care and medical services, housing facilities and services, transport and communication, and miscellaneous goods and services were relatively small and ranked third to eighth respectively. This pattern is consistent across the three regions, but it is worth noting that indirect CO_2 emissions from food in the high Theil region are the highest compared to the other two regions.

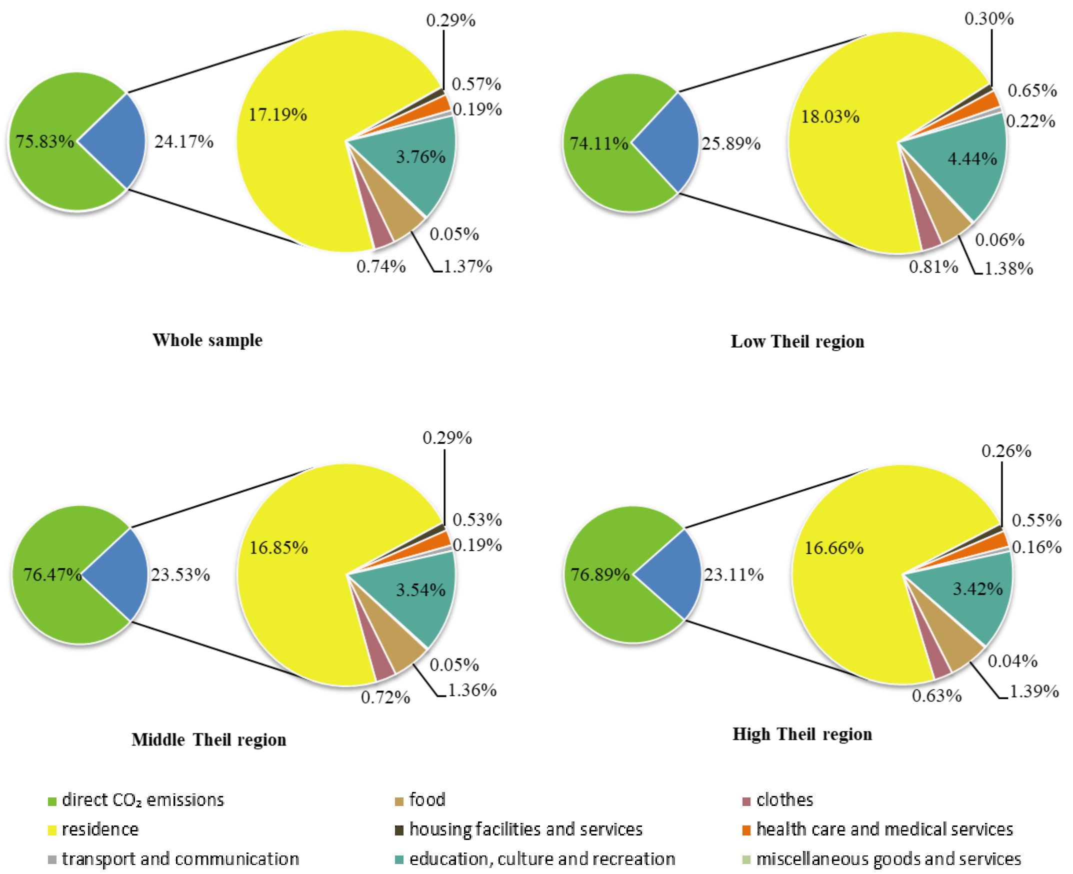

Fig.3. Indirect CO_2 emissions structure in the nation and three regions

3.3 Regression results

3.3.1 Results of direct CO_2 emissions in three regions

As shown in Tables 1-3, in the first group of regression model for three regions, the explained variable we use is direct household CO_2 emissions. Meanwhile, the key explanatory variables refer to the Theil index. All variables in regression equation are the logarithmic values. As indicated from model 5, 9 and 15, the coefficient of Theil index are all significant correlated with direct household CO_2 emissions under the level of 5% or lower. When the rate of Theil index increases every 1%, direct household CO_2 emissions will increases by 0.25% and 0.23% in low and high Theil regions, respectively. On the contrary, the direct household CO_2 emissions will correspondingly decrease 0.14%

when the Theil index increases every 1% in middle Theil region.

There are some other control variables associated with direct household CO_2 emissions. Except industry structure variable in high Theil region is non-significant, all explanatory variables are positive and statistically significant in the three regions. In low Theil region (Table 1), population, per capita consumption level, energy intensity, urbanization and industry structure influence direct household CO_2 emissions with the elasticities of 0.984, 0.738, 0.672, 0.703 and 0.456. It's worth mentioning that the impact of urbanization and industry structure on direct household CO_2 emissions differs across regions, with the greatest impact on low Theil region, followed by middle Theil region and high Theil region. The estimated results for middle Theil region is shown in Table 2. The coefficients of population, per capita consumption level, energy intensity, urbanization and industry structure are 1.012, 0.848, 1.034, 0.460 and 0.283 respectively, which means all these variables have positive effect on direct household CO_2 emissions. It can be seen in high Theil region (Table 3), the influence factors on direct household CO_2 emissions have strong explanatory power with elasticities of 1.037, 1.156, 1.089, 0.330 and 0.071. Moreover, the effect of population, per capita consumption level and energy intensity on direct household CO_2 emissions of this region is greater than that of the other two regions. Therefore, this influence can’t be overlooked.

Table 1

Estimation results: Direct CO_2 emissions model for low Theil region during 2000-2015.

Variable	FE(1)	FGLS(2)	PCSE(3)	DK(4)	N-W(5)
lnTI	-0.0539	0.250^{***}	0.250^{***}	0.250^{***}	0.250^{***}
	(0.0493)	(0.0542)	(0.0620)	(0.0614)	(0.0590)
lnP	0.171	0.984^{***}	0.984^{***}	0.984^{***}	0.984^{***}
	(0.129)	(0.0348)	(0.0318)	(0.0491)	(0.0454)
lnCL	0.764^{***}	0.738^{***}	0.738^{***}	0.738^{***}	0.738^{***}
	(0.0652)	(0.0446)	(0.0465)	(0.0441)	(0.0611)
lnEI	0.583^{***}	0.672^{***}	0.672^{***}	0.672^{***}	0.672^{***}
	(0.0784)	(0.0458)	(0.0303)	(0.0252)	(0.0422)
lnURB	0.816^{***}	0.703^{***}	0.703^{***}	0.703^{***}	0.703^{***}
	(0.221)	(0.164)	(0.186)	(0.209)	(0.229)
lnIS	0.416^{***}	0.456^{***}	0.456^{***}	0.456^{***}	0.456^{***}
	(0.0875)	(0.0588)	(0.0430)	(0.0699)	(0.0571)
Constant	0.752	-4.673^{***}	-4.673^{***}	-4.673^{***}	-4.673^{***}
	(1.232)	(0.500)	(0.485)	(0.390)	(0.541)
R-squared	0.927		0.958	0.958	
Number of id	8	8	8		
Heteroskedasticity	chi2(6)=1210.04***				

test					
Autocorrelation test	$F(1,7)=47.947^{***}$				
Cross-sectional independence test	CD=-0.386				
Observations	128	128	128	128	128

*** p<0.01,
** p<0.05,
* p<0.1

Table 2

Estimation results: Direct CO_2 emissions model for middle Theil region during 2000-2015.

Variable	FE(6)	FGLS(7)	PCSE(8)	DK(9)	N-W(10)
lnTI	0.0542	-0.144^{***}	-0.144^{***}	-0.144^{**}	-0.144^{***}
	(0.0394)	(0.0472)	(0.0551)	(0.0527)	(0.0532)
lnP	0.434^{***}	1.012^{***}	1.012^{***}	1.012^{***}	1.012^{***}
	(0.154)	(0.0175)	(0.0176)	(0.0340)	(0.0189)
lnCL	0.949^{***}	0.848^{***}	0.848^{***}	0.848^{***}	0.848^{***}
	(0.0350)	(0.0340)	(0.0260)	(0.0465)	(0.0348)
lnEI	0.941^{***}	1.034^{***}	1.034^{***}	1.034^{***}	1.034^{***}
	(0.0361)	(0.0188)	(0.0161)	(0.0181)	(0.0190)
lnURB	0.215^{***}	0.460^{***}	0.460^{***}	0.460^{***}	0.460^{***}
	(0.0818)	(0.0771)	(0.0523)	(0.123)	(0.0950)
lnIS	0.505^{***}	0.283^{***}	0.283^{***}	0.283^{***}	0.283^{***}
	(0.0684)	(0.0639)	(0.0616)	(0.0935)	(0.0713)
Constant	-2.782^{**}	-7.113^{***}	-7.113^{***}	-7.113^{***}	-7.113^{***}
	(1.120)	(0.362)	(0.276)	(0.327)	(0.337)
R-squared	0.976		0.977	0.977	
Number of id	16	16	16		
Heteroskedasticity test	$chi2(6)=9436.73^{***}$				
Autocorrelation test	$F(1,15)=57.181^{***}$				
Cross-sectional independence test	$CD=2.822^{***}$				
Observations	256	256	256	256	256

*** p<0.01,
** p<0.05,
* p<0.1

Table 3

Estimation results: Direct CO_2 emissions model for high Theil region during 2000-2015.

Variable	FE(11)	FGLS(12)	PCSE(13)	DK(14)	N-W(15)
lnTI	0.472^{***}	0.226^{***}	0.226^{***}	0.226^{***}	0.226^{***}
	(0.0896)	(0.0679)	(0.0500)	(0.0594)	(0.0853)
lnP	1.291^{***}	1.037^{***}	1.037^{***}	1.037^{***}	1.037^{***}
	(0.314)	(0.0154)	(0.0179)	(0.0213)	(0.0226)
lnCL	1.570^{***}	1.156^{***}	1.156^{***}	1.156^{***}	1.156^{***}
	(0.114)	(0.0497)	(0.0428)	(0.0504)	(0.0550)
lnEI	1.051^{***}	1.089^{***}	1.089^{***}	1.089^{***}	1.089^{***}
	(0.0733)	(0.0247)	(0.0259)	(0.0420)	(0.0230)
lnURB	-0.463^{**}	0.330^{***}	0.330^{***}	0.330^{***}	0.330^{**}
	(0.211)	(0.116)	(0.109)	(0.0976)	(0.140)
lnIS	-0.483^{***}	0.0714	0.0714	0.0714	0.0714
	(0.175)	(0.110)	(0.115)	(0.103)	(0.0897)
Constant	-15.75^{***}	-9.478^{***}	-9.478^{***}	-9.478^{***}	-9.478^{***}
	(2.763)	(0.471)	(0.441)	(0.350)	(0.490)
R-squared	0.975		0.987	0.987	
Number of id	6	6	6		
Heteroskedasticity test	$chi2(6)=6955.84^{***}$				
Autocorrelation test	F(1,5)=2.552				
Cross-sectional independence test	CD=-0.073				
Observations	96	96	96	96	96

*** p<0.01,

** p<0.05,

* p<0.1

3.3.2 Results of indirect CO_2 emissions in three regions

The second group of regression model for the three regions is represented in Tables 4-6. In this set of models, indirect household CO_2 emissions is the dependent variable, while the main independent variable is Theil index, the same as direct household CO_2 emissions model. All variables in regression equation remain the logarithmic values. According to the estimation results from model 19, 24 and 29, the effect of Theil index in low Theil region on indirect household CO_2 emissions is positive and statistically significant, while the estimated effects in the other two additional regions are negative and non-significant. The coefficient of Theil index is 0.232 in low Theil region, -0.217 in middle region and -0.250 in high Theil region separately.

The components of the control influencing factors are consistent with the direct household CO_2 emissions model. As shown in Tables 4-6, the elasticities of the population on indirect household CO_2 emissions are significant and positive in three regions, with 0.918 in low Theil region, 1.048 in middle Theil region and 1.084 in high Theil region, respectively. Compared with direct carbon emission model, the estimated effect of per capita consumption level and urbanization on indirect household CO_2 emissions is still marked but slightly decreases in low Theil region in the level of significance. The coefficients of per capita consumption are 0.249, 0.331 and 0.402, while the elasticity of urbanization on indirect household CO_2 emissions is 0.655, 0.634 and 0.741 in low, middle and high Theil regions separately. Also, in addition to the energy intensity variable in low Theil region, the energy intensity and industry structure variables are not significant in the three regions. In terms of low Theil region, a 1% increase in energy intensity will lead to a 0.54% reduction on indirect household CO_2 emissions. The coefficients of industry structure are positive in low and middle Theil regions, while turn to negative in high Theil region. Overall speaking, the effect of population, per capita consumption level, energy intensity and urbanization on indirect household CO_2 emissions in high Thiel region is greater than that in low and middle Theil region, which deserves our more attention.

Table 4

Estimation results: Indirect CO_2 emissions model for low Theil region during 2000-2015.

Variable	FE(16)	FGLS(17)	PCSE(18)	DK(19)	N-W(20)
lnTI	0.247^{**}	0.232^{***}	0.232^{***}	0.232^{***}	0.232^{***}
	(0.117)	(0.0882)	(0.0784)	(0.0503)	(0.0872)
lnP	0.128	0.918^{***}	0.918^{***}	0.918^{***}	0.918^{***}
	(0.308)	(0.0566)	(0.0264)	(0.0227)	(0.0515)
lnCL	0.0671	0.249^{***}	0.249^{**}	0.249^{*}	0.249^{***}
	(0.155)	(0.0726)	(0.113)	(0.126)	(0.0729)
lnEI	-0.841^{***}	-0.540^{***}	-0.540^{***}	-0.540^{***}	-0.540^{***}
	(0.187)	(0.0745)	(0.0405)	(0.0551)	(0.0724)
lnURB	0.926^{*}	0.655^{**}	0.655^{***}	0.655^{*}	0.655^{***}
	(0.527)	(0.266)	(0.241)	(0.326)	(0.241)
lnIS	-0.655^{***}	0.0834	0.0834	0.0834	0.0834
	(0.208)	(0.0956)	(0.0715)	(0.113)	(0.124)
Constant	6.491^{**}	-1.103	-1.103	-1.103	-1.103
	(2.932)	(0.813)	(1.129)	(1.457)	(0.919)
R-squared	0.766		0.896	0.896	
Number of id	8	8	8		
Heteroskedasticity	chi2(6)=				

test	1041.49***				
Autocorrelation test	F(1,7)=137.506***				
Cross-sectional independence test	CD=14.223***				
Observations	128	128	128	128	128

*** p<0.01,

** p<0.05,

* p<0.1

Table 5

Estimation results: Indirect CO_2 emissions model for middle Theil region during 2000-2015.

Variable	FE(21)	FGLS(22)	PCSE(23)	DK(24)	N-W(25)
lnTI	-0.254***	-0.217***	-0.217**	-0.217	-0.217***
	(0.0743)	(0.0519)	(0.0914)	(0.129)	(0.0545)
lnP	1.010***	1.048***	1.048***	1.048***	1.048***
	(0.290)	(0.0193)	(0.0154)	(0.0214)	(0.0210)
lnCL	0.309***	0.331***	0.331***	0.331***	0.331***
	(0.0660)	(0.0375)	(0.0652)	(0.103)	(0.0407)
lnEI	0.0450	-0.000200	-0.000200	-0.000200	-0.000200
	(0.0680)	(0.0207)	(0.0237)	(0.0448)	(0.0237)
lnURB	0.882***	0.634***	0.634***	0.634***	0.634***
	(0.154)	(0.0849)	(0.0744)	(0.126)	(0.0796)
lnIS	-0.247*	0.103	0.103	0.103	0.103
	(0.129)	(0.0704)	(0.0719)	(0.130)	(0.0809)
Constant	-3.670*	-4.016***	-4.016***	-4.016***	-4.016***
	(2.111)	(0.398)	(0.648)	(1.039)	(0.434)
R-squared	0.859		0.976	0.976	
Number of id	16	16	16		
Heteroskedasticity test	chi2(6)=3420.18***				
Autocorrelation test	F(1,15)=49.771***				
Cross-sectional independence test	CD=24.561***				
Observations	256	256	256	256	256

*** p<0.01,

** p<0.05,

* p<0.1

Table 6

Estimation results: Indirect CO_2 emissions model for high Theil region during 2000-2015.

Variable	FE(26)	FGLS(27)	PCSE(28)	DK(29)	N-W(30)
lnTI	0.00957	-0.250***	-0.250**	-0.250	-0.250**
	(0.142)	(0.0940)	(0.120)	(0.144)	(0.105)
lnP	1.564***	1.084***	1.084***	1.084***	1.084***
	(0.496)	(0.0213)	(0.0175)	(0.0232)	(0.0227)
lnCL	0.723***	0.402***	0.402***	0.402***	0.402***
	(0.180)	(0.0689)	(0.0732)	(0.126)	(0.0740)
lnEI	-0.0916	0.0408	0.0408	0.0408	0.0408
	(0.116)	(0.0343)	(0.0367)	(0.0584)	(0.0342)
lnURB	0.0557	0.741***	0.741***	0.741***	0.741***
	(0.334)	(0.160)	(0.140)	(0.159)	(0.160)
lnIS	-0.591**	-0.309**	-0.309**	-0.309	-0.309*
	(0.277)	(0.153)	(0.154)	(0.219)	(0.166)
Constant	-11.88***	-4.987***	-4.987***	-4.987***	-4.987***
	(4.372)	(0.653)	(0.677)	(1.158)	(0.719)
R-squared	0.888		0.978	0.978	
Number of id	6	6	6		
Heteroskedasticity test	chi2(6)=3959.96***				
Autocorrelation test	F(1,5)=15.445**				
Cross-sectional independence test	CD=8.401***				
Observations	96	96	96	96	96

*** p<0.01,

** p<0.05,

* p<0.1

4. Discussions

4.1 The effect of income inequality on CO_2 emissions

Based on the results of direct and indirect CO_2 emissions models in three regions, the Theil index has a generally smaller impact on carbon emissions than other factors, indicating that income inequality may not be the dominant factor affecting carbon emissions. Except for the direct CO_2 emissions model in high Theil region, the regions with higher income inequality has not high CO_2 emissions in total. A possible explanation is that greater income equality is associated with higher levels of CO_2 emissions (Ravallion, 2000). Income equality produces large numbers of middle-class people with carbon-intensive lifestyles, which in turn generates more CO_2 emissions. In addition, according to the Keynesian theory of diminishing marginal consumption tendency, the marginal consumption tendency of low-income households is higher than that of higher-income households. The reduction of inequality will increase the income of the poor and lead to more CO_2 emissions accordingly. As for the positive correlation between income inequality and CO_2 emissions in low Theil region, we deem that it may be related to the high level of technology in the region with low Theil index and the low-carbon consumption tendency of residents. Moreover, income inequality has positive and significant impact on direct CO_2 emissions in high Theil region. Based on the Veblen effect (Jorgenson et al., 2017), the wealthy have more resources to consume expensive and high-carbon goods to gain status because of the existence of income inequality. Households with relatively low income, limited to the resources, will increase visible commodity expenditure keep pace with the lifestyle of high-income households. This would bring about a dual effect of the amount of direct carbon emissions.

4.2 The effect of control variables on CO_2 emissions

According to the regression results, population, per capita consumption level and urbanization have positive impacts on CO_2 emissions. Among them, population has the largest impact on CO_2 emissions, especially on the indirect carbon emissions in three regions. With the increasing of population, the indirect energy consumption to meet the needs of various commodities and services required by residents has been greatly increased, which leads to more indirect CO_2 emissions to a certain extent. The positive relationship between per capita consumption level and CO_2 emissions is more pronounced in the high Theil region. This may due to the fact that the consumption expenditure of high-carbon products is relatively large in total expenditure, such as automobile and housing consumption in the high income inequality region. The income distribution in China promotes the effective upgrading of the consumption demand structure at least in the short and medium term (Liu et al., 2013). However, people have a strong awareness of low carbon and environmental protection in the region where income is relatively balanced, so they more incline to consume energy-saving and environment-friendly products. Urbanization has a positive and significant impact on the direct and indirect components of carbon emissions as well as population and per capita consumption level. The difference is that the impact of urbanization on indirect CO_2 emissions is generally greater than that of direct CO_2 emissions in three regions. In particular, the growth of indirect CO_2 emissions caused by 1% urbanization in high Theil region is 0.411%, which is higher than that of direct CO_2 emissions. This may be related to people's consumption needs and behaviors. With the constant improvement of the urban and rural residents' living standards, the difference between direct energy consumption in meeting the basic life of lighting, heating, cooking and so on is not very obvious. On the contrary, the consumption of non-energy products or services, such as clothing, food, health care and travel, accounts for a large proportion in resident's daily life. The CO_2 emissions generated by these products are indirect carbon emissions.

In addition to the above three control variables, the impact of energy intensity and industrial structure on CO_2 emissions is relatively complex. In terms of energy intensity, it is widely believed that energy intensity is positively correlated with carbon emission, that is, the reduction of energy intensity caused by technological progress will lead to the reduction of carbon emission, which is well verified in the three regions of the direct CO_2 emission model. While the relationship between energy intensity and indirect CO_2 emissions in low Theil region is negative and statistically significant at the level of 1%. The results suggest that the improvement of technical level does not necessarily result in the decrease of indirect CO_2 emissions due to the existence of energy rebound effects. Energy rebound effect refers to the effect that the energy saving obtained by the improvement of energy efficiency is partially or completely offset by the behavior of expansionary energy consumption (Wang et al., 2018a; Wang et al., 2018b). Indirect energy rebound effect refers to the reduction of the price of a certain kind of energy, which correspondingly leads to the reduction of the price of the products or services that use this energy as the factor of production, furthermore increasing the demand for these products (Xue et al., 2011). Low Theil region is mainly composed of provinces with higher levels of economic development. The price reduction of products and services caused by technological progress in these provinces often stimulate household consumption, which forming a significant indirect rebound effect. Besides, the effect of energy intensity on indirect CO_2 emission is not significant in middle Theil region.

In terms of industrial structure, it has not significant effect on indirect CO_2 emissions in the three regions. It is generally known that the tertiary industry is the main source of indirect CO_2 carbon emissions, so there are not exist obvious relationship between industrial structure and indirect CO_2 emissions. As for the direct CO_2 emissions, the influence of industry structure is much more significant. However, the effect varies from region to region, among which the low and middle Theil regions are more obvious. On the one hand, the low Theil region covers the old industrial bases in three provinces in northeast China, which is dominated by extensive development pattern. On the other hand, the middle Theil region includes most of the western provinces, where mainly promotes the rapid economic development through large-scale industrialization. Therefore, a large amount of CO_2 have been generated due to the low energy use efficiency of these regions.

5. Conclusion and policy implications

This paper investigates the impact of income inequality on both direct and indirect carbon emissions of 30 provinces in China from 2000 to 2015 based on the STIRPAT model. Theil index is selected to measure income inequality and population, household consumption level, energy intensity, urbanization and industry structure are chose as control variables. The results indicate that income inequality is negatively correlated with CO_2 emissions in middle and high Theil regions, while positively correlated in low Theil region. Population, per capita consumption level and urbanization have positive impacts on CO_2 emissions. Among them, the effect of population on CO_2 emissions is the largest, especially on the indirect carbon emissions in three regions. Energy intensity is positively correlated with direct CO_2 emission in the three regions, while industrial structure has not significant effect on indirect CO_2 emissions in the three regions.

The above conclusions provide some implications for the formulation of reasonable energy conservation policies and carbon emission mitigation strategies. Firstly, income inequality has relatively small effect on CO_2 emissions. Therefore, it is not enough to achieve carbon emission reduction only by promoting the equitable distribution of income. As there are great differences in the technology level of carbon emission reduction between regions, it is very essential to strengthen the exchange and cooperation of energy saving and emission reduction technologies among regions when promoting income equality. This measure can reduce the promotion of carbon emissions in high income inequality region. Secondly, introducing advanced technology and improving energy intensity are significant ways to achieve the goal of energy conservation and emission reduction at present. Meanwhile, it is suggested to pay attention to the energy rebound effect caused by the improvement of energy efficiency. To better account for the energy rebound effect in the process of policy-making, it is necessary to make clearly distinguish whether the increase of energy consumption is caused by rebound effect. For example, in some economically underdeveloped regions, the increased energy consumption may be related to the technical level and the low quality of economic growth. Besides, the government should consider the type of rebound effect. Direct energy rebound effect can be suppressed by establishing a reasonable energy price system, while indirect energy rebound effect can be supplemented by the guidance of correct consumption concept. Thirdly, reasonable controlling population size, guiding the concept of low carbon consumption, slowing down the urbanization process and adjusting the industrial structure are still effective ways to control carbon emissions.

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