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The Impact of the Income Gap on Carbon Emissions: Evidence from China

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Abstract: The income gap and global warming have always been topics of common concern to scholars worldwide. Internationally, there is no consensus yet about the impact of the income gap on carbon emissions, and there are few studies about that in China. To explore the effect of the income gap on carbon emissions at the provincial level in China, this paper first theoretically and qualitatively analyzes the non-linear impact of the income gap on carbon emissions. Then, the Gini coefficient of the resident income of different regions in China from 2010 to 2019 is calculated. Finally, a threshold regression model is used to quantitatively test the existence of a threshold effect between the income gap and carbon emission intensity in China. The threshold value is the per capita disposable income of residents. The results show that the income gap is positively related to carbon emission intensity in poor regions. In high-income areas, the widening income gap inhibits the increase in carbon emission intensity. Based on this, this paper proposes policy recommendations to narrow the income gap and reduce the intensity of carbon emissions.

Keywords: income gap; carbon emissions; carbon neutrality; economic growth

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1. Introduction

Since the 20th century, worldwide economic development has entered a fast lane. However, to a certain extent, this is the result of too much consumption of energy and extreme damage to the health of the earth. One of the significant effects of excessive energy consumption is global warming. Greenhouse gases are dominated by carbon dioxide, and it is the huge emission of carbon dioxide that causes global warming. "Climate Change 2007: The Fourth Assessment Report of the United Nations Intergovernmental Panel on Climate Change" predicted that by 2012, the combined surface temperature of global land and the ocean would increase by 0.74 °C. In fact, it was 0.11 °C higher than the expected value. According to statistics from the International Energy Agency (IEA), global carbon emissions reached 33.1 billion tons in 2018. They grew by 1.7% over the same period, hitting a record high. Climate warming disrupts ecological balance and causes many environmental problems, such as melting glaciers. These negative impacts do not only exist in one country or one place. Climate change is a global issue and is a shared risk facing the sustainable economic growth of all countries worldwide.

After reforming and opening up, China's GDP rose rapidly. In 2021, China's per capita GDP exceeded 12,551 USD. China's economic growth has slowed down in the last decade, and the GDP growth rate has hovered around 10%. In 2020, due to the pandemic at home and abroad, the growth rate of China's GDP was only 3%. China's economy did not fully recover to pre-pandemic levels by the end of 2021. With steady economic growth in recent years, the Chinese government and academia have gradually realized that simply pursuing GDP growth brings many negative impacts, such as environmental pollution, extreme climate change, widening income gaps, etc. In 2007, China became the world's largest carbon emitter. According to the World Bank Development Index, China's total carbon emissions were about 8.29 billion tons in 2010. From 1980 to 2010, the average growth rate of China's carbon emissions was as high as 6%. Since then, the Chinese government has begun to address the issue of carbon emission reduction. Nearly 200 parties reached the Paris Agreement at the Paris Climate Change Conference in 2015. In the agreement, China pledged to "reduce China's carbon emission intensity by 60–65% based on the data of 2005 by 2030; carbon dioxide emissions will reach carbon peak around 2030 and strive to achieve carbon neutrality by 2060". The Chinese government has formulated a series of regulations to restrain carbon emissions. However, energy consumption is closely related to economic production and people's lives. There is also a ripple effect among the harmful effects of economic development.

In addition to the climate problems caused by carbon emissions, China also faces growing income inequality. The long-term changes in China's income gap can be roughly divided into three stages. The first stage is the period from the early days of the founding of the People's Republic of China to the period of reform and opening up. China's income gap first decreased and then increased, but it ultimately stayed at a low-income hole dynamic. The second stage is the period 30 years after reforming and opening up. The literature suggests that the income gap in China continued to widen during this period (Gustafsson et al., 2008; Shi and Sato, 2013) [1,2]. The third stage is the period from the financial crisis in 2008 to the present. There is a disagreement among academic circles concerning China's income gap changes during this period. The National Bureau of Statistics estimates that China's income Gini coefficients were 0.484, 0.467 and 0.468 in 2007, 2017 and 2020, respectively. China's income Gini coefficient has been exceeding the international warning line of 0.4 for a long time. Compared with other economies in the world, the latest data released by the World Bank believes that China ranks among the ten economies with the most significant income gap. The average Gini coefficient of the 137 economies given in the 2016 Human Development Report is 0.393. China ranks in the top 15% of economies with significant income gaps. Income gaps in China are widespread across regions and industries. The current income gap in China is mainly reflected in the urban–rural income gap and in the income gap within areas, affecting society's stable and sound development.

Income inequality and environmental pollution are two significant issues of academic concern. Improving ecological quality and optimizing income distribution are also the only ways towards modernization in China. They can also promote sustainable development and reduce carbon emission intensity while achieving economic growth and increasing residents' income levels. They can also narrow the income gap while improving the income distribution system. This largely depends on coordinated emission reduction actions and low-carbon transitions at China's provincial and regional levels. Moreover, this also depends on adjusting the income distribution system and the redistribution of environmental pollution taxes. Therefore, is there any heterogeneity in the impact of income gaps on carbon emission intensity between regions in China? Does the widening income gap positively or negatively affect carbon emission intensity? How can carbon emission intensity be reduced while adjusting the income gap? This paper answers these questions based on data analysis at the provincial level in China from 2010 to 2019. Based on measurements of the regional income gap and carbon emissions, this paper uses the threshold regression model to test the relationship between them empirically. The rest of the article is organized as follows. Section 2 presents a literature review and theoretical hypotheses on related topics. Section 3 uses the Gini coefficient to measure urban and rural income inequality within regions in China separately. Then, this paper estimates the regional income gap and carbon emissions in different areas of China with the standard coal method. Section 4 sets the threshold model, gives variable descriptions and data sources and analyzes the empirical results. Section 5 presents the conclusions, policy recommendations and future research directions of this paper.

2. Literature Review and Research Hypothesis

2.1. Literature Review

Since the 20th century, the rapid rise of global carbon emissions has brought many environmental problems. The academic community believes that the development of industrialization is the main reason for the increase in carbon dioxide. Therefore, research on the influencing factors of carbon emissions has focused on energy and consumption structure (Sigman, 2005) [3], urbanization (Helland and Whitford, 2003) [4], industrial structure (Lipscomb and Mobarak, 2017) [5] and other factors. With increases in income level, residents' carbon consumption has been growing and taking up a high proportion of overall carbon emissions. Therefore, some scholars have studied income and carbon emissions from residents' labor time, human capital and labor productivity (Cropper, 2017; Smulders and Gradus, 1996) [6,7]. Many scholars have analyzed the impact of economic development on various environmental indicators and have verified the existence of an inverted U-shaped non-linear relationship between economic growth and environmental pollution (Grossman and Krueger, 1995; Hu and Jiang, 2015) [8,9]. Panayotou (1993) [10] defined this inverted U-shaped curve relationship as the environmental Kuznets curve. Chen and Huo (2021) [11] found that green innovation efficiency has a nonlinear relationship with carbon emission intensity, showing an inverted U-shaped trend. In addition to the research on the relationship between environmental pollution and economic development, there is also the effect of income level on environmental pollution and the impact of the income gap on environmental pollution. There are three main academic views on the relationship between the income gap and environmental pollution.

(1) The widening income gap increases carbon emissions. In this regard, scholars have studied three main aspects. Firstly, the widening income gap makes the distribution of political power more favorable to high-income groups. Although the wealth accumulation of high-income groups is generally based on the destruction of the environment, low-income groups bear higher ecological costs (Boyce, 1994) [12]. Marsiliani and Renström (2000) [13] studied the relationship between the income gap and carbon dioxide emissions in OECD countries with cross-sectional and time-series data. They concluded that the income gap is positively associated with carbon emissions. Secondly, per capita carbon consumption varies significantly between households with different incomes. Direct and indirect carbon consumption of high-income households is much higher than that of low-income families (Golley and Meng, 2012) [14]. Marsiliani and Renström (2018) [15] believed that the income gap can affect carbon emissions through the consumption possibility curve. More consumption of non-low carbon commodities by low-income groups quickly leads to the weakening of environmental policies. Thirdly, the "middle man voting" theory suggests that, ultimately, the middle group in society determines the quality of the environment (Kempf, 2005) [16]. High-income groups have higher environmental requirements, whereas low-income groups lack the power to speak. The ecological quality of a society depends on the preferences of the median voter when the income gap widens. Overall, the income gap may affect carbon emissions by affecting urbanization and residents' consumption structure (Sun, 2016) [17]. Widening income gaps can increase carbon emissions, whereas narrowing income gaps can improve environmental quality (Padilla and Serrano, 2006) [18].

(2) Widening income gaps can reduce environmental pollution caused by carbon emissions. Heerink, Mulatu and Bulte (2001) [19] found a negative relationship between the income gap and carbon emissions. They used statistics data from Sweden and Italy. Ghalwash (2008) [20] as well as Castellucci and D'Amato (2009) [21] obtained the same findings that suggest that a widening income gap can reduce carbon emissions. Using statistics data from China, Lu and Gao (2005) [22] found that the widening income gap may inhibit environmental pollution when economic development reaches a particular stage.

(3) There is no single linear relationship between the income gap and carbon emissions. Soytas, Sari and Ewing (2007) [23] found no causal relationship between economic development and carbon emissions using US statistics data from 1960 to 2004. The relationship between income inequality and the environment is heterogeneous (Ravallion, Heil and Jalan, 2000) [24]. Han et al. (2018) [25] found that the income gap across economies is positively related to carbon emissions. However, the relationship between them is not uncertain for regions with different incomes. Jorgenson et al. (2016) [26] used a two-way fixed-effects model to study the relationship between carbon emissions and the income gap. It was found that there is a non-linear relationship between them, and there is heterogeneity in different countries. Zhanhua (2016) [27] found that, in regions with high per capita income, narrowing the income gap can curb carbon emissions. Ma Xiaowei et al. (2019) [28] found a non-linear positive relationship between income and carbon emissions from residents' consumption in China. For provinces in different income groups, when the income group changes, carbon emission inequality shows different trends. Zhang Yunhui and Hao Shiyu (2022) [29] used Chinese provincial panel data from 2005 to 2017 to conduct an empirical test. The effect and mechanism of income disparity and economic agglomeration on carbon emissions were investigated, and the results show that there is a significant "U" shaped relationship between the income gap and carbon emissions in China.

The development of the digital economy brings new paths for carbon emission reduction. Moreover, the construction of new smart cities must also address the problems of environmental pollution, traffic waste, excessive use of resources and excessive consumption of energy (Faris. A. Almalki et al., 2021) [30]. The academic community has proposed the green Internet of Things based on the development of the digital economy, i.e., machines, sensors, communications, the cloud and the Internet working together to achieve the common goal of improving energy efficiency and reducing carbon emissions (S. H. Alsamhi et al., 2019) [31]. The UAV infrastructure is the technical foundation for achieving the green Internet of Things, and it is also a path to build a new type of smart city (S.H. Alsamhi et al., 2021) [32]. Carbon emission reduction is closely related to the construction of new green cities. Sustainable development should also be accompanied by fairness in income distribution. Narrowing the income gap is fundamental to building harmonious and smart cities.

In summary, the existing studies agree that a specific relationship exists between the income gap and carbon emissions. However, the academic community has not yet reached a consistent conclusion. Scholars choose different research regions, times and methods, and they obtain different research results. This also proves from the side that, due to various factors such as regional economic development level, per capita income and urbanization level, the impact of the income gap on carbon emission intensity is also different. Based on this, this paper studies the regional heterogeneity of the effect of the income gap on carbon emissions from the perspective of the per capita disposable income of residents. The possible innovations of this paper are as follows. Firstly, this paper estimates the regional Gini coefficients from 2010 to 2019 in China using unequal income groups. Before studying the relationship between carbon emission reduction and the income gap, the regional differences and spatial correlation of carbon emissions in China are analyzed. Secondly, this paper chooses the per capita disposable income of residents as the threshold variable. A threshold regression model is used to verify the different effects of the income gap on carbon emission intensity in other per capita income regions.

2.2. Influence Mechanism and Research Hypothesis of the Income Gap on Regional Carbon Emission Intensity

(1) Influence mechanism

According to the environmental Kuznets curve, in the early stages of economic development, the limitations of productivity and technological level lead to the need to sacrifice the environment for economic growth. As income levels increase, people become more concerned about clean energy and physical health, and the quality of the environment improves with economic growth (Grossman and Kruger, 1995). Based on this, it is assumed that a region can be divided into a high-income area A and a low-income area B. The carbon emission intensity of different income regions and the income level of that region are consistent with the traditional environmental Kuznets curve. Assume that the greenhouse gas Kuznets function is $f(x)$. Due to unbalanced regional economic development, region B is already in a stage in which greenhouse gas emissions decrease with increases in income. At the same time, the income of region B is Y_B, and the intensity of greenhouse gas emissions is $f(Y_B)$. On the other hand, region A is still in the rising stage. Its income is Y_A, and the greenhouse gas emission intensity is $f(Y_A)$. Then, the average greenhouse gas emission intensity in this region can be calculated as $\frac{f(Y_A)+f(Y_B)}{2}$. According to the Kuznets curve, greenhouse gas emission intensity corresponds to the average value that is lower than the average income of the two regions, which is $f\left(\frac{Y_A+Y_B}{2}\right)$. The difference between the two depends on the locations of region A and region B, i.e., the income distribution in these areas. Specifically, it is assumed that the income of region A decreases by ω and that the income of region B increases by ω. At this point, the average income level of the region remains unchanged. However, the regional income gap increases by 2ω. According to the Kuznets curve, the intensity of greenhouse gas emissions in the region at this time is $\frac{f(Y_A-\omega)+f(Y_B+\omega)}{2}$. Equation (1) can be obtained from Lagrange's mean value theorem.

$$\frac{f(Y_A-\omega)+f(Y_B+\omega)}{2}-\frac{f(Y_A)+f(Y_B)}{2}=\frac{\omega}{2}[f(\varsigma_2)-f(\varsigma_1)] \tag{1}$$

where ς_1 is the value between $(Y_A-\omega)$ and Y_A, and ς_2 is the value between $(Y_B+\omega)$ and Y_B. Since the environmental Kuznets curve is a quadratic function with a downward opening, the second derivative is $f''(x)<0$. It can be seen that, when the overall income level of the region is constant, i.e., when $\frac{Y_A+Y_B}{2}$ (the average income of the two regions) remains unchanged, the greater that the income gap is within the region, the lower that the average greenhouse gas emission intensity is.

Both high-income and low-income regions within the region are simultaneously in a stage in which greenhouse gas emissions decrease with increasing income, and changes in intra-regional income gaps have different effects on the average greenhouse gas emission intensity. When both high-income and low-income regions are simultaneously in a stage in which greenhouse gas emissions increase with income, changes in regional income gaps have different effects on greenhouse gas carbon emissions. In summary, the intra-regional income gap has a certain impact on the regional average carbon emission intensity, and this impact has regional heterogeneity with different income levels.

In summary, the intra-regional income gap affects regional average carbon emission intensity. There is a causal relationship between the two, and there is also regional heterogeneity. Next, this section discusses the impact mechanism of the income gap on carbon emission intensity in real economic life with respect to the consumption effect and the income effect. In addition, research hypotheses are proposed.

(2) Research hypothesis

Carbon emissions involve all aspects of a region's economic activities and social life and are influenced by various factors. Since carbon consumption is closely related to income, there are two main effects of the income gap on carbon emission intensity. One is the consumption effect, and the other is the income effect. The specific analysis is as follows.

Firstly, for the consumption effect, the income gap changes the consumption structure of the government and residents. As the income gap widens, low-income people tend to over-exploit natural resources and use carbon-intensive commodities to maintain a necessary standard of living. In addition, high-income people are reluctant to pay high fees for clean energy (Boyce, 1994; Magnani, 2000) [12,33]. As a result, differences in residents' consumption structure hinders the promotion of low-carbon lifestyles at the household level (Ravallion, Heil and Jalan, 2000) [24]. If the income gap widens, the relative income of the "income middleman" decreases, eventually leading to lower consumption of clean energy in society as a whole. In addition, as a result of the existence of the comparison effect, the widening income gap increases the consumption of a region and makes the proportion of enjoyment-based consumption significantly increase.

Secondly, for the income effect, the income gap results in different marginal pollution propensities of varying income groups. An income's marginal propensity to pollute has diminishing properties (Scruggs, 1998) [34]. The marginal pollution propensity of high-income groups is lower than that of low-income groups, i.e., the high-income class has higher requirements for the environment. A widening income gap makes social wealth more concentrated in high-income groups, which helps reduce carbon emissions (Coondoo and Dinda, 2008) [35]. In addition, a widening income gap increases the proportion of high-income people. The pursuit of green and healthy food by middle-income and high-income groups effectively reduces household carbon emissions. Moreover, higher requirements for travel, heating and cooking and increases in the rate of higher education also increase residents' attention to the environment. In this way, widening income gaps can curb carbon emissions.

From the perspective of the consumption effect and income effect, a widening income gap may have both positive and negative impacts on regional carbon emission intensity. The magnitude of the two effects is uncertain, so Hypothesis 1 is proposed.

Hypothesis 1. *There is a non-linear relationship between the income gap and carbon emissions.*

Combined with the above analysis, it can be seen that, when the consumption effect of a region is greater than the income effect, the widening income gap between residents leads to increases in carbon emission intensity. When the consumption effect is smaller than the income effect, the widening income gap between residents can restrain carbon emissions. Combined with the analysis of reality, governments in low-income regions are more inclined to sacrifice the environment for economic growth. To prevent the income gap from widening, the government introduces relevant policies to increase the inflow of human capital. The government also encourages the development of labor-intensive and resource-intensive industries to improve economic growth in the short term. At this time, the consumption effect in this region is significantly higher than the income effect. Low-income people may no longer be able to maintain average production and living standards and can only seek carbon-intensive-linked commodities. Although high-income groups have higher requirements for environmental quality, the needs of high-income groups for low-carbon life cannot be met while prioritizing economic development in the entire region. However, high-income areas have already experienced a series of adverse effects of sacrificing the environment to develop the economy. Therefore, the government can pay more attention to protecting the environment. Moreover, it can also encourage the opening of clean energy and can provide policy support for innovative green enterprises. During this period, the income effect of the region is much higher than the consumption effect. The upgrading and optimization of industrial structure, accompanied by high income, bring about rising proportions of the GDP of the tertiary section. The use of the Internet affects the productivity of factors such as capital, labor and information. Increases in factor productivity also improve energy efficiency. Widening income gaps are also mainly caused by the tertiary sector in income distribution.

In summary, there may be a threshold effect between the income gap and carbon emission intensity, with residents' per capita income level as the threshold. In different threshold intervals, income gaps affect carbon emission intensity. Therefore, this paper proposes Hypothesis 2 and Hypothesis 3.

Hypothesis 2. *In low-income regions, the widening income gap between residents causes an increase in carbon emission intensity.*

Hypothesis 3. *In high-income regions, the widening income gap between residents suppresses carbon emission intensity.*

3. Measurement of the Income Gap and Carbon Emissions

Based on the literature review, this paper explores the possible threshold effect of residents' per capita income between the income gap and carbon emission intensity from a qualitative perspective. Before quantitative verification, it is also necessary to measure income inequality and carbon emissions in different regions of China.

3.1. Calculating the Income Gap between Provinces in China

(1) Estimation method of the Gini coefficient of provincial resident income

The most widely used index to measure the income gap is the Gini coefficient because it can objectively reflect income differences between residents. In calculating the Gini coefficient, the curve fitting method has solid operability and applicability (Deaton, 1997) [36]. The different curve equations used for fitting can be divided into the polynomial function method, the generalized quadratic function method, etc. (Zhao Yuxia, 2011) [37]. In addition, another method is the discrete form of the Gini coefficient calculation formula (Liu Xueliang and Tian Qing, 2009) [38]. However, regardless of the calculation method, the income sample must be divided equally. Income data at the inter-provincial level in China are not presented in equal groupings. According to the unequal grouping Gini coefficient calculation method proposed by Thomas et al. (2000) [39], the calculation method of the Gini coefficient is deduced as shown in the following Formula (2):

$$G_{u,r} = \frac{PY - \sum_{i=1}^{n}(Y_i + Y_{i-1}) \cdot P_i}{PY} \tag{2}$$

where G_u and G_r are, respectively, the Gini coefficient of the regional urban residents' income and the Gini coefficient of the rural residents' income. P is the total population of the region, Y is the total income of the residents in the region after grouping the income samples and Y_i is the income accumulated in the i group after income grouping. The Gini coefficient of the region can be measured by the sample size and the income of each income subgroup. In the actual estimation, under the dual structure of urban and rural areas in China, the statistical caliber is generally counted separately in urban and rural areas. To measure the inter-provincial income gap more accurately, the Gini coefficients of urban and rural areas are estimated separately. Then, the Gini coefficients of regional residents' income are calculated by the weighted grouping method (Sundrum, 1990) [40]. The data for measuring the income gap in different regions in China come from the statistical yearbooks of each province over the years. On the basis of calculating the Gini coefficient of urban and rural residents' income in different regions by Equation (2), the calculation method of the regional residents' income Gini coefficients is as follows:

$$G = {P_u}^2 \frac{y_u \cdot G_u}{y} + {P_r}^2 \frac{y_r \cdot G_r}{y} + P_u \cdot P_r \frac{y_u - y_r}{y} \tag{3}$$

where G is the Gini coefficient of the overall residents' income in the region, and y is the per capita disposable income of the residents in the region. P_u and y_u are the total regional urban population and the per capita disposable income of the regional urban residents, respectively, and P_r and y_r are the total regional urban population and the per capita disposable income of urban residents in the region, respectively.

(2) Analysis of the results of the income gap between provincial residents

According to the regional Gini coefficient calculation method, the Gini coefficients of residents' incomes in Chinese provinces can be calculated. The measured data of the regional Gini coefficient come from the "China Statistical Yearbook (Calendar Years)", the "China Household Survey Yearbook (Calendar Years)" and provincial survey yearbooks over the years. Due to the unavailability of data in some regions, the calculation results exclude data from Tibet, Hong Kong, Macau and Taiwan. Table 1 shows the Gini coefficients of residents' per capita income from 2010 to 2019. From Table 1, it can be seen that the income gap between regions is relatively large. In 2010, the three provinces with the highest Gini coefficients were Beijing with 0.4747, Shanghai with 0.4732 and Tianjin with 0.4113. By 2015, the three provinces with the highest Gini coefficients were still the same three cities, and their Gini coefficients rose to 0.5616, 0.4724 and 0.4511, respectively. Since 2014, the Gini coefficient of Beijing has exceeded 0.5, and by 2019, there were six provinces with Gini coefficients of more than 0.4. Provinces with more developed economies also faced higher income disparities, and the Gini coefficients of less developed regions are generally lower.

Table 1. Gini coefficient of per capita income of local residents from 2010 to 2019.

Province	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.4747	0.4941	0.4904	0.4910	0.5221	0.5616	0.5863	0.5880	0.5788	0.5738
Tianjin	0.4113	0.4208	0.4175	0.4185	0.4704	0.4511	0.4756	0.4725	0.4719	0.4693
Hebei	0.2315	0.2377	0.2414	0.2616	0.2971	0.2842	0.3170	0.3248	0.3276	0.3287
Shanxi	0.2625	0.2801	0.2860	0.3028	0.3421	0.3276	0.3605	0.3588	0.3595	0.3572
Inner Mongolia	0.3168	0.3298	0.3344	0.3335	0.3768	0.3581	0.3819	0.3828	0.3788	0.3736
Liaoning	0.3264	0.3451	0.3537	0.3680	0.4224	0.3985	0.4179	0.4108	0.4105	0.4016
Jilin	0.2737	0.2831	0.2822	0.2909	0.3237	0.3068	0.3274	0.3232	0.3259	0.3265
Heilongjiang	0.2702	0.2775	0.2761	0.2777	0.3434	0.3246	0.3429	0.3386	0.3355	0.3322
Shanghai	0.4732	0.4692	0.4546	0.4707	0.4986	0.4724	0.4970	0.4943	0.4940	0.4920
Jiangsu	0.3068	0.3255	0.3314	0.3395	0.3980	0.3825	0.4084	0.4100	0.4139	0.4149
Zhejiang	0.3208	0.3348	0.3344	0.3303	0.3674	0.3499	0.3784	0.3805	0.3809	0.3822
Anhui	0.2189	0.2363	0.2434	0.2372	0.2840	0.2661	0.2943	0.2965	0.2999	0.2958
Fujian	0.2944	0.3095	0.3124	0.3151	0.3628	0.3443	0.3708	0.3728	0.3750	0.3724
Jiangxi	0.2093	0.2284	0.2362	0.2415	0.2796	0.2620	0.2901	0.2962	0.2985	0.3000
Shandong	0.2622	0.2745	0.2791	0.2864	0.3220	0.3113	0.3445	0.3502	0.3483	0.3432
Henan	0.2023	0.2203	0.2269	0.2278	0.2685	0.2436	0.2722	0.2754	0.2788	0.2801
Hubei	0.2449	0.2621	0.2682	0.2633	0.3009	0.2837	0.3134	0.3160	0.3168	0.3157
Hunan	0.2220	0.2393	0.2444	0.2506	0.2973	0.2802	0.3120	0.3193	0.3219	0.3232
Guangdong	0.3585	0.3668	0.3679	0.3644	0.4089	0.3868	0.4079	0.4073	0.4072	0.4037
Guangxi	0.2225	0.2357	0.2393	0.2366	0.2735	0.2532	0.2764	0.2765	0.2786	0.2741
Hainan	0.2374	0.2481	0.2506	0.2473	0.2974	0.2788	0.3031	0.3065	0.3096	0.3071
Chongqing	0.2790	0.2918	0.2917	0.2968	0.3522	0.3353	0.3663	0.3697	0.3727	0.3725
Sichuan	0.1987	0.2148	0.2224	0.2183	0.2655	0.2455	0.2749	0.2792	0.2832	0.2794
Guizhou	0.1949	0.2063	0.2128	0.2203	0.2580	0.2448	0.2751	0.2744	0.2768	0.2792
Yunnan	0.1930	0.2177	0.2257	0.2205	0.2577	0.2437	0.2703	0.2742	0.2729	0.2707
Shanxi	0.2458	0.2660	0.2769	0.2814	0.3200	0.3023	0.3308	0.3352	0.3373	0.3377
Gansu	0.2845	0.3016	0.3101	0.3149	0.3513	0.3462	0.3739	0.3768	0.3776	0.3731
Qinghai	0.2373	0.2563	0.2594	0.2644	0.3020	0.2824	0.3178	0.3166	0.3270	0.3158
Ningxia	0.1031	0.1145	0.1187	0.1229	0.1563	0.1364	0.1644	0.1630	0.1628	0.1579
Xinjiang	0.1922	0.2004	0.2054	0.2111	0.2502	0.2431	0.2688	0.2710	0.2759	0.2702

To further analyze the income gap and changing trends among regions in China, Figure 1 shows a ranking map of Gini coefficients in China in 2010, 2013, 2016 and 2019. From the perspective of the regional nature of the income gap, the income gaps of residents in the eastern coastal region are significantly higher than those of residents in the northwest region. The Gini coefficients of provinces vary considerably in the central area. Some provinces, such as Shaanxi, Heilongjiang, Shandong, Shanxi and Chongqing, rank higher in income Gini coefficients, whereas Henan, Sichuan, Guizhou, Guangxi and Anhui have lower income inequality. From the perspective of time evolution, income inequality patterns between regions did not change much during the ten years from 2010 to 2019. Different provinces have widened residents' income gap at a similar rate, forming a pattern of high-income holes at both ends and low-income intervals in the middle.

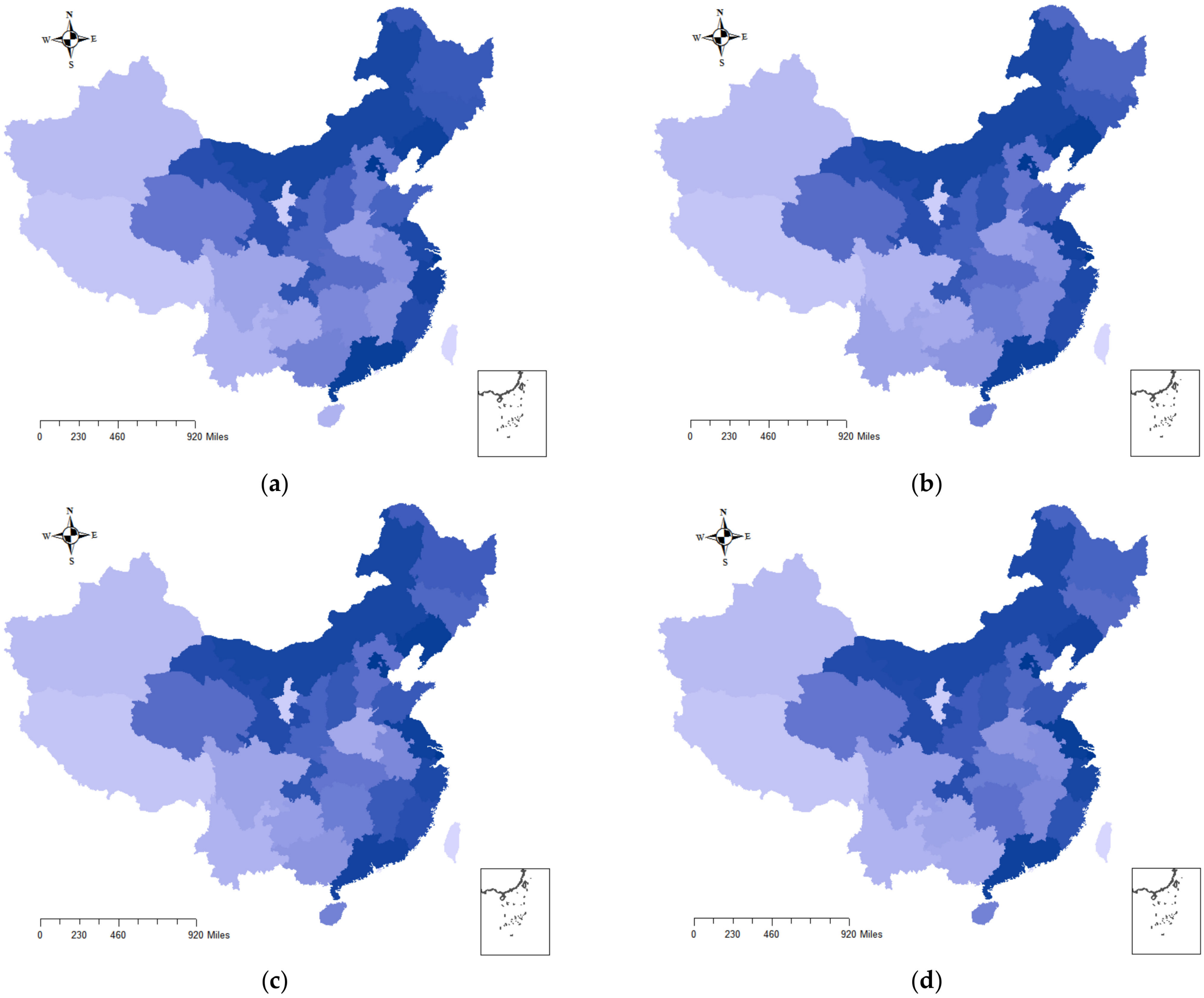


Figure 1. (**a**) 2010; (**b**) 2013; (**c**) 2016; (**d**) 2019. China's Gini coefficient rankings by region in 2010, 2013, 2016 and 2019. Note: Since regional Gini coefficients have minor differences in value, the map is drawn by order. The darker that the color is, the greater that the Gini coefficient of regional residents' income is.

In 2018, China's individual income tax law was revised again, which raised the tax threshold and increased the deduction items for personal income tax. From the perspective of household income, the revision of individual income tax has adjusted the income gap in China and has effectively slowed down the expansion of household income inequality. According to data from the Chinese National Bureau of Statistics, the Gini coefficients in 2018, 2019 and 2020 were 0.486, 0.465 and 0.468, respectively. The Chinese income gap has stabilized and has remained relatively high in the past decade. The growth of residents' disposable income has slowed down, and the growth rate has remained below 10% after 2015. The urban–rural income ratio has remained at a relatively sound level. The urban–rural income ratios in 2018, 2019 and 2020 were 2.69, 2.64 and 2.56, respectively. The inequality of residents' income affects residents' energy consumption, regional industrial structure, the proportion of non-agricultural employment, etc., and is closely related to provincial carbon emission intensity.

3.2. Estimating Provincial Carbon Emissions in China

(1) Methodology for estimating provincial carbon emissions in China

Carbon emissions are involved in all aspects of human production and life. There are currently no direct data on carbon emissions. Carbon consumption mainly involves eight energy inputs: raw coal, coke, crude oil, natural gas, fuel oil, gasoline, kerosene and diesel. To avoid double calculation, the electricity is removed here. This paper uses the standard coal method to estimate carbon emissions in different regions of China. The energy carbon emission factor and common coal conversion factor are based on the Intergovernmental Panel on Climate Change (IPCC) data in 2006. The estimation method also refers to the method proposed by IPCC, and the specific calculation is shown in Equation (4).

$$CO_{2it} = \sum_{j=1}^{8} CO_{2itj} = \sum_{j=1}^{8} C_{itj} \cdot e_j \cdot q_j \cdot \frac{44}{12} \tag{4}$$

where CO_{2it} represents the carbon emissions of the i region and the t year. The sum of the carbon emissions calculated by the eight energy forms is the region's total carbon emissions. C_{itj} represents the consumption of the j energy in the i area and the t year, and e_j and q_j are the standard coal conversion coefficient and carbon emission coefficient of the j fossil energy, respectively. The essential data for carbon emission estimation come from the China Energy Statistical Yearbook (Calendar Years) and China Statistical Yearbook (Calendar Years) for 2010–2019. The missing values in some regions and some years are obtained by interpolation. The estimation results also exclude data from Tibet, Hong Kong, Macau and Taiwan due to the unavailability of data in some regions.

(2) Differences in carbon emissions

The method of estimating carbon emissions by the standard coal is given above. This paper assesses the carbon emissions of different regions in China in 2010. To further understand the overall trend of carbon emissions in the other areas of China and the degree of differences in carbon emissions between regions, Figure 2 shows the average value and Theil index of carbon emissions in the different areas of China from 2010 to 2019.

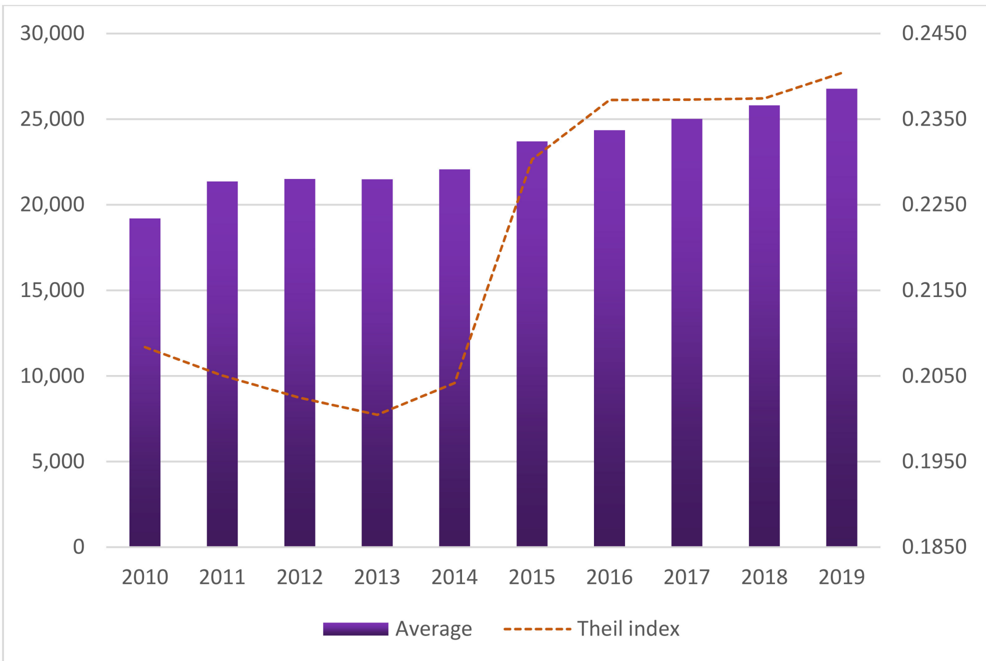


Figure 2. The average and Theil index of carbon emissions in different regions of China from 2010 to 2019.

The average value is calculated as the arithmetic mean of carbon emissions by region for each year. The Theil index is a measure of the income gap (or inequality) between individuals or regions. Figure 2 shows the Theil index of regional carbon emissions. The specific calculation is shown in Equation (5).

$$T_{co_2} = \frac{1}{n}\sum_{i=1}^{n}\frac{C_i}{\overline{C}}\left[\ln\left(\frac{C_i}{\overline{C}}\right)\right] \quad (5)$$

where n is the number of regions, C_i is the carbon emissions of the i region and $\overline{C}$ is the average carbon emissions of the region. The Theil entropy index is more sensitive to changes in the upper quantitative levels than the Gini coefficient. The Theil index is positively correlated with the degree of inequality of carbon emissions. The higher that the Theil index is, the greater that the difference in carbon emissions between regions is.

From Figure 2, it can be seen that China's carbon emissions have two main characteristics from 2010 to 2019. Firstly, the average carbon emissions in China have steadily increased, but the growth rate is lower than that of GDP in China. The regional average carbon emissions were less than 200 million tons in 2010, and this value has been exceeding 200 million tons for a long time since 2010. In 2011, the growth rate was 11.23%. The growth rate was maintained at around 3% in the following years. In 2013, the regional average carbon emissions decreased by 0.10%. However, except for a few years, the average growth rate of carbon emissions in China was much lower than the growth rate of per capita GDP in China. In 2011, 2015 and 2019, the average growth rate of carbon emissions in China was 11.23%, 7.39% and 3.79%, respectively, and the GDP per capita in China was 17.24%, 5.96%, 7.73%, respectively. China's manufacturing industry is large in scale and has a solid ability to drive GDP growth. Most of these industries are dominated by resource-intensive sectors, which indicates that the development of the manufacturing industry is mainly dependent on driving raw coal, coke and other coal-fuel-based energy. At present, China is in a period of economic development and transformation, and it pays more attention to industrial optimization and upgrading. Moreover, the goal of "carbon neutrality" and the need for green development all require that the growth rate of carbon emissions be curbed while GDP grows steadily. Secondly, the differences in carbon emissions between regions first decreased and then continued to expand. The Theil index measures the income gap (or degree of inequality) between individuals or regions. It is used in this paper to estimate the degree of difference in carbon emissions between regions in China. Judging from the Theil index of carbon emissions from 2010 to 2019, the degree of variation in the Theil index between regions in China has experienced a process of going from small to large. It declined from 2010 to 2013, with the lowest Theil index of 0.2005 in 2013. Since then, it has continued to rise.

The Theil indices of carbon emissions were 0.2042, 0.2372 and 0.2374 in 2014, 2016 and 2018, respectively, reaching a peak of 0.2404 in 2019. In recent years, China has attached great importance to environmental protection while developing its economy. Economically developed cities reduce their carbon emissions by relocating resource-intensive enterprises and expanding tertiary industries. On the other hand, less developed regions receive manufacturing companies that migrate from developed regions because they must create resource-intensive and industry-intensive enterprises to increase economic growth and employment rates. This is also in line with the environmental Kuznets hypothesis. As a result of this, the differences in carbon emissions between regions in China have gradually expanded.

(3) Moran index of carbon emissions

This paper uses the Moran index to analyze the regional spatial autocorrelation based on the geographic weight matrix to further understand the spatial correlation of provincial carbon emissions in China. Table 2 shows the global spatial autocorrelation of Moran's I index of provincial carbon emissions in China starting in 2010.

Table 2. Spatial correlation test of carbon dioxide (CO_2) emissions in China from 2010 to 2019.

Year	Moran's I	Z (I)	*p*-Value
2010	0.179 **	2.283	0.011
2011	0.185 **	2.328	0.010
2012	0.180 **	2.288	0.011
2013	0.189 ***	2.375	0.009
2014	0.183 **	2.327	0.010
2015	0.194 ***	2.484	0.007
2016	0.180 ***	2.346	0.009
2017	0.178 **	2.332	0.010
2018	0.189 ***	2.423	0.008
2019	0.182 **	2.333	0.010

Note: (1) Z (I) indicates that the new variable is multiple standard deviations under the standard normal distribution. The *p*-value is obtained according to the significance test method. (2) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

As shown in Table 2, there are two characteristics of the spatial correlation of provincial carbon emissions in China. Firstly, China's regional carbon emissions have a significant positive spatial correlation. The significance of the spatial correlation of carbon emissions from 2010 to 2019 is above 5%, indicating that regional carbon emissions are not randomly distributed in space but have a significant spatial correlation. Regional carbon emission intensity is closely related to energy structure and factor endowment. China is blessed with vast land and abundant resources. Geographically similar regions have similar energy structures and similar industrial structures, which results in a significant positive spatial spillover effect on carbon emissions. To curb the growth rate of carbon emissions in general, it is necessary to use the inter-regional carbon emissions linkage mechanism. Secondly, the spatial correlation of carbon emissions is relatively stable and is maintained at a low level. In general, the Moran index of carbon emissions remained between 0.17 and 0.2 in China from 2010 to 2019. Among those years, the highest Moran index was 0.194 in 2015, corresponding to a significant increase in the Theil index of carbon emissions in 2015. Differences in factor endowments between regions also limit the spatial correlation of carbon emissions. Although China has established a national carbon emissions trading market, the trading market is dominated by electricity and needs to be further improved.

4. Research Design and Empirical Results

4.1. Model Setting and Variable Description

In Section 2, this paper theoretically analyzes that there may be a non-linear relationship between the income gap and carbon emission intensity in the context of the Chinese economy. When the per capita disposable income of regional residents is low, the widening income gap increases carbon emission intensity. When the per capita disposable income of regional residents is high, the widening income gap may suppress carbon emission intensity. To verify the relationship between the income gap and carbon emission intensity, this paper uses the threshold panel model of Hansen (1999) [41] to construct a threshold regression model with the per capita disposable income of residents as the threshold variable. Assuming that there are n thresholds in the threshold model, taking the per capita disposable income of residents as the threshold, the threshold regression model of the impact of the income gap on carbon emission intensity is as follows:

$$\begin{gathered} CR_{i,t} = \alpha + \rho_1 gin_{i,t} \cdot I(inco < \omega_1) + \rho_2 gin_{i,t} \cdot I(\omega_1 \le inco < \omega_2) + \\ \cdots\cdots + \rho_n gin_{i,t} \cdot I(\omega_{n-1} \le inco < \omega_n) + \gamma_n X_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \tag{6}$$

where $\rho_1, \rho_2 \ldots \rho_n$ is the coefficient of the core explanatory variable in different zones, $inco$ is the threshold variable per capita disposable income, $CR_{i,t}$ is the explained variable carbon emission intensity and gin is the explanatory variable regional income gap. $I(\cdot)$ is an indicative threshold function, in which if the expression in parentheses is true, then $I(\cdot) = 1$; otherwise, if the declaration in parentheses is false, then $I(\cdot) = 0$.

$\omega_1, \omega_2 \cdots \omega_n$ is the threshold value with estimation, endogenously determined by the selected sample data. X is the control variable, γ_n is the coefficient of the control variable and u, λ and ε represent the regional fixed effect, time fixed effect and random interference term of the regression model, respectively. This paper lists the explanatory variables, explained variables, threshold variables and selected control variables of the threshold regression model.

(1) Explained variable: carbon emission intensity (CR)

In the previous section of this paper, we estimated the provincial carbon emissions in China. This paper uses carbon intensity, the amount of carbon dioxide emissions per unit of output, as the explained variable. Compared with carbon emissions, carbon emission intensity can better reflect changes in carbon emissions in economic growth. The calculation method of carbon emission intensity is shown in Equation (7).

$$\text{carbon emission intensity } CR_{it} = \frac{CO_{2it}}{GDP_{it}} \tag{7}$$

where CO_{2it} is the carbon emissions of the i region in the t year, and GDP_{it} is the i region's gross national product in the t year. Due to the unavailability of data in some areas, this paper excludes data from Tibet, Hong Kong, Macau and Taiwan. It only calculates the carbon emission intensity of 30 regions in China from 2010 to 2019.

(2) Explanatory variable: income gap (gin).

This paper uses the Gini coefficient of regional residents' income to measure the income gap, which is calculated above.

(3) Threshold variable: per capita disposable income of residents ($inco$).

There has been extensive academic literature studying the relationship between economic growth and carbon intensity. To better verify the non-linear relationship between income gap and carbon emission intensity, this paper uses the per capita disposable income of residents as a threshold variable to test the impact of the income gap on carbon emission intensity in different income subgroups.

(4) Control variables. The control variables selected in this paper are as follows:

Human capital level (edu): In general, environmental quality is also related to residents' quality. People with higher academic education pay more attention to clean energy and products. This paper uses the years of education per capita (years) to represent the level of human capital in a region.

Foreign direct investment (fdi): The "pollution shelter" effect of foreign direct investment directly affects regional carbon emissions. In this paper, the proportion of the actual utilization of foreign capital to the provincial GDP represents the opening degree of a region.

Infrastructure construction (inf): The foundation of regional economic development is infrastructure construction. A convenient life leads to higher productivity. This paper uses per capita urban road area (square meters) as an indicator of infrastructure construction.

Government financial support (gov): The government formulates environmental regulations and affects the efficiency of the green innovation of enterprises through public budgets, thereby affecting carbon emissions. Therefore, this paper uses the proportion of fiscal general public budget expenditure to GDP to represent government support.

Urbanization level (urb): The level of urbanization is closely related to the intensity of environmental protection and represents the progress of civilization and the level of socialization of a city. This paper uses the proportion of an urban population to the total population at the end of the year to measure the level of urbanization.

Industrial structure (is): The upgrading of the industrial structure is a process in which the status and relationship of various industries in the industrial structure are transformed towards a higher and more coordinated direction. In general, the higher that the industrial and agricultural output value is, the greater that the carbon emission intensity of a region is. This paper uses the ratio of the added value of the tertiary industry to the secondary sector to measure the industrial structure.

The explanatory variables of the threshold regression model in this paper are measured in the previous section. The explained variables are calculated based on estimated carbon emissions. The data of threshold variables and control variables are all derived from China's 2010–2019 yearbook, including the China Statistical Yearbook, the China Information Yearbook, the China Industrial Statistical Yearbook, the China Urban Statistical Yearbook, the China Science and Technology Statistical Yearbook, the National Bureau of Statistics website and the China Economic and Social Development Statistical Database. Some indicators, such as industrial structure and urbanization level, are calculated based on statistical data. From 2010 to 2012, the Chinese government did not uniformly provide all residents' per capita disposable income. However, it only announced the per capita disposable income of urban and rural residents in different regions. Therefore, the per capita disposable income of residents in those three years can be derived by calculation. The calculation formula is: per capita disposable income = (disposable income of urban residents * urban population + net income of rural residents * rural population)/total population. In addition, considering the special characteristics and data availability of Tibet, Hong Kong, Macao and Taiwan, the data of these four regions are excluded from data collation. The final analysis sample of this paper comprises data from 30 regions. Table 3 shows descriptive statistical analyses of each variable.

Table 3. Descriptive statistical analysis.

Variable	Definition	Mean	Std	Min	Max
CR	carbon emission intensity	2.3744	1.7114	0.32	8.24
gin	income gap	0.3157	0.0836	0.1031	0.588
$inco$	per capita disposable income	2.1973	1.1005	0.7	7.22
edu	human capital level	0.0193	0.0050	0.008	0.0345
fdi	foreign direct investment	1632.43	2671.18	23	19533
inf	infrastructure Construction	15.325	4.6797	4.04	26.2
gov	government Financial Support	0.2456	0.1022	0.106	0.628
urb	urbanization level	57.73	12.61	33.81	89.6
is	industrial structure	1.174	0.6665	0.52	5.17

4.2. Empirical Results

From the research results of the previous section, it can be seen that carbon emissions have prominent spatial aggregation characteristics, and the spatial correlation of regional carbon emissions from 2010 to 2019 is relatively stable. According to theoretical analysis, the impact of the income gap on the regional carbon emission intensity is also different in regions with varying income levels. Therefore, this paper uses residents' per capita disposable income as a threshold variable, trying to verify the non-linear relationship between the provincial income gap and carbon emission intensity in China. Based on the threshold model given above, the number of thresholds needs to be determined to determine the form of the threshold model before proceeding with the empirical evidence. This paper refers to the "self-sampling" method of the threshold model from Lian and Cheng (2006) [42] and estimates the model under the setting having no threshold, one threshold and two thresholds in turn. The regression results of the threshold effect test are shown in Table 4.

From Table 4, the p-value corresponding to the triple threshold test is 0.7467, which is not significant at the 10% level, indicating no triple threshold in the model. In the single threshold test, the p-value of the model is 0.0133, which is significant at the 5% level. In the double threshold test, the model has a p value of 0.0000, which is significant at the 1% level. This shows that the model has both a single threshold and a double threshold, i.e., residents' per capita disposable income can be used as the threshold value. To discuss the non-linear relationship between the income gap and carbon emission intensity more accurately, this paper chooses the double threshold model to estimate the threshold. Table 5 presents the estimation results of the threshold value with the per capita disposable income of residents as the threshold.

Table 4. Regression results of threshold effect test.

			Critical Value		
	F-Value	***p*-Value**	**1%**	**5%**	**10%**
single threshold test	33.41	0.0133	37.385	25.227	21.598
double threshold test	33.25	0.0000	29.229	22.816	19.997
triple threshold test	13.00	0.7467	56.377	40.093	34.290

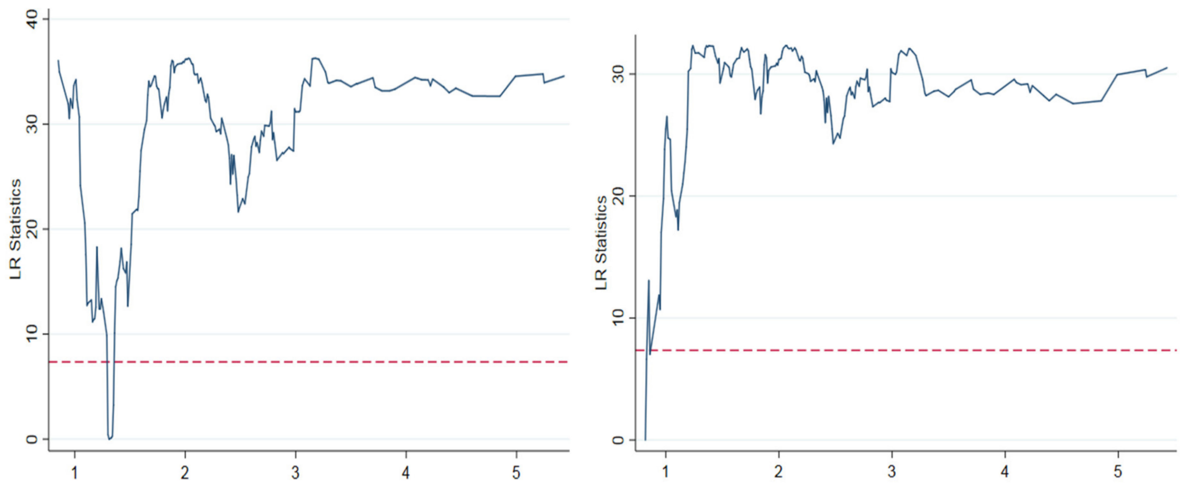
Note: p values and critical values are obtained by repeatedly sampling 300 times using the "self-sampling method" (Bootstrap).

Table 5. Threshold estimation results.

	Estimated Value	**95% Confidence Interval**
Threshold value γ_1	0.82	[0.817, 0.824]
Threshold value γ_2	1.31	[1.295, 1.330]

By combining Tables 4 and 5, it can be seen that there is a significant threshold effect between the income gap and carbon emission intensity, and the estimated values of the threshold variables are 0.82 and 1.31, respectively. The estimated value of the double threshold can divide the per capita income of residents into three intervals, namely the low-income region ($inco < 0.82$), the middle-income region ($0.82 \leq inco < 1.31$) and the high-income region ($inco \geq 1.31$). In the table of estimates and 95% confidence intervals for the double thresholds, the 95% confidence interval for the first threshold estimate is [0.817, 0.824], and the 95% confidence interval for the second threshold estimate is [1.295, 1.330]. It can be seen that there is a non-linear relationship between the income gap and carbon emission intensity. To further observe the construction of the threshold value and the confidence interval, this paper uses the least-squares likelihood ratio statistic LR to identify the threshold value. Figure 3 presents a plot of the likelihood ratio function for the double threshold estimate, where the red horizontal dashed line is the 95% confidence interval. The blue curves are the trajectories of the different threshold collection points. The ordinate corresponding to any point on the curve represents the likelihood ratio of the threshold value. The interval formed by the intersection of the curve with the dotted line defined by the 95% confidence level is the 95% confidence interval. When the confidence interval is small, the threshold model is less affected by unobservables. This also shows that the threshold regression results are more accurate.

As shown in Figure 3, the interval between the estimated values of the first threshold and the second threshold under the 95% confidence level is relatively small, and the accuracy of the second threshold is higher than that of the first threshold. Overall, the LR chart proves that the model has better estimation results with the per capita disposable income of residents as the threshold. Moreover, it also verifies that there is a non-linear relationship between the income gap and carbon emission intensity. Therefore, how is there a linear relationship between them? This paper estimates the parameters of the double-threshold model based on the result of the double-threshold estimation. The specific threshold regression results are shown in Table 6, and the control variables are the same as above.



(1) first threshold (2) second threshold

Figure 3. Threshold estimates and confidence intervals.

Table 6. Threshold regression results.

Variable	First Interval	Second Interval	Third Interval
$gin(inco < 0.82)$	3.4714 *** (4.92)		
$gin(0.82 \leq inco < 1.31)$		1.088 *** (4.10)	
$gin(inco \geq 1.31)$			−2.017 *** (−8.53)
edu	−133.48 *** (−8.34)	−122.52 *** (−7.31)	−89.15 *** (−5.59)
fdi	−0.00004 *** (−3.07)	−0.00004 *** (−3.15)	−0.00004 *** (−3.37)
inf	−0.0428 *** (−3.00)	−0.0357 ** (−2.45)	−0.0174 (−1.28)
gov	1.827 ** (2.08)	2.063 ** (2.29)	3.456 *** (4.09)
urb	0.0039 ** (2.02)	0.0035 * (1.78)	0.0021 (1.18)
is	−0.6355 *** (−7.83)	−0.4365 *** (−5.54)	−0.2085 ** (−2.58)
Constant term	4.986 *** (16.62)	4.603 *** (13.61)	4.008 *** (12.95)
Province effect	yes	yes	yes

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

From the results of threshold regression in Table 6, the per capita disposable income of residents can be used as the threshold to divide China into low-income, middle-income and high-income regions. When the per capita disposable income of residents is lower than the first threshold of 0.82, the effect of the income gap on carbon emission intensity is positive. Its coefficient is 3.4714, which is significant at the 1% level, i.e., the widening income gap also increases the carbon emission intensity of the region. When residents' per capita disposable income is in the second interval, the income gap is significant and positive at the 1% level, and its coefficient is 1.088. Although the narrowing of the income gap also suppresses the regional carbon emission intensity, the suppression effect is significantly lower than that in the first interval. When the per capita disposable income of regional residents is in the third interval, the influence coefficient of the income gap on carbon emission intensity is −2.017. It also passes the 1% significance level test. In the third interval, the effect of the income gap on carbon emission intensity changes from positive to negative, and the widening of the income gap suppresses the regional carbon emission intensity. In addition, no threshold effect changes the direction of impact in the control variables. Most of the control variables have a weakening effect on carbon emission intensity when per capita income increases from the first interval to the third interval. For example, increasing the level of urbanization increases the intensity of carbon emissions. The influence coefficients in the first, second and third intervals are 0.0039, 0.0035 and 0.0021, respectively, and those from the first and second intervals are significant at the 5% and 1% levels, respectively. The optimization of the industrial structure suppresses carbon emission intensity. The influence coefficients in the first, second and third intervals are −0.6355, −0.4365 and −0.2085, which are significant at the 1%, 1% and 5% levels, respectively. This is also consistent with the actual situation. An increase in the proportion of the tertiary sector naturally reduces the carbon emission intensity of a region. In particular, China is currently in a period of economic transformation, and the rapid development of the digital economy has further promoted regional carbon emission reduction.

Compared with previous related studies, the results of this paper well demonstrate the regional heterogeneity of residents' income gap on carbon emission intensity. Zhang Y. (2022) [29] conducted a study using provincial panel data from 2005 to 2017 in China and concluded that carbon emission intensity, income gap and economic agglomeration all have significant spatial spillover effects. In addition, economic agglomeration plays a mediating role in the impact of the income gap on carbon emissions. Based on provincial panel data from 2010 to 2019 in China, Chang W (2021) [43] found that the widening income gap worsens air quality in China, using the urban–rural per capita income gap as the research object. Ma X. et al. (2019) [28] conducted research using provincial panel data from 2002 to 2012 in China. The results of intra-group and inter-group analyses on the inequality of carbon emissions from household consumption are similar to those of this paper. From a national perspective, there is a negative correlation between the income gap and carbon emissions from household consumption, but the relationship between the two in the income group is uncertain. Some scholars also take household carbon emissions as the research object and use micro-data to find that households in counties with higher income inequality have more carbon emissions (Liu, Zhang and Liu, 2020) [44]. In addition, there is a bidirectional causal relationship between the interaction variables of income inequality, financial stability, fossil fuel use, trade openness, industrialization, economic growth and carbon emissions (Yang et al., 2020) [45].

The results of this study show that there are regional differences in the impact of the income gap on carbon emission intensity. There is a threshold effect between residents' per capita disposable income. In low-income and middle-income regions, widening income gaps increase carbon intensity. In high-income areas, the widening income gap suppresses carbon emission intensity. In the low-income stage, economic growth is accompanied by a widening income gap. In this process, the income gap affects regional carbon emission intensity through two mechanisms.

(1) Due to the limitation of green innovation technology and the neglect of the environment in a rush to economic development, some people have obtained high incomes through the destruction of the environment. The income gap widens and generates a higher pollution effect, which causes an increase in carbon emission intensity.
(2) The widening income gap leads to consumption upgrades, which leads to an increase in carbon emission intensity. Under the comparison effect, the widening of intra-regional income inequality significantly increases the consumption of a region. In addition, it makes the proportion of enjoyment-oriented consumption increase significantly. Specifically, the income gap can change market supply and demand by affecting commodity markets and factor markets, affecting carbon emission intensity. On the one hand, this is also related to the ratio of access to higher education by regional residents. In low-income regions, residents have low rates of access to higher education. As a result, there is less emphasis on clean energy and products, and they prefer to consume inexpensive but carbon-intensive commodities. On the other hand, consumption upgrades have increased households' fuel demand for travel,

heating and cooking, increasing households' direct carbon emissions. However, in the low-income stage, reducing carbon emission intensity cannot be achieved solely by narrowing the income gap because it inhibits economic development. Firstly, with the per capita income of residents gradually increasing, the impact of the widening income gap on carbon emission intensity decreases. When per capita income enters a high-income stage, the digital economy develops rapidly. The use of the Internet affects the productivity of factors such as capital, labor and information. Changes in factor productivity, in turn, affect the demand for capital and labor. The widening of the income gap at this stage is mainly due to the distributional role of the tertiary sector on income. Although the income gap has widened further with economic development, carbon emission intensity has been suppressed. Secondly, more people have entered the middle class, and the consumption structure of Chinese residents has changed. The pursuit of green and healthy food by middle-income and high-income groups has effectively reduced household carbon emissions. Higher demands on travel, heating and cooking and higher education rates have also increased residents' attention to the environment. In the high-income stage, the widening income gap inhibits the growth of carbon emission intensity. By 2019, the per capita disposable income of most residents in China exceeded ¥13,100. This is the interval in which the widening income gap suppresses the intensity of carbon emissions. At the same time as economic development, narrowing the income gap without increasing carbon emission intensity is an idea that needs to be considered for relevant policies and institutions in China in the future. It is also a way and a reference for less developed regions to take advantage of the narrowing of the income gap to reduce the intensity of carbon emissions.

5. Conclusions and Recommendations

5.1. Contributions and Conclusions

The income gap and environmental pollution in China are serious. At present, achieving sustainable development and building a modern society requires vigorous implementation of energy conservation and emission reduction measures. While achieving environmental friendliness, we aim to improve the income distribution system and narrow the income gap. Therefore, this paper takes regional residents' income Gini coefficient and regional carbon emission intensity as the research objects. The main contributions of this paper are as follows: (1) Previous studies have mainly used the per capita income gap between urban and rural areas as an indicator of the regional income gap. This paper estimates the Gini coefficients of China by region from 2010 to 2019 using the unequal group Gini coefficient calculation method. (2) There is no direct statistical caliber for provincial carbon emissions. This paper uses the standard coal method to estimate carbon emissions in different regions of China and obtains the carbon emissions of different regions in China from 2010 to 2019. (3) Previous studies have not reached a unified conclusion on the relationship between the income gap and carbon emission intensity. Based on the assumption of regional heterogeneity, this paper uses a threshold regression model to empirically verify that there is a threshold effect on the per capita income of residents between income gaps and carbon emission intensity.

Based on the statistical data from 2010 to 2019, this paper first measures China's provincial income gap and carbon emissions. Then, the threshold regression model is used to test the effect of the income gap on regional carbon emission intensity. The following three main conclusions are drawn.

Firstly, after measuring the Gini coefficients of provincial residents' income, this paper finds that the income gap is gradually widening within regions in China. Among them, provinces with more developed economies also face higher income gaps. The Gini coefficient is generally lower in less developed areas. From the perspective of time evolution, the pattern of income inequality between regions has changed little during the decade of 2010 to 2019. Different provinces have widened income gaps at similar rates. The pattern of the income gap between the two high ends and the middle ground is formed.

Secondly, after using the standard coal method to estimate carbon emissions in different regions, this paper finds two main characteristics of carbon emissions in China from 2010 to 2019. On one hand, average carbon emissions have risen steadily in China, but this increase is lower than that of China's GDP. On the other hand, differences in carbon emissions between regions first decreased and then continued to expand. The spatial correlation of provincial carbon emissions in China has two characteristics. On one hand, China's regional carbon emissions have a significant positive spatial correlation. On the other hand, the spatial correlation of carbon emissions is more stable and has been maintained at a low level.

Thirdly, in general, there are regional differences in the impact of the income gap on carbon emission intensity. There is a threshold effect between residents' per capita disposable income. In low-income and middle-income regions, widening income gaps increase carbon emission intensity. In high-income areas, the widening income gap suppresses carbon emission intensity.

5.2. Policy Recommendations

In 2020, the Chinese government proposed that: "China will increase its independent national contribution, adopt more powerful policies and measures, strive to peak carbon dioxide emissions by 2030 and strive to achieve carbon neutrality by 2060." This is not only for the purpose of assuming international responsibility. Carbon reduction is also effectively related to the living environment of Chinese residents. Based on the conclusions drawn above, the Chinese government needs to formulate appropriate policies according to local conditions, accounting for uneven regional economic development and differences in carbon emission intensity in China. Based on this, this paper proposes the following recommendations:

(1) Environmental policies should be formulated according to regional income levels and local conditions. This paper explicitly analyzes the threshold effect of the per capita disposable income of residents between the income gap and carbon emission intensity. For low-income regions, narrowing the income gap to reduce carbon emission intensity affects economic development, and the gains outweigh the losses. For high-income areas, it is necessary to reduce carbon emission intensity while narrowing the income gap. Therefore, on one hand, a progressive environmental pollution tax can be levied on high-income groups, and environmental pollution subsidies can be provided to low-income groups. On the other hand, environmental policies should be formulated for different regions according to local conditions, and developed areas should be given heavier ecological protection and governance responsibilities. Moreover, different environmental policies should be formulated for different regions according to local conditions. Developed areas can be given heavier responsibilities for environmental protection and governance. While reducing ecological responsibility, improving environmental supervision for less developed regions is also necessary.

(2) The energy structure should be optimized, and green innovation should be encouraged. The energy mix is closely related to carbon emission intensity. Based on stable and healthy economic development, it is necessary to promote the green innovation of enterprises and to increase investment in research on low-carbon energy. The government should bear most of the cost of carbon emission reductions and should eliminate outdated production capacity. Improving energy utilization increases low-income groups' income level and narrows the income gap between households.

(3) Low-carbon life should be advocated, and consumption structure should be adjusted. The issue of growth in household carbon emissions also needs attention. When income levels increase, it is also essential to pay more attention to the problem of high-speed growth in carbon consumption due to consumption upgrades. Therefore, on one hand, the government needs to encourage low-carbon life. For high-income groups, the government can appropriately increase the consumption tax rate for luxury goods

with high carbon emissions, lower the price of low-carbon energy and encourage low-income groups to use low-carbon energy. On the other hand, the government needs to adjust the consumption structure of residents. Government departments can subsidize low-carbon commodities and use prices to guide residents' low-carbon life and low-carbon consumption.

5.3. Research Outlook

This paper empirically tests the relationship between regional income gaps and carbon emission intensity based on qualitative analysis. Limited by the availability and applicability of data, this paper only uses provincial-level data from 2010 to 2019. Due to the small sample size, the research in this paper has some limitations regarding depth and breadth. In future research, we will continue to focus on developing a low-carbon economy in China. We will retrieve data at the prefecture-level and at the city-level to study the heterogeneity of the relationship between the income gap and carbon emission intensity in urban and rural areas. In addition, a comprehensive understanding and scientific assessment of the relationship between the income gap and carbon emission intensity is the premise of developing a low-carbon economy and advocating a low-carbon life for residents. This paper only explores the threshold effect between them from the perspective of residents' income levels, which is not comprehensive enough. Its specific impact mechanism needs to be further studied.

However, research on China's low-carbon economy lacks a micro-level perspective, using household micro-adjustment data to study the influencing factors of household carbon emissions. Therefore, future analyses can check the household carbon emission reduction theory at the micro-level. The impact of the income gap on household carbon emissions can also be studied from the perspectives of household size, population aging and consumption upgrading. Combining macro research with micro research and combining Chinese experience with international experience provides different paths for China to achieve carbon emission reduction targets.

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