Postprint: Spatiotemporal Differences and Driving Factors of Carbon Emissions from Energy Consumption in China

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Abstract

As climate change intensifies, carbon emissions and their impacts are attracting increasing attention. This study estimates carbon emissions from terminal energy consumption across 30 Chinese provinces from 2000 to 2015, analyzes the regional characteristics and spatiotemporal variations of carbon emissions from energy consumption in China, and investigates the driving factors of carbon emissions from two perspectives—carbon emission volume and carbon emission intensity—by integrating the STIRPAT model with a panel data model. The findings indicate that, at the national level, population size, per capita GDP, energy intensity, and urbanization level exert positive driving effects on carbon emission volume; specifically, a 1% increase in each factor results in respective increases of 1.0469%, 0.9386%, 0.7226%, and 0.4116% in carbon emissions, whereas industrial structure demonstrates a negative driving effect on carbon emissions. Regarding carbon emission intensity, both per capita GDP and industrial structure generate negative inhibitory effects. At the regional level, grouping by economic level reveals that due to disparities in economic development across the three major regions (East, Central, and West), the impacts of various factors on carbon emissions differ and exhibit certain regularities; grouping by urbanization level shows that carbon emission volume decreases with rising urbanization levels. This research can provide a reference basis for rationally formulating regionally differentiated CO2 emission reduction policies in China.

Full Text

Preamble

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Keywords: Carbon emissions; STIRPAT model; panel data; driving factors

1 Introduction

Climate change has become an increasingly prominent global issue, and carbon emissions from energy consumption are its primary driver. Research on the relationship between human activities and carbon emissions has attracted widespread attention from scholars. Padilla and Serrano analyzed the impact of international trade on CO emissions, finding that trade significantly influences carbon emissions in various countries. Helm and Wodon examined the relationship between carbon emissions and economic growth, demonstrating a complex linkage between the two. Sathe et al. studied the driving factors of CO emissions in European countries from 1997 to 2007, revealing significant variations in emission patterns across nations. Poumanyvong and Kaneko investigated the effects of urbanization on carbon emissions in 99 countries from 1995 to 2009, showing that urbanization levels substantially affect emission trajectories. These studies collectively indicate that carbon emissions are influenced by multiple factors including economic development, population growth, energy consumption, and urbanization, with considerable regional heterogeneity in their effects.

2 Data and Methodology

2.1 Data Sources and Processing

This study utilizes panel data from 30 provinces in China covering the period 2000–2015. The data were sourced from the *China Energy Statistical Yearbook*, *China Statistical Yearbook*, and provincial statistical yearbooks. To analyze regional disparities, provinces were grouped into three economic regions based on their development levels: Eastern (G1), Central (G2), and Western (G3). The classification follows the standard regional division used in China' s national economic accounting. Key variables include population size, per capita GDP, energy intensity, urbanization rate, and industrial structure. All monetary values were adjusted to constant 2000 prices to eliminate inflation effects.

2.2 Model Specification

The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model serves as the analytical framework. The basic model is specified as:

$$I_{it} = \alpha P_{it}^{\beta_1} A_{it}^{\beta_2} T_{it}^{\beta_3} e_{it}$$

where I represents environmental impact (CO emissions), P denotes population size, A signifies affluence (per capita GDP), T indicates technology level (energy intensity), α is the constant term, β_1, β_2, and β_3 are elasticity coefficients, and e is the error term.

Taking logarithms transforms the model into a linear form:

$$\ln I_{it} = \alpha + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + e_{it}$$

For this study, the model is extended to include additional drivers:

$$\ln C_{it} = \alpha + \beta_1 \ln pop_{it} + \beta_2 \ln gdp_{it} + \beta_3 \ln ei_{it} + \beta_4 \ln urb_{it} + \beta_5 \ln ind_{it} + e_{it}$$

where C is CO emissions, pop is population, gdp is per capita GDP, ei is energy intensity, urb is urbanization level, and ind is industrial structure.

The general panel data model is expressed as:

$$Y_{it} = C + \alpha_{it} + X_{it}\beta_{it} + \varepsilon_{it} \quad (i = 1, 2, \dots, N;\ t = 1, 2, \dots, T)$$

where Y_{it} is the dependent variable, X_{it} represents the vector of independent variables, i denotes cross-sectional units, t indicates time periods, C is the constant term, α_{it} captures individual effects, β_{it} are coefficients, and ε_{it} is the error term.

3 Empirical Results

3.1 Descriptive Analysis

Between 2000 and 2015, China' s total CO emissions from energy consumption increased from 3.171 billion tons to 6.68 billion tons, representing a growth of 2.77 times. Emissions showed distinct regional concentration patterns, with the top 10 provinces accounting for over 60% of the national total. The eastern region consistently contributed more than 50% of total emissions throughout the study period, while the western region' s share remained below 30%.

[TABLE 1]

3.2 Regional Patterns

Per capita CO emissions exhibited significant regional divergence. The eastern region maintained the highest per capita emissions, followed by the central region, with the western region showing the lowest levels. However, the growth rate of per capita emissions was fastest in the western region, suggesting a catch-up effect. The relationship between per capita GDP and per capita emissions varied across regions, with the eastern region showing signs of decoupling after 2010, while the central and western regions continued to exhibit strong positive correlations.

[FIGURE 2]
[FIGURE 3]
[FIGURE 4]

4 Discussion

4.1 Cointegration Analysis

Before estimating the panel model, cointegration tests were conducted to examine long-term equilibrium relationships. The Levin-Lin-Chu (LLC) test and Fisher-ADF test were employed for unit root testing. Results indicate that all variables are integrated of order one, I(1), and cointegration exists among the variables. The panel cointegration test statistics are significant at the 1% level, confirming stable long-run relationships between carbon emissions and the driving factors.

[TABLE 2]

4.2 Panel Model Estimation

4.2.1 National-Level Results The Hausman test supports the use of a fixed-effects model. Estimation results for the national sample show that all driving factors significantly affect carbon emissions:

- **Population**: A 1% increase in population raises CO emissions by 1.0469%
- **Per capita GDP**: A 1% increase in per capita GDP increases emissions by 0.9386%
- **Energy intensity**: A 1% increase in energy intensity raises emissions by 0.7226%
- **Urbanization**: A 1% increase in urbanization level increases emissions by 0.4116%
- **Industrial structure**: Shows a negative coefficient (-0.0577), indicating that a higher share of secondary industry reduces emissions, though this effect is not statistically significant

The model explains 99.04% of the variation in carbon emissions (R^2 = 0.9904), indicating excellent fit.

[TABLE 3]

4.2.2 Regional Heterogeneity Regional estimations reveal significant differences across the three economic zones:

Eastern Region (G1): Per capita GDP has the strongest effect (elasticity = 1.2), reflecting the region' s energy-intensive development pattern. Urbanization shows a positive but diminishing effect on emissions.

Central Region (G2): Energy intensity is the primary driver (elasticity = 0.85), indicating reliance on energy-heavy industries. Population growth has a moderate effect (0.92).

Western Region (G3): All factors show higher elasticities than the national average, suggesting that economic development in this region is particularly carbon-intensive. The urbanization effect is most pronounced (elasticity = 0.68).

The industrial structure coefficient is negative and significant in the eastern region (-0.12), suggesting that structural upgrading reduces emissions, while it remains positive in the central and western regions.

4.3 Robustness Checks

4.3.1 Alternative Specifications To ensure robustness, the model was re-estimated using: (1) carbon intensity as the dependent variable, (2) dynamic panel GMM estimation, and (3) different regional groupings. Results remain consistent across specifications. When using carbon intensity, per capita GDP shows a negative coefficient (-0.0304), confirming the Environmental Kuznets Curve hypothesis at the national level. The dynamic GMM estimation addresses potential endogeneity issues and yields similar coefficient estimates.

4.3.2 Urbanization-Level Grouping An alternative grouping by urbanization rate reveals that provinces with higher urbanization levels (>60%) exhibit lower emission elasticities for all drivers compared to less urbanized areas. This suggests that advanced urbanization may facilitate emission reduction through improved technology and efficiency. The threshold effect appears around 55-60% urbanization rate, beyond which the marginal emission impact of urbanization declines significantly.

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Abstract: With accelerating climate change, carbon emissions and their influencing factors are receiving increasing attention. This paper calculated CO emissions from energy consumption covering 30 provinces from 2000 to 2015, and analyzed the regional characteristics and spatiotemporal differences of carbon emissions in China. Based on the STIRPAT model and panel data approach, the driving factors of carbon emissions were analyzed from two perspectives: carbon emissions and carbon intensity. The study found that at the national level, population scale, per capita GDP, energy intensity, and urbanization level have positive driving effects, and a 1% increase in each factor will increase carbon emissions by 1.0469%, 0.9386%, 0.7226%, and 0.4116%, respectively. However, industrial structure has a negative effect on carbon emissions. For carbon intensity, per capita GDP and industrial structure have negative inhibitory effects. At the regional level, three economic regions of the East, Middle, and West of China were defined by grouping individual areas based on their economic level. Due to differences in economic development level, the effects of each factor on carbon emissions were also different and showed certain regularity. Grouping by urbanization level showed that carbon emissions decreased along with the increase of urbanization level. This study provides a reference for the government to make reasonable and differentiated policy about CO emission reduction

based on the region.

Keywords: carbon emissions; STIRPAT model; panel data; driving factors

Note: Figure translations are in progress. See original paper for figures.