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Gini Coefficient Decomposition and Influencing Factors for Provincial Disparities of Carbon Emissions in China

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Abstract: *This paper explores the contributions of various kinds of fossil energy to provincial disparities in per capita carbon emissions within China between 2007 and 2018, considering both sources of and incremental changes in carbon emissions via Gini coefficient decomposition. We apply a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and discuss the effects of economic growth, energy intensity, industry production, urbanization rate, and energy savings/emissions reduction expenditures on changes in provincial disparities of carbon emissions. The findings indicate that China's economic development, technological progress in energy savings and emissions reductions, urbanization rate and the Chinese government's related financial investments, have so far significantly changed carbon emissions. As one measure of technological progress, the increase of industry proportion will significantly increase carbon emissions only in economically underdeveloped areas.*

Keywords: *Carbon emissions; Gini coefficient decomposition; STIRPAT Model; China*

1. Introduction

Under the threat of a warming global climate, implementing energy savings and emissions reduction policies to accomplish concomitant economic and environmental development has become a key challenge for countries worldwide.

On November 12th 2014, in Sino-US joint statement on climate change, China first officially declared that it planned to ascend to the peak of carbon dioxide emissions around 2030 and would endeavor to arrive at the peak even faster. By 2030, China would make the share of non-fossil energy within the primary energy consumption, which reaches approximately 20%, and plan to continue to work on this and to increase its intensity over time. However, it is proving quite difficult for China to reduce its carbon dioxide emissions currently, as China remains at a critical stage of economic transformation with a coal-centered energy structure, severe resource shortages, and a fragile ecological environment. Meanwhile, even in provinces with comparable levels of social and economic development, there can be notable differences in emissions between them [1]; reducing CO_2 emissions thus requires recognizing the origins of inter-province differences in carbon emissions, as well as the factors that influence these differences. Only by understanding the main causes of these differences can policymakers craft better targeted energy savings and emissions reduction policies.

In the 1970s, the Impact, Population, Affluence, and Technology (IPAT) Model developed from the debates between Ehrlich and Holdren [2] and Commoner [3]. Commoner [3] believed that technology was the most important factor affecting the environment, while Ehrlich and Holdren [2] explained that the environment was significantly impacted by population, wealth, and technology. As such, an improved IPAT model, the Stochastic Impacts via Regression on Population, Affluence, and Technology (STIRPAT) model, which allows discussion of various influencing elements and is universally used in the relevant research [4-7]. The majority of readers have concluded that economic growth and increasing population constitute two major factors influencing CO_2.

Most studies have concentrated on a specific country or region while neglecting differences in geographic conditions, resource endowments, economic structures, and other characteristics between regions. Therefore, the number of studies on regional disparities in carbon emissions has steadily grown in recent years. He et al. [8] used the emissions Gini coefficient to compare carbon emissions

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inequality across Chinese provinces from 2007-2017, and explained that persistent disparities in the decoupling of development and emissions across regions are responsible for the increasing inequality in the geographical distribution of carbon emissions. Wu and Chen [9] utilized city-level data in China from 2005-2020 to calculate a modest decline in the Gini coefficient of carbon emissions, a carbon economy concentration index and a Kakwani index indicating an asymmetry between carbon emissions and economic development, concluding that energy-intensive characteristics are responsible for a large share of carbon inequality.

This paper will thus analyze provincial differences in carbon emissions using the Gini coefficient, which will be decomposed in terms of both sources and incremental changes. In this way, we will be able to identify the main sources of and factors influencing regional differences in carbon emissions in China, thus providing crucial empirical information for policymakers. The existing studies that decompose the Gini coefficient in terms of source and increment changes had only looked at carbon emissions from coal and different sectors [10].

The remainder of the paper is structured as follows. Section 2 introduces the analytical methods and relevant data sources. Section 3 presents results, quantitatively analyzing the contributions of various types of energy to provincial differences in carbon emissions via Gini coefficient decomposition and applying the STIRPAT model to discuss the elements impacting carbon emissions. Section 4 concludes, offering relevant policy suggestions.

2. Methods and Data

2.1 Measurement and Calculation of Carbon Emissions

When calculating carbon emissions, we use a widely applied method described by Intergovernmental Panel on Climate Change (IPCC) in its 2006 IPCC Guidelines for National Greenhouse Gas Inventories[11]. For the sake of minimizing possible errors in the division of primary energy sources, we included all 17 energy types specified in China Energy Statistical Yearbook [12]. Using such method and energy consumption in various provinces/cities (from the China Statistical Yearbook [13]), we will then be able to calculate regional carbon emissions.

2.2 Gini Coefficient Decomposition of Provincial Differences of Carbon Emissions

The combustion of fossil fuels produces CO_2. Decomposing the Gini coefficient of carbon emissions ("emissions Gini coefficient") is conducive to analyzing the roles of these different fossil energy sources in driving provincial disparities in carbon emissions. It is easiest to decompose the Gini coefficient in line with sources:

$$G = \sum_{i=1}^{n} I_i G_i \tag{1}$$

In equation (1), Gi is the pseudo-Gini coefficient calculated for energy type i. In such cases, we will get different Gini coefficients for the ith energy source when calculated based on the Lorenz Curve and equation (1). I_i gives the ratio of total carbon emissions that are produced by the ith energy source. The rate at which energy i contributes to the overall difference can thus be expressed as: $I_i G_i / G\%$. Using this equation, the contribution of each energy type's emissions Gini coefficient to overall regional differences can be calculated from 2007 to 2018.

We will thus also decompose changes in the Gini coefficient as a way to explore in depth changes in provincial inequality in carbon emissions, 2007-2018. There are two methods to approach this decomposition. First, this paper decomposes the 2007-2018 changes in emissions Gini coefficients between provinces in line with regional carbon emissions, regional emissions ranking, and population share. It can be expressed as:

$$\Delta G = \Delta G_X + \Delta G_R + \Delta G_P \tag{2}$$

In this equation, ΔG_X refers to changes in the Gini coefficient brought about by changes in carbon emissions while the regional emissions ranking and population share are maintained at the level of the base period; ΔG_R reflects those resulting from changes in the regional emissions ranking; and ΔG_P refers to those caused by changes in various regions' population shares, with emissions and regional

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emissions ranking kept at the base level.

The second method involves dynamically decomposing the overall Gini coefficient from different carbon emissions sources. The equation is:

$$\Delta G = G^{(1)} - G^{(0)} = \sum_{i=1}^{s} G_i^{(0)} \Delta I_i + \sum_{i=1}^{s} I_i^{(0)} \Delta G_i + \sum_{i=1}^{s} \Delta I_i \Delta G_i \tag{3}$$

In Equation (3), $\Delta I_i = I_i^{(1)} - I_i^{(0)}$ and $\Delta G_i = G_i^{(1)} - G_i^{(0)}$ respectively show the proportion and concentration (pseudo-Gini coefficient) changes in emissions from energy i spanning the base and end periods. Three components account for the variation in the Gini coefficient: the structural effect caused by the energy structure; the concentration effect due to changes in carbon concentrations of the energy types; and the comprehensive effect due to changes in both.

The provincial carbon emissions data required for the Gini coefficient decomposition comes from our calculations; year-end population data originates from China Statistical Yearbook. [13]

2.3 Construction of the STIRPAT Model

We investigate the elements impacting carbon emissions via the STIRPAT model, using the standard form:

$$\ln I = a + b \ln P + c \ln A + d \ln T \tag{4}$$

In this paper, I refers to per capita CO_2 emissions, P indicates population size, A indicates per capita GDP, and T indicates energy intensity.

Since CO_2 is the most prevalent emitted greenhouse gas (GHG) and has a significant effect on the environment, we use ***per capita CO_2 emissions*** as a measure of impact and come to explore the impact of various economic factors on them.

Urbanization is the principal force driving China's economic growth and energy demand. Therefore, we replace the population indicator in the model with the ***urbanization rate***, to reflect changes in energy consumption and carbon emissions brought about by population shifts.

Per capita GDP is used to reflect an economy's state of development; different economic development phases entail different energy consumption characteristics.

Energy intensity is often used to capture the economic efficiency of energy utilization , also known as energy consumption per unit of GDP and is an important indicator of technological progress. However, energy intensity fails to reveal the impact of industrial structure on carbon emissions. Therefore, we include the economy's ***industry proportion*** in the model as a secondary indicator for energy intensity.

Though it will not be possible to curtail carbon emissions by merely depending on the market, economic instruments can effectively help the government to play a guiding role. Research has shown that levying taxes on carbon emissions and increasing financial expenditures can effectively reduce emissions [14-15]. Therefore, we will include ***government expenditures*** on energy savings and environment protection among the explanatory variables so as to explore its influence on regional emissions differences.

Our STIRPAT model thus includes per capita GDP, energy intensity, industry proportion, urbanization rate, and per capita spending on energy savings and emissions reductions (reflecting the effects of economy, technology, population, and policy, respectively, on carbon emissions). Hence, the logarithmic panel model can be represented as shown below:

$$\ln ce_{it} = \rho_0 + \rho_1 \ln gdp_{it} + \rho_2 (\ln gdp_{it})^2 + \rho_3 \ln ene_{it} + \rho_4 \ln ind_{it} + \rho_5 \ln urb_{it} + \rho_6 \ln fp_{it} + \varphi_i + \varepsilon_{it} \tag{5}$$

In equation (5), ce_{it} refers to CO_2 emissions, and we decompose economic growth into two parts, $\ln gdp_{it}$ and $(\ln gdp_{it})2$, by considering the inverted U correlation between carbon emissions and economic development; gdp refers to per capita regional GDP. ene_{it}, ind_{it}, urb_{it}, and fp_{it} represent energy intensity, industry proportion, urbanization rate, and per capita expenditures on energy savings and emissions reductions, respectively; φ_i is an individual effect, while ε_{it} is a random disturbance.

As the Chinese government changed the statistical definition of its expenditures on energy savings

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and emissions reductions in 2007, we use 2007-2018 panel data for 30 provinces (excluding Tibet). In the model, data on year-end population, regional GDP, energy consumption, urbanization rate, industry portion, and fiscal expenditures on energy savings and environment protection come from 2008-2019 *China Statistical Yearbook*.

3. Results

3.1 Decomposition of Gini Coefficient for Provincial Carbon Emissions

3.1.1 Decomposition According to Emissions Sources

Table 1: Gini Coefficients and Contribution Rates of Various Fossil Energy Sources to Inequality in Provincial Carbon Emissions

	Coal		Coke products		Petroleum		Natural Gas		Energy
2007	0.2273	68.98	0.3162	18.21	0.1784	12.81	0.0453	0	0.2310
2008	0.2330	69.32	0.3281	18.89	0.1733	11.79	0.0394	0	0.2363
2009	0.2232	67.33	0.3385	20.49	0.1745	12.17	0.0293	0	0.2315
2010	0.2248	68.89	0.3461	21.29	0.1503	9.82	0.0212	0	0.2308
2011	0.2382	81.54	0.3604	24.06	0.1521	10.58	0.0444	0	0.2309
2012	0.2535	72.58	0.3454	19.83	0.1263	7.59	0.0676	0	0.2476
2013	0.2696	75.35	0.3364	19.33	0.0903	5.33	0.0936	0	0.2526
2014	0.2842	77.65	0.3195	18.4	0.0656	18.4	0.0964	0	0.2557
2015	0.2980	78.93	0.3153	17.26	0.0617	3.81	0.0884	0	0.2623
2016	0.3099	78.87	0.3194	17.3	0.0632	3.82	0.0612	0	0.2709
2017	0.3125	79.62	0.3266	16.93	0.0570	3.45	0.0877	0	0.2724
2018	0.3268	78.57	0.3917	19.14	0.0425	2.28	0.0847	0	0.2915

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks.
Note: As coke products result from secondary combustion, they also release CO_2 during combustion. Therefore, they are included in the table.

As shown in Table 1, inequality of carbon emissions in Chinese provinces, as measured by the Gini coefficient, increases from 0.2310 in 2007 to 0.2915 in 2018. The largest inter-regional difference is in carbon emissions from coke products, for which the average Gini coefficient is 0.3370. Comparatively, provincial disparities in carbon emissions from coal and total carbon emissions are similar, between 0.22 and 0.33, followed by petroleum, with an average Gini coefficient of 0.1113. Natural gas boasts the smallest Gini coefficient, below 0.1.

In line with equation (1), we calculate the rate at which each energy source contributes to provincial inequality in carbon emissions. Differences in carbon emissions from coal make the largest contribution to overall carbon emissions inequality, responsible for more than 67% from 2007 to 2018, with an annual average increase rate of 1.19%. Compared to other fossil energy sources over the same period, coke products' contribution rate increases from 18.21% to 19.14%, and that of petroleum decreases from 12.81% to 2.28%, while natural gas contributes close to 0 to provincial differences in carbon emissions.

To more precisely consider the CO_2 emissions differences between coal, coke products, and petroleum, we use equation (1) to decompose the Gini emissions coefficient in terms of these different sources. The results are shown in Tables 2-5.

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Table 2: 2007-2018 Provincial Emissions Gini Coefficients and Contribution Rates of Various Types of Coal

	Gini Coefficient				Contribution Rate %			
	Raw Coal	Washed Coal	Other cleaned coal	Briquette	Raw Coal	Washed Coal	Other cleaned coal	Briquette
2007	0.2374	0.2713	0.4189	0.1420	95.46	1.87	2.95	0.28
2008	0.2425	0.2975	0.4338	0.0118	94.79	2.2	2.98	0.03
2009	0.2385	0.1656	0.3663	0.0131	95.94	1.48	2.55	0.03
2010	0.2427	0.0376	0.2952	0.0480	97.04	0.61	2.24	0.11
2011	0.2557	0.0512	0.2491	0.0828	97.4	0.58	1.85	0.17
2012	0.2697	0.0135	0.3666	0.1665	97.12	0.16	2.7	0.34
2013	0.2847	0.0801	0.2733	0.1528	97.05	0.94	1.72	0.29
2014	0.3026	0.0189	0.2662	0.1972	97.70	0.23	1.71	0.36
2015	0.3182	0.0167	0.2690	0.2374	97.85	0.17	1.55	0.43
2016	0.3264	—	0.2641	0.1723	97.49	—	2.18	0.33
2017	0.3311	—	0.3257	0.1107	97.47	—	2.46	0.17
2018	0.3369	—	0.4498	0.0789	97.53	—	2.47	0.12

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks.
Note: Owing to the absence of data on Washed Coal consumption in 2016-2018, there is no related carbon emission data.

As Table 2 shows, from 2007 to 2018, the carbon emissions inequalities arising from raw coal generally grew, while the carbon emission inequality of washed coal decreased year by year. For other washed coal and briquette, the Gini coefficient fluctuate significantly. In 2018, other cleaned coal accounted for the greatest proportion of regional carbon emissions differences arising from coal, with a Gini coefficient of 0.4498. This is followed by raw coal and briquette, with respective Gini coefficients of 0.3369 and 0.0789. Raw coal plays a dominant role in regional emissions inequality: its contribution rate to regional differences in coal-based carbon emissions remains over 94% for the entire period.

Table 3: 2007-2018 Provincial Emissions Gini Coefficients and Contribution Rates of Various Coke Products

	Gini Coefficient				Contribution Rate %			
	Coke	COG	Other Gases	Other Coke Products	Coke	COG	Other Gases	Other Coke Products
2007	0.4037	0.5419	0.3864	0.5639	93.13	0.69	2.22	3.96
2008	0.4119	0.4913	0.3411	0.5877	93.35	0.63	1.92	4.09
2009	0.4146	0.4480	0.3697	0.5370	93.53	0.54	2.29	3.64
2010	0.4188	0.4216	0.1156	0.5273	95.62	0.57	0.04	3.77
2011	0.4362	0.4479	0.0937	0.525	95.76	0.58	0.04	3.62
2012	0.4281	0.4321	0.0782	0.4762	96.44	0.56	0.03	2.97
2013	0.4300	0.4431	0.0240	0.4427	95.86	0.59	0.01	3.55
2014	0.4210	0.4243	0.0462	0.4038	95.88	0.56	0.01	3.56
2015	0.4236	0.4205	0.0231	0.3979	95.78	0.55	0.01	3.66
2016	0.4287	0.4163	0.1033	0.4461	95.26	0.54	0.03	4.17
2017	0.4289	0.4039	0.1965	0.4637	95.05	0.53	0.05	4.37
2018	0.4682	0.4072	0.1232	0.5299	96.12	0.50	0.03	3.35

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks.

The Gini emissions coefficients of coke, COG and other coke products are relatively high, generally

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above 0.4 (Table 3). Regional differences are thus relatively pronounced. The emissions Gini coefficients of COG, other gases, and other coke products decrease by reaching 24.86%, 68.12%, and 6.03%, respectively. However, the emissions Gini coefficient for coke increases from 0.4037 to 0.4682. The contribution rates show that coke itself contributes the most to cross-regional inequality in carbon emissions from coke products, with a contribution rate in excess of 93% and growing by 3.21% between 2007 and 2018.

Table 4: 2007-2018 Emissions Gini Coefficients for Various Petroleum Products

	Crude Oil	Gasoline	Kerosene	Diesel	Fuel Oils	LPG	Refinery Dry Gas	Other Petroleum Products
2007	0.5408	0.2610	0.4917	0.2243	0.6211	0.4365	0.4665	0.4615
2008	0.4450	0.2672	0.5195	0.2159	0.605	0.3864	0.4866	0.4504
2009	0.5198	0.2831	0.5191	0.2122	0.5857	0.3977	0.4704	0.4458
2010	0.5576	0.2629	0.4952	0.2152	0.588	0.3718	0.4524	0.3156
2011	0.5707	0.2562	0.4701	0.1978	0.5557	0.356	0.4559	0.3994
2012	0.4637	0.2426	0.4839	0.1791	0.5746	0.3322	0.4332	0.3582
2013	0.3824	0.2028	0.5139	0.1322	0.5327	0.2961	0.5017	0.3596
2014	0.4789	0.2119	0.4847	0.1199	0.5384	0.3073	0.4834	0.3600
2015	0.4125	0.1863	0.4761	0.4761	0.4901	0.3162	0.4684	0.4130
2016	0.4116	0.1798	0.4770	0.1062	0.5144	0.2197	0.4638	0.3894
2017	0.269	0.1856	0.4961	0.1026	0.5459	0.303	0.4357	0.4379
2018	0.3314	0.1713	0.4990	0.1153	0.5135	0.2982	0.4029	0.4597

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks.

Table 5: 2007-2018 Contribution Rates of Emissions from Various Petroleum Products' to Provincial Differences

	Crude Oil	Gasoline	Kerosene	Diesel	Fuel Oils	LPG	Refinery Dry Gas	Other Petroleum Products
2007	5.00	14.76	5.25	22.92	20.03	8.04	3.19	20.80
2008	3.22	15.77	6.19	24.13	19.17	7.44	3.62	20.46
2009	4.02	17.11	6.29	24.07	16.62	7.51	3.63	20.73
2010	5.14	19.98	7.43	29.56	16.48	7.98	4.39	9.03
2011	5.50	20.79	7.37	27.93	14.58	7.97	4.63	11.24
2012	3.44	22.09	8.65	27.44	14.74	7.63	4.61	11.4
2013	3.54	20.88	11.31	22.32	14.56	7.61	6.21	13.58
2014	5.70	21.92	11.23	19.68	14.06	7.72	6.13	13.56
2015	3.97	21.13	12.06	12.06	12.74	8.15	6.24	16.10
2016	3.68	23.02	14.42	18.12	13.77	4.55	6.49	15.95

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2017	1.46	23.48	15.53	16.6	12.52	7.93	6.23	16.24
2018	1.67	23.10	17.13	18.92	11.36	8.06	6.25	13.51

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks.

Tables 4 and 5 give provincial Gini coefficients and contribution rates of carbon emissions from various types of oils. In 2007, the regional emissions Gini coefficients for crude oil, kerosene, fuel oils, LPG, refinery dry gases, and other petroleum products all exceed 0.4, indicating large emissions gaps between regions. However, differences in emissions from all petroleum products except kerosene decrease between 2007 and 2018. Diesel shows the maximum average annual decline, nearly 5.9%. Fuel oil has the largest average Gini coefficient, followed by kerosene and refinery dry gas. The contribution rates of diesel and gasoline increase by 21.46 and 19.28 percentage points, respectively, between 2007 and 2018, becoming the two petroleum products with the largest contributions. This may result from constant economic growth, which has improved living standards and increased sales and use of vehicles, making gasoline and diesel the main sources of gaps in regional emissions from petroleum products.

In sum, differences in emissions from raw coal, coke, and gasoline and diesel are the dominant contributors to differences in emissions from coal, coke, and petroleum products, respectively.

3.1.2 Decomposition of Gini Coefficient Changes

Changes in the Gini coefficients can be decomposed based on carbon emissions, regional emissions ranking, and population or based on structural, concentration, and comprehensive effects. Either way will indicate certain key factors behind changes in the Gini coefficient; we will thus apply both approaches.

In 2012, the State Council of China officially issued the Twelfth Five-Year Plan for Energy Conservation and Emission Reduction. We thus use the year 2012 as the critical turning point to explore carbon emissions changes in two periods, 2007 to 2012 and 2012 to 2018. Using Equations (2) and (3), we decompose changes in the inter-provincial emissions Gini coefficients in these two periods (Table 6).

Table 6: Decomposition Results of Changes of Provincial Carbon Emissions Differences in China

Project		2007-2012	2012-2018	2007-2018
G_0		0.2310	0.2476	0.2310
ΔG		0.0166	0.0439	0.0605
Decomposition by carbon emissions, regional emissions ranking, and population	ΔG_X	0.0045	0.034	0.0269
	ΔG_R	0.0119	0.0083	0.0317
	ΔG_P	0.0020	-0.0016	-0.0013
	$\Delta G/G_0$	7.19%	17.73%	26.19%
	$\Delta G_X/ G_0$	1.95%	13.73%	11.65%
	$\Delta G_R/ G_0$	5.15%	3.35%	13.72%
	$\Delta G_P/ G_0$	0.09%	-0.65%	-0.56%
Decomposition by effects	Structural Effect	0.0215	-0.0208	0.0034
	Concentration Effect	0.0136	0.0525	0.0573
	Comprehensive Effect	-0.0185	0.0122	-0.0001
	Structural Effect/G_0	9.32%	-8.40%	1.46%
	Concentration Effect//G_0	5.89%	21.20%	24.79%
	Comprehensive Effect/G_0	-8.02%	4.93%	-0.05%

Source: Authors' calculations using carbon emissions data and year-end population from the 2008-2019 China Statistical Yearbooks. G0 refers to the provincial Gini coefficient of carbon emissions in base period; see Eqns. (2) and (3) for definitions of other variables.

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Table 6 shows that from 2007 to 2012, the emissions Gini coefficient increases by 0.0166 or 7.19%; from 2012 to 2018, the coefficient increases by 0.0439. This may be related to the Chinese government's newfound policy focus on reducing GHG emissions. Changes in carbon emissions in various regions have increased inter-regional emissions differences—i.e., as carbon emissions have increased, so has the Gini emissions coefficient. This is mainly because economic growth increases carbon emissions in different regions by different degrees, thereby expanding inequalities. During the 12 years between 2007 and 2018, carbon emissions and regional emissions ranking changes have increased the emissions Gini coefficient by 11.65% and 13.72% respectively, while population reduced it by 0.56%. These effects offset one another, and the Gini coefficient rises by 26.19%.

After decomposing the Gini coefficient in terms of different effects, we find that changes in energy structure make emissions inequality increase by 1.46% between 2007 and 2018. From 2007 to 2012, the structural effect is responsible for an increase of 9.32% compared to a decrease of 8.4% from 2012 to 2018, suggesting that the energy structural effect has some changes since 2012. The concentration effect, resulting from changes in the carbon emissions concentrations of diverse energy sources, increases emissions inequality by 24.79%, thus having the largest influence on the overall Gini coefficient. The combined effect of the changes of carbon emissions structure and concentration reduces inter-provincial emissions inequality by 0.05%.

In sum, among the different effects, changes in the concentration of various energy sources are the main source of variations in inter-provincial emissions inequality. Next, we will explore the root cause of these emissions changes and empirically analyze various factors' influences on carbon emissions differences between provinces.

3.2 Factors Influencing Carbon Emissions in China

The STIRPAT model results are shown in Table 7 and Table 8.

Table 7: Panel Model Regression Results

Panel	(1)	(2)	(3)	(4)
	OLS	OLS	2SLS	2SLS
ln*urb*	0.174 [0.184]	0.325* [0.178]	0.345* [0.204]	0.379* [0.206]
ln*gdp*	2.587*** [0.464]	1.909*** [0.461]	1.708*** [0.598]	1.825*** [0.596]
$(\text{lngdp})^2$	-0.081*** [0.022]	-0.044* [0.022]	-0.036 [0.029]	-0.044 [0.029]
ln*ene*	1.018*** [0.060]	1.011*** [0.057]	0.934*** [0.060]	0.934*** [0.060]
ln*ind*		0.026 [0.063]		0.091 [0.068]
ln*fp*		-0.141*** [0.024]		-0.231*** [0.053]
Sargan-p			0.000	0.000
Cragg-Donald Wald F statistic			95.315	94.562
R-sq	0.722	0.750	0.6742	0.6753
Obs	360	360	330	330
Controls	Yes	Yes	Yes	Yes

Note: * (**, ***) indicates rejecting the null hypothesis at significant level of 10% (5%, 1%).

As Table 7 shows, Panel(1) and Panel(3) incorporates three common variables: population size, per capita GDP and energy intensity. Panel (2) and (4) add variable lnind, which also examines the impact

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of energy intensity, and lnfp which examines government policies on emission reduction. The results indicate that industrial rate is insignificant at the 10% level. Per capita GDP, energy intensity, urban population size, and the Chinese government's financial investments in energy savings and emissions reductions have thus succeed to significantly change carbon emissions. And these four factors' significance decreases sequentially. This result undoubtedly verifies our finding in Section 3.1 that coal is a major contributor to regional disparity in carbon emissions, since the coal consumption has a significant impact on industry proportion and urbanization proportion. Since the Sargan test p value is 0 and the Cragg-Donald Wald F statistic value is over 90, we accept that all instrumental variables are effective.

In sum, economic growth and technology progress have great effects while urbanization and government policy have less significance on carbon emissions in China.

However, this panel model merely reflects the link between national average carbon emissions and GDP, industry proportion, and so on; it is unable to further explain the specific situations of various regions. Hence, we will analyze this issue via group analysis.

Table 8: Panel Model Regression Results by Group

Panel	(5)	(6)	(7)	(8)	(9)	(10)
	Higher *urb*	Lower *urb*	Higher *gdp*	Lower *gdp*	Higher *ene*	Lower *ene*
ln*urb*	0.556* [0.317]	-1.089*** [0.320]	0.143** [0.069]	-0.820*** [0.228]	-1.320*** [0.448]	0.177 [0.169]
ln*gdp*	2.142** [0.861]	1.038 [0.860]	4.336*** [1.446]	0.555 [0.875]	-1.221 [1.067]	2.954*** [0.442]
$(\text{lngdp})^2$	-0.061 [0.041]	-0.002 [0.043]	-0.158** [0.066]	0.019 [0.043]	0.125** [0.052]	-0.093*** [0.022]
ln*ene*	1.003*** [0.125]	0.914*** [0.072]	0.898*** [0.161]	0.930*** [0.062]	0.787*** [0.088]	0.896*** [0.071]
ln*ind*	0.032 [0.100]	0.056* [0.031]	0.060 [0.122]	0.045* [0.028]	0.101* [0.065]	0.072 [0.061]
ln*fp*	-0.150*** [0.034]	-0.066* [0.034]	-0.164*** [0.033]	-0.053 [0.033]	-0.074 [0.052]	-0.065*** [0.024]
R-sq	0.753	0.799	0.780	0.798	0.865	0.785
Obs	135	225	120	240	120	240
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: * (**, ***) indicates rejecting the null hypothesis at significant level of 10% (5%, 1%).

In this study, provinces were split into different groups according to urbanization, economic development and technology progress. The results displayed in Table 8.

Panel (5) and (6) reflect that, areas with higher urbanization are more affected by various factors than areas with low urbanization. More particularly, increased urbanization will reduce carbon emissions in less urbanized areas. The explanation could be that urbanization influences carbon emissions through infrastructure construction, public goods supply and other ways, and the increase in urban population in areas with low urbanization cannot increase these ways significantly, but will reduce per capita carbon emissions due to population growth.

Panel (7) to (10) demonstrate that the groups with higher gdp and lower energy intensity (higher technological progress) shows similar characteristics to the group with higher urbanization. In other words, areas with higher gdp and higher technology progress are influenced by Per capita GDP, energy intensity, and the Chinese government's expenses on carbon reduction, more significantly than that with lower gdp and lower technology progress. In addition, in areas with low urbanization, less developed economies or lower technological levels, the increase of industry proportion will significantly arise regional carbon emissions. It may because of the extensive industrial production in economically underdeveloped areas.

4. Conclusions and Policy Implications

This paper has explored the contributions of various fossil energy sources to provincial differences in per capita carbon emissions in China between 2007 and 2018, considering both sources and incremental changes in carbon emissions via Gini coefficient decomposition. To discover the variables affecting carbon emissions, we examined the impacts of per capita GDP, energy intensity, industry proportion, urbanization, and per capita expenditures on energy savings and emissions reductions on provincial differences in carbon emissions using the STIRPAT Model. Three main conclusions were reached.

First, carbon emissions differences are primarily driven by coal consumption, changes in regional emissions ranking affected by carbon emissions, and concentrations of carbon emissions. Differences in emissions from raw coal, coke, and gasoline and diesel are the dominant contributors to differences in emissions from coal, coke, and petroleum products, respectively.

Second, the primary factors influencing carbon emissions, in order, are per capita GDP, energy intensity, urbanization rate, and the government's fiscal investments in energy savings and emissions reductions. It's also worth noting that the increase of industry proportion in economically underdeveloped areas will significantly increase carbon emissions, while it in the developed areas will not affect carbon emissions obviously.

Based on the foregoing results, we make two key recommendations accordingly. First, the Chinese government need to start by attempting to minimize fossil energy consumption. Improving energy efficiency and saving energy involve multiple sectors of the economy, particularly high energy-consuming and heavily polluting ones like the chemical, metallurgy, construction, transportation, and electricity industries. Improving energy efficiency requires a variety of approaches, including revising regulations related to energy conservation and environmental protection as a means of guiding and regulating the behavior of governments, companies and citizens. Chinese policymakers must thus modify and optimize the industrial structure and energy mix while actively promoting the healthy and prosperous development of the modern service industry.

Second, it is time to transform traditional industries with emerging technologies and embark on a new road of sustainable development. Traditional industries, such as chemicals, machinery, metallurgy, and building materials, must be developed through technological innovation to create high value-added and high-tech goods. The Chinese government may stimulate research, development, and promotion of technologies like high-efficiency, low-emission energy in both production and consumption by enhancing its technological innovation system. Meanwhile, by further enhancing international cooperation, China can benefit from Western countries' advanced carbon-reductions technologies.

Finally, heeding the link between regional carbon emissions and the factors influencing them, the Chinese government can formulate regional relevant emissions reduction policies targeting CO_2 emissions.

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