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THE NONLINEAR IMPACT OF ECONOMIC GROWTH ON CARBON EMISSIONS IN CHINA'S YELLOW RIVER BASIN USING DIFFERENCE-IN-DIFFERENCES MODELS

Abstract: The present empirical investigation sets out to systematically unpack the multifaceted effects of aggregate economic expansion on anthropogenic carbon discharge across China's vast Yellow River Basin, with targeted analytical emphasis placed on unpacking the non-monotonic, curved associations between advancing economic activity levels and greenhouse gas output, as well as the underlying causal pathways that generate these complex interplays. Considering that most of the existing studies focus on the direct economic-carbon emission relationship, this paper adopts a double-difference model to analyse the mediating effect of economic growth through factors such as industrial structure, urbanisation level and regional innovation capacity. The empirical results show that there is an inverted U-shaped nonlinear relationship between economic growth and carbon emissions, with carbon emissions rising in the early stage of economic development, but gradually declining as the economy matures and the industrial structure transforms. In addition, the optimisation of industrial structure, the acceleration of urbanisation and the enhancement of regional innovation capacity play an important mediating role between economic growth and carbon emissions. The theoretical significance of this study is that it enriches the research framework of the nonlinear relationship between economic growth and environmental pollution, and the practical significance is that it provides empirical support for the formulation of differentiated carbon emission policies. The results of the study provide an important policy basis for promoting the transition to a low-carbon economy and the sustainable development of the region.

Keywords: differences-in-differences, carbon emissions, economic development, intermediary effect, Yellow River Basin

Introduction

Economic expansion can raise production and living standards while increasing energy demand and environmental pressure. This tension is especially important in the Yellow River Basin, where energy production and heavy industry remain prominent and coal continues to account for a substantial share of energy use. At the same time, the basin is undergoing industrial upgrading towards services and technology-intensive activities. Its limited water resources and ecological vulnerability make the environmental consequences of this transition particularly important. The region therefore provides a useful setting in which to examine whether the effect of economic growth on carbon

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emissions changes as development proceeds. Stretching across the heart of northern China's primary energy and heavy manufacturing zones, the Yellow River Basin exhibits an outsized reliance on conventional high-carbon fuel sources - most notably coal - an entrenched pattern that has sustained persistently elevated carbon emission intensity across the region for decades. This longstanding structural dynamic, however, exists alongside two increasingly influential concurrent trends that position the basin as an uniquely informative study site for coupled human-environment systems. First, the past decade has brought steady, incremental shifts in the region' s industrial composition, with fast-growing service sectors and advanced high-technology industries now steadily displacing legacy heavy industrial operations, while surging regional economic output has generated a rich, granular longitudinal dataset ideal for rigorous analysis of the bidirectional, evolving links between macroeconomic growth and associated environmental outcomes. Second, the entire basin carries a formal, high-priority national mandate for large-scale ecological stewardship, a governance requirement made far more complex by the region's systemic freshwater scarcity and inherently fragile ecological conditions, factors that have sharply amplified structural frictions between priorities for expanding local economic opportunity and safeguarding critical environmental health. Therefore, exploring the impact of economic development on carbon emissions in the Yellow River Basin is not only of theoretical significance, but also can provide practical guidance for realising the goal of regional sustainable development. Although a large amount of literature has studied the relationship between economic growth and carbon emissions, most of them focus on the direct correlation between the level of economic development and the total amount of emissions, ignoring the role of multivariate moderating factors. For example, traditional studies have seldom explored the specific role of mediating variables such as industrial structure, urbanisation level and regional innovation capacity in the process of economic growth affecting carbon emissions. In addition, most studies fail to pay sufficient attention to the impact of regional differences on the findings, while the policy environment, resource endowment and level of technological development in different regions may significantly affect the relationship between economic development and carbon emissions. To address these gaps, we analyse panel data for cities in the Yellow River Basin from 2011 to 2021. The empirical framework combines a difference-in-differences design with mediation models. It tests whether economic development has an inverted U-shaped relationship with carbon emissions. The analysis also examines whether industrial structure, urbanisation and regional innovation capacity transmit part of this effect. Regional comparisons are conducted to determine whether the estimated relationships vary across the basin. The findings provide evidence for designing emission-reduction policies that reflect regional conditions and different stages of economic development.

A substantial literature has examined how economic growth affects carbon emissions, but several questions remain unresolved. Much of this work estimates only the direct relationship and gives limited attention to possible transmission channels. Industrial restructuring, urbanisation and innovation may influence emissions by changing energy use and production patterns, yet these mechanisms remain insufficiently examined. Existing studies also often rely on a single empirical method and pay limited attention to regional variation. Differences in development levels, resource endowments and industrial structures may cause the effect of economic growth to vary considerably across regions. Data limitations create an additional gap. Cross-sectional datasets and short panel periods cannot

fully capture changes in the growth-emissions relationship over time. Evidence on nonlinear effects also remains fragmented, particularly for China. Further research should therefore integrate mediating mechanisms, regional heterogeneity and nonlinear dynamics within a unified empirical framework.

Literature review

In the context of the current global climate change, the issue of carbon emission has attracted extensive attention from the international community. As industrialisation and urbanisation continue to advance, regional economic activities have an increasingly significant impact on the environment, especially the contribution of increasing carbon emissions to global warming. Therefore, it has become an urgent issue to evaluate the impact of regional economic activities on carbon emissions and formulate strategies to control and mitigate carbon emissions while promoting economic growth. Based on the empirical analysis of spatial Durbin model, Li and Li [1] studied the impact of energy investment on carbon emissions. The results show that while economic growth drives energy demand growth, technological progress brought about by energy investment mitigated carbon emissions to a certain extent. However, with the continuous economic growth, there is still a significant positive correlation between energy consumption and carbon emissions. Li and Wang [2] expand on this topic further by investigating the impact of the digital economy on carbon emissions. Their city-level analysis indicates that digital-economy development can curb carbon emissions through more efficient resource allocation and energy use. Notably, in rapidly developing economies such as China, the application of digital technologies has enabled economic activities to achieve higher output with less energy consumption. Therefore, the digital economy is recognised as an important tool for promoting regional economic growth while reducing emissions. A study by Bruckner et al. [3] examined the impact of poverty reduction on carbon emissions from a global perspective. This study uses empirical data to analyse the dual impacts of poverty reduction policies on national and global carbon emissions. The findings show that while poverty reduction policies have improved people's living standards and boosted economic development, they have also increased energy demand and led to increased carbon emissions. It is worth noting that in developing countries, as income levels rise, the consumption structure shifts to energy-intensive goods and services, which intensifies carbon emission. Raihan and Tuspekova's [4] study looked at the dynamic effects of economic growth, energy use, urbanisation, agricultural productivity and forest cover on carbon emissions in Kazakhstan. Using time series data, they found that economic growth and urbanisation significantly contributed to the increase in carbon emissions, while improvements in agricultural productivity and the expansion of forest cover somewhat slowed the rate of carbon emissions growth. The study shows that there are significant differences in the impact of different economic sectors on carbon emissions. Therefore, policymakers should take into account the heterogeneity of these sectors and adopt differentiated policy measures to address carbon emissions [4]. In the study of the relationship between digital economy and carbon emissions, Yi et al. [5] provided new evidence. By analysing the context of China, the study came to similar conclusions as Li and Wang [2], showing that the development of the digital economy can help reduce carbon emissions. Specifically, digital technologies can significantly reduce carbon emissions from economic activities by improving energy efficiency, reducing energy waste,

and optimising production processes . The study therefore highlights the digital economy as a key force driving the development of a green economy, achieving carbon reduction targets while achieving economic growth.

Differential models are widely used as a powerful econometric tool to assess the impact of a policy or intervention on a specific outcome. In the field of environmental economics, DID models can be used to estimate the impact of regional economic policies on carbon emissions, and identify the real policy effects by comparing the differences before and after the implementation of policies and between the treatment group and the control group. Hong et al. [6] used a difference-in-differences model to assess the impact of carbon emissions trading on energy efficiency using a sample of 276 Chinese cities from 2003 to 2016. They found that the pilot policy significantly improved both single-factor and total-factor energy efficiency through green innovation and improved resource allocation. Ma and Xu [7] used difference-in-differences, mediation-effect and spatial difference-in-differences models to examine the impact of China's carbon emissions trading policy on carbon emissions from the power sector. Their results showed that the policy significantly reduced power-sector carbon emissions in the pilot regions, and the findings remained robust after addressing potential endogeneity. Improvements in technological capability and power-conversion efficiency partly mediated the emission-reduction effect, while optimisation of the power-generation structure represented another potential mechanism. The policy also produced a negative spatial spillover effect on power-sector carbon emissions in neighbouring non-pilot regions. The reduction effect was strongest in central China, whereas the spatial spillover effect was most pronounced in eastern China.

Recent econometric research has also highlighted important methodological considerations in DID applications. De Chaisemartin and d'Haultfoeuille [8] reviewed the performance of two-way fixed-effects estimators under heterogeneous treatment effects and showed that conventional estimators may not recover meaningful average treatment effects when policy impacts differ across groups or over time. Kahn-Lang and Lang [9] discussed the promise and potential pitfalls of DID designs, particularly the need to evaluate whether the treatment and control groups exhibit comparable trends. Roth et al. [10] synthesised recent advances in DID methodology, including issues related to heterogeneous treatment effects, staggered treatment adoption and pre-trend testing. Olden and Møen [11] examined the triple-difference estimator, which introduces an additional comparison dimension and can help distinguish policy effects across groups, regions or periods.

The Environmental Kuznets Curve (EKC) hypothesis proposes that environmental degradation may initially increase with economic development and subsequently decline after a certain turning point. However, its empirical validity varies across pollutants, regions, development stages and model specifications. Using provincial panel data from China, Fang et al. [12] examined the mechanisms influencing CO_2 emissions and provided empirical evidence of a nonlinear relationship between economic development and carbon emissions. Focusing on the Yellow River Basin, Zhang et al. [13] investigated the decoupling relationship between transport-sector economic expansion and CO_2 emissions and identified substantial spatial heterogeneity across the basin. Ma et al. [14] examined total factor carbon productivity in the nine provinces of the Yellow River Basin and found significant spatial agglomeration and regional differences. Taken together, these studies indicate that the relationship between economic development and carbon emissions is shaped by industrial structure, energy use, environmental policy and regional conditions

[12-14]. Pan et al. [15] used a difference-in-differences model to evaluate the effect of China's climate policy on carbon-emission efficiency and found that the policy significantly improved carbon-emission efficiency, although its effects varied across regions. Wang and Zhong [16] examined China's smart-city pilot policies and found that digital-economy development reduced carbon-emission intensity through industrial upgrading and technological innovation. Li et al. [17] showed that a coal-dominated energy structure increased carbon emissions, whereas digital-economy development helped mitigate emissions by promoting technological progress and optimising resource allocation. At the firm level, Chen [18] found that the digital economy reduced corporate carbon-emission intensity and identified resource allocation as an important mediating mechanism. Evidence from resource-based cities also indicates that the digital economy can reduce carbon dioxide emissions, although the magnitude of this effect varies according to regional and industrial conditions [19]. In the power sector, Huang and Lin [20] found that digital transformation contributed to decarbonisation by improving energy efficiency and facilitating the integration of renewable energy. From a regional perspective, Yang [21] identified marked spatial disparities in the coordination of carbon reduction, pollution reduction, green expansion and economic growth. Liang et al. [22] further showed that green bonds produced both local and neighbouring carbon-mitigation effects, highlighting the spatial role of green finance in low-carbon development.

The impact of regional economic activities on carbon emissions has been explored from different perspectives. Some studies focus on the role of economic growth, energy investment and digital economy, and find that technological progress of energy investment and optimisation of resource allocation in digital economy can inhibit carbon emissions while promoting economic growth, but these studies mostly focus on a single factor and lack comprehensive analysis of multiple factors [1, 2, 5, 16-20]. Other studies have analysed the impact of poverty reduction policies and economic sector heterogeneity on carbon emissions from a global or country-specific perspective, and pointed out the complex relationship between economic development and carbon emissions [3, 4]. In terms of research methods, difference-in-differences (DID) models are widely used for policy evaluation, with modern extensions accommodating multiple treatment periods and doubly robust estimation [23, 24]. But its treatment of heterogeneity, treatment effect and time trend has limitations, which may lead to estimation bias [8-10]. In general, existing studies have conducted multidimensional exploration of the relationship between regional economy and carbon emissions, but there are the following shortcomings: the research perspective is relatively homogeneous, the application of the model has limitations, and the regional heterogeneity is not paid enough attention to. In contrast, the innovation of this study is as follows: first, it comprehensively analyses the impact of economic growth, energy investment, digital economy and other factors on carbon emissions; Secondly, the improved double difference model is used to effectively solve the heterogeneity of processing effect and time trend, and improve the estimation accuracy. Finally, the differences of economic development levels and resource endowments on carbon emissions of different cities in the Yellow River Basin are discussed in depth to provide scientific basis for the formulation of differentiated carbon emission reduction policies. This study aims to provide a new perspective and method for the study of the relationship between regional economy and carbon emissions, and provide more accurate decision support for policy makers. Compared with other econometrics techniques (such as integrated control methods, panel regression, etc.), DID model has the following advantages: it can capture the dynamic effect of

policies, and is applicable to scenes of multiple treatment groups and multiple time points. It is not required that the processing group and the control group are the same, but only that the parallel trend hypothesis is satisfied [23-26]. However, the DID model also has limitations, such as strong dependence on the parallel trend hypothesis, and may be affected by unobserved heterogeneity [24, 25, 27-29]. In order to improve the reliability of the research results, this paper introduced lagging variables in the robustness test and excluded abnormal samples to minimise the interference of these potential problems on the analysis results.

Research methodology

Using a difference-in-differences framework, this study examines the nonlinear relationship between economic growth and carbon emissions in the Yellow River Basin. The analysis draws on panel data for 69 cities from 2011 to 2021 and evaluates the roles of economic activity, industrial structure, urbanisation and regional innovation capacity.

Data sources

This research involved an empirical analysis of 69 cities within the Yellow River Basin over the period from 2011 to 2021. The primary data sources were the China Urban Statistical Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, and China Environmental Statistical Yearbook. The carbon emissions for each region were computed, with the detailed circumstances outlined in Table 1.

Table 1

Descriptive statistics of each variable

Variable	Variable symbol	Mean value	ρ	Standard deviation	Min.	Max.
Economic index	$\ln de$	–1.40	–1.32	0.50	–2.74	–0.71
Square of economic index	$\ln de^2$	2.2	1.7	1.6	0.5	7.5
Total carbon emissions	$\ln ce$	7.80	7.88	0.50	6.44	8.50
Per capita carbon emissions	$\ln pca$	2.03	1.91	0.76	0.38	5.33
Energy consumption	$\ln pa$	5.15	5.24	0.59	3.30	6.38
Population density	$\ln dy$	5.5	5.6	1.1	1.6	7.2
Per capita income	$\ln pgdp$	10.61	10.60	0.55	8.77	12.46
Human capital	$\ln hp$	–0.3	–0.3	1.2	–5.1	2.6
Financial development	$\ln fe$	4.43	4.37	0.55	2.81	7.17
Foreign investment	$\ln fda$	1.0	1.2	1.6	–4.8	6.5

Variable selection

Variable selection

In the course of the study, total carbon emissions and per capita carbon emissions were selected as the dependent variables.

Total carbon emissions comprise three components. The first includes direct urban emissions from transport, buildings, industrial production, forestry, land-use change and

waste management; secondly, indirect emissions from energy sources in non-urban areas, mainly including electricity, heating, cooling, among others.

Carbon emissions: Calculate the percentage of total carbon emissions relative to the urban population. Pairwise conversion of total carbon emissions into per capita carbon emissions.

Core explanatory variables

In the investigation of how regional economic activities affect carbon emissions, the identification of key explanatory variables that align with the study's core focus is of utmost importance.

Initially, the assessment of a region's economic growth was based on using the GDP growth rate, with a focus on the correlation between economic development and carbon emissions in that area. Secondly, energy consumption intensity serves as a critical measure to evaluate the energy usage per unit of GDP within a region, and it is also a significant indicator for gauging regional energy efficiency and environmental impact. Moreover, the industrial product ratio indicates the industry's contribution to the national economy. Given the significant energy usage and carbon emissions associated with corporate production processes, this index aids in a deeper comprehension of the influence of industrial structure on carbon emissions. Finally, the R&D expenditure ratio represents the degree to which a region values innovation and new technology investment, especially investment in clean energy technologies. Research indicates that the impact of R&D on carbon emissions is substantial. Incorporating these key explanatory variables through the double-difference model allows for a more comprehensive assessment of the contribution of economic activities to carbon emissions, offering theoretical support for the development of appropriate environmental policies in China.

Control variables

Energy consumption: Expressed as total urban electricity consumption for the year. Energy consumption is a direct source of carbon emissions, and controlling for it allows for a more accurate assessment of the impact of other factors on carbon emissions.

Population density: The ratio of the total population of a city to the size of its administrative area. Higher population densities are likely to lead to increased traffic congestion and energy consumption, thus increasing carbon emissions.

Income per capita: Ratio of GDP to urban population. The level of per capita income affects the consumption structure and energy demand of residents, which in turn affects carbon emissions.

Human capital: The ratio of the number of students enrolled in general tertiary education in the city to the total population. The higher the level of human capital, the more favourable it is for technological innovation and the application of low-carbon technologies, thus reducing carbon emissions.

Financial development: The ratio of RMB loan balance of financial institutions to GDP at the end of the year. The level of financial development affects the ability of enterprises to finance and invest in technological innovation, which in turn affects carbon emissions.

Foreign investment: Actual foreign investment as a percentage of GDP. Foreign investment may bring advanced technology and management experience, but may also increase energy consumption and carbon emissions. The transmission relationship among

core explanatory variables, mediating variables and explained variables of this study is shown in Figure 1.

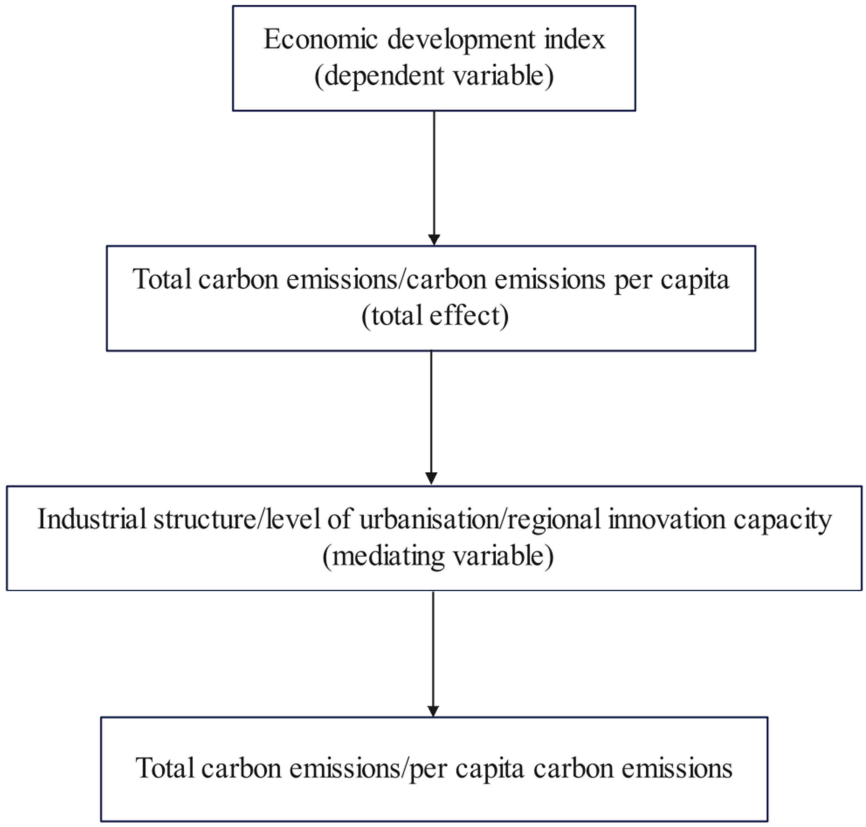


Fig. 1. Variable interpretation chart

Research hypothesis

The interplay between economic expansion and environmental health has emerged as a pivotal topic within environmental economics. Central to this discourse is the "Environmental Kuznets Curve" hypothesis, which posits that during the initial phases of economic advancement, a rise in per capita GDP might result in heightened environmental degradation. Nevertheless, as the economy continues to grow, it is anticipated that environmental quality will subsequently improve. This theory delves into the inherent connection between economic progress and carbon emissions [30].

During its nascent stages of development, the Yellow River Basin typically experiences rapid industrial and urban growth, necessitating substantial energy consumption, particularly from a fossil fuel-dominant energy mix, leading to elevated carbon emissions. Currently, China’s economic growth is largely driven by industries that are resource and pollution-intensive, resulting in significant carbon emissions. Nonetheless, the Yellow River Basin holds the potential for industrial restructuring as part of its

economic development. On the one hand, both the government and market forces are increasingly focusing on environmental conservation and sustainable development, encouraging a shift towards a more low-carbon and technologically advanced industrial structure. On the other hand, as the average national income rises, there is a growing demand for improved environmental quality, compelling government bodies and enterprises to embrace greener production and consumption practices [13, 14].

As urbanisation advances, there is a concurrent trend towards enhanced environmental quality. In China, ongoing enhancements in urban planning and infrastructure have led to a more pronounced trend in energy conservation and emission reduction. Moreover, the process of urbanisation facilitates the dissemination of knowledge and technology, thereby elevating the societal awareness of environmental protection and the level of innovation.

Economic growth may affect carbon emissions through changes in industrial structure, urbanisation and innovation capacity. Industrial upgrading is therefore an important pathway for emission reduction. As the Yellow River Basin develops, replacing pollution- and energy-intensive industries with low-carbon and circular production systems could further reduce emissions. Urbanisation not only alters living habits but also enhances energy efficiency and encourages the greening of infrastructure. In the course of urban development, both governments and businesses are increasingly focusing on establishing sustainable transport systems to lower carbon dioxide emissions.

Enhancing the capability for independent innovation is crucial for advancing China's low-carbon development trajectory. The expansion of the economy has spurred research and development, leading to the progression of novel technologies and products, which in turn aids in enhancing energy efficiency and reducing carbon emissions. Renewable energy technology advancements, for instance, can significantly decrease reliance on fossil fuels, thereby lowering carbon dioxide emissions.

When using difference-in-differences (DID) models, the parallel trend assumption is the central premise of their causal inference. This assumption requires that the outcome variables in the treatment group (policy-affected area) and the control group (policy-unaffected area) had similar trends prior to the implementation of the policy or intervention. If this assumption does not hold, then the causal inference of the model may be invalidated by differences between groups. The parallel trend assumption centres on the fact that the treatment and control groups had the same trend in carbon emission levels before the policy was implemented. In other words, in the absence of policy intervention, the changes in carbon emissions of the treatment and control groups should be parallel. In this paper, it is implicitly assumed in the model construction that the trend of carbon emissions among different cities in the Yellow River Basin is similar before the policy implementation. Regional differences in economic development, industrial composition and energy-use patterns may violate this assumption. Its validity must therefore be tested empirically.

H1: The economic development in the Yellow River Basin has an inverted U-shaped nonlinear relationship with carbon emissions, which first promotes and then suppresses.

H2: The economic development of the Yellow River Basin indirectly affects carbon emissions by influencing industrial structure, urbanisation, and innovation capacity.

H3: Before the implementation of the policy, the carbon emission trends of different cities in the Yellow River Basin were not significantly different between the treatment group

(policy-affected area) and the control group (area not affected by the policy), and the trends of carbon emission changes in the two groups were parallel.

Research models

Double difference model

This study examines how regional economic development affects urban carbon emissions. Currently, the academic community widely uses methods such as difference-in-differences (DID) and synthetic control (SCM) to evaluate the effectiveness of a certain policy. The synthetic control method is a method of weighting multiple control groups to synthesise a control group with the same trend as the treatment group for comparison. However, the synthetic control method can only evaluate one object that is subject to policy implementation and requires a large sample size, otherwise a good fitting result cannot be obtained. The double difference method can simultaneously evaluate multiple objects affected by a certain policy, and allows for inherent differences between groups.

The DID model has significant advantages in assessing the net effect of policies, dealing with differences between groups, coping with heterogeneous treatment effects, and time trends. First, the DID model can effectively assess the net effect of regional economic policies on carbon emissions, and accurately capture the impact of economic development on carbon emissions by comparing the differences between the treatment and control groups before and after the implementation of the policies, and by controlling for other potential influencing factors. Second, the DID model allows for inherent differences between groups and only requires the control group to have the same trend of change as the treatment group to obtain the treatment effect of the policy, which is consistent with this study's focus on the trend of carbon emission changes in multiple cities under different policy shocks. When its identifying assumptions hold and treatment heterogeneity is explicitly addressed, the DID framework can estimate how effects vary across cities. This approach helps assess whether development levels and resource endowments shape carbon emissions differently across the Yellow River Basin, providing evidence for region-specific reduction policies. Meanwhile, the DID model avoids the endogeneity problem to a large extent, and makes the estimation more scientific and accurate by setting a dummy variable for whether the policy occurs or not.

This study employs the difference-difference method to examine the impact of carbon emissions during the regional economic development in China. Building upon the double difference approach, the paper formulates the subsequent regression model:

$$\ln c\,e_{it} = \alpha_0 + \beta_1 \ln d\,e_{it} + \beta_1 \ln d\,e_{it}^2 + \gamma Z_{it} + \mu_t + \lambda_i + \varepsilon_{it} \quad (1)$$

$$\ln p\,ac_{it} = \alpha_0 + \beta_1 \ln d\,e_{it} + \beta_1 \ln d\,e_{it}^2 + \gamma Z_{it} + \mu_t + \lambda_i + \varepsilon_{it} \quad (2)$$

where: $\ln c\,e$and $\ln p\,ca$ represent the natural logarithm of the carbon emission intensity or per capita carbon emission intensity of region i, year t. $\ln d\,e_{it}$ is the core explanatory variable, which is the natural logarithm of the economic index of region i in year t. $\ln d\,e_{it}^2$ is the square term of the core explanatory variable, used to test whether there is a nonlinear relationship between economic indices and carbon emission intensity. Z_{it} is a series of control variables, including energy consumption, population density, per capita income, human capital, financial development, and foreign investment. μ_t represents the time fixed effect, which controls for the time trend experienced by all regions, λ_i represents the

individual fixed effect, which controls for region specific factors that do not change over time, and ε_{it} is the random error term.

Mediation effect model

Overall, economic expansion positively influences the enhancement of industrial structure, the augmentation of regional innovation capabilities, and the advancement of urbanisation. To verify the above inference, a mediation effect model was used for validation, and stepwise regression analysis was conducted.

Initially, the correlation between economic growth and carbon emissions is examined through regression analysis:

$$Y_{it} = \beta_0 + \beta_1 \ln d\, e_{it} + \beta_2 \ln d\, e_{it}^2 + \delta Z_{it} + \gamma_{1it} \tag{3}$$

where $\gamma_1$is the random error term.

Secondly, regression estimation is conducted with industrial structure, urbanisation level, and regional innovation capability as the dependent variables, and economic index as the explanatory variable:

$$Q_{it} = \pi_0 + \pi_1 \ln d\, e_{it} + \pi_2 \ln d\, e_{it}^2 + \delta Z_{it} + \gamma_{2it} \tag{4}$$

where Q_{it} represents the industrial structure, urbanisation level, and regional innovation capability of region i in year t; γ_2 is the random error term. Building upon this, carbon emissions are considered the dependent variable, with economic indicators serving as the explanatory variable. Industrial structure, urbanisation levels, and regional innovation capacity are treated as moderating variables, and regression analysis is subsequently conducted:

$$Y_{it} = \beta_0 + \beta_1 \ln d\, e_{it} + \beta_2 \ln d\, e_{it}^2 + \eta Q_{it} + \gamma_{3it} \tag{5}$$

where η is the regression coefficient of carbon emissions; γ_3 is the random error term.

This paper adopts the mediation effect model to examine how the economic development of the Yellow River Basin indirectly affects carbon emissions by influencing industrial structure, urbanisation level and regional innovation capacity. Mediation analysis examines whether an independent variable affects an outcome through an intermediate variable. The procedure involves the following steps:

(1) Test the total effect of the independent variables on the dependent variable. In this paper, the effect of economic development index (independent variable) on total carbon emissions and per capita carbon emissions (dependent variable) is tested first.
(2) Test the effect of independent variables on mediating variables. Regression analyses were conducted with industrial structure, urbanisation level and regional innovation capacity (mediating variables) as dependent variables and economic development index as independent variable respectively.
(3) To test the effect of mediating variables on dependent variables and the change of the effect of independent variables on dependent variables after adding mediating variables.
(4) Test the significance of the mediating effect. The significance of the mediating effect is further verified by Sobel test or Bootstrap method.

Results and discussion

Benchmark regression results

Table 2 presents the benchmark estimates for the Yellow River Basin. Columns (1) and (2) use total carbon emissions as the dependent variable, while columns (3) and (4) use per-capita emissions. Control variables are excluded from columns (1) and (3) but included in columns (2) and (4). Across all specifications, the coefficient on economic development is positive, whereas its squared term is negative. Both coefficients are statistically significant at the 1 % level. This suggests that both total and per capita carbon emissions in the Yellow River Basin exhibit an inverted U-shaped relationship with economic growth. This project, using the Yellow River Basin as a case study, examines the theoretical assumption that during the early stages, enterprises incur substantial resources and costs in the pursuit of digitisation and digitalisation due to technological immaturity, resulting in elevated carbon emissions. The swift advancement of digital technology has facilitated the green transformation and innovation of businesses, initially causing an increase in carbon emissions. Nonetheless, as digital technologies evolve and reach a more advanced phase, the early investments yield a net positive impact, including enhanced energy efficiency, better industrial structure, increased productivity, reduced pollution control efforts, and improved economies of scale, ultimately leading to reduced urban carbon emissions.

Table 2

Regression results of the impact of the Yellow River Basin economy on carbon emissions

Variable	(1)	(2)	(3)	(4)
	$\ln ce$		$\ln pca$	
	Control variable not added	Add control variables	Control variable not added	Add control variables
$\ln de$	0.454*** (16.921)	0.119*** (4.044)	0.436*** (16.034)	0.104*** (3.463)
$\ln de^2$	–0.104*** (–13.332)	–0.025*** (–3.339)	–0.101*** (–12.850)	–0.023** (–2.953)
$\ln pa$		0.113*** (11.661)		0.111*** (11.198)
$\ln dy$		0.318** (2.660)		–0.198 (–1.619)
$\ln pgdp$		0.142*** (6.692)		0.132*** (6.100)
$\ln hp$		0.038*** (3.661)		0.067*** (6.311)
$\ln fe$		0.065*** (5.015)		0.067*** (5.100)
$\ln fda$		–0.019* (–2.181)		–0.0160 (–1.883)
Fixed time	Yes	Yes	Yes	Yes
Individual fixed				
$cons$	8.440*** (223.360)	3.573*** (5.085)	2.640*** (68.951)	0.814 (1.135)

Note: The "*", "**", and "***" in the table indicate significant *P*-values at the 10 %, 5 %, and 1 % levels, respectively; The value in "()" is the value of *t*. Same below

Robustness test

Post-processing delays, regression analyses were conducted for each economic development indicator, with the outcomes presented in Table 3 (1) and (2). A significant correlation was identified between total carbon emissions and per capita carbon emissions in the Yellow River Basin at a 1 % significance level, displaying an inverted U-shaped curve that initially promotes and then inhibits emissions. This finding is consistent with previous studies, thereby affirming the robustness of the present study.

Table 3

Robustness test

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Lag by one period		1 % percentile bilateral tail retraction		Exclude samples from Qinghai Province	
	$\ln ce$	$\ln pca$	$\ln ce$	$\ln pca$	$\ln ce$	$\ln pca$
$\ln de$	0.080* (2.512)	0.083* (2.555)	0.112*** (3.816)	0.095** (3.112)	0.130*** (4.164)	0.108*** (3.359)
$\ln de^2$	–0.0254*** (–3.35)	–0.0229** (–2.96)	–0.0237** (–3.09)	–0.0209** (–2.67)	–0.0293*** (–3.53)	–0.0263** (–3.09)
$\ln pa$	0.111*** (10.756)	0.110*** (10.457)	0.111*** (11.430)	0.111*** (11.105)	0.096*** (9.984)	0.096*** (9.708)
$\ln dy$	0.298* (2. 118)	–0.233 (–1.624)	0.397** (2.716)	–0.257 (–1.702)	0.453** (2.991)	–0.207 (–1.330)
$\ln pgdp$	0.154*** (6.392)	0.140*** (5.699)	0.148*** (6.933)	0.144*** (6.547)	0.145*** (6.948)	0.139*** (6.499)
$\ln hp$	0.038** (3.125)	0.067*** (5.486)	0.039*** (3.521)	0.070*** (6.054)	0.055*** (4.242)	0.098*** (7.307)
$\ln fe$	0.082*** (5.879)	0.082*** (5.764)	0.079*** (5.454)	0.085*** (5.680)	0.076*** (5.284)	0.080*** (5.417)
$\ln fda$	–0.031** (–3.122)	–0.029** (–2.835)	–0.0150 (–1.773)	–0.0130 (–1.519)	–0.0120 (–1.424)	–0.0100 (–1.092)
Fixed time Individual fixed	Yes	Yes	Yes	Yes	Yes	Yes
$cons$	3.483*** (4.197)	0.875 (1.035)	3.066*** (3.706)	0.978 (1.146)	2.887*** (3.352)	0.823 (0.931)

Mediating effects and regional heterogeneity

Mediating effect

Consequently, the Yellow River Basin has been chosen as the focus of this research project. Using a mediation model, the study examines how economic growth affects carbon emissions across different parts of the basin through industrial structure, urbanisation and regional innovation capacity. The results are presented in Table 4. The research employs the ratio of tertiary and secondary industry added values to gauge industrial structure, the ratio of year-end urban to total population to indicate urbanisation levels, and assesses regional innovation capacity using the number of green invention patents and regional patent applications as proxies.

Based on the data from Tables 1 and 4, it is evident that economic growth significantly affects industrial structure and urbanisation levels, with statistical significance at the 1 % and 10 % levels, respectively. Moreover, the development of the Yellow River Basin has a significant impact on regional innovation capacity, which follows an inverted

U-shaped nonlinear pattern. At a significance level of 10 %, the industrial structure and urbanisation level of the Yellow River Basin significantly influence regional innovation capacity. By integrating industrial structure, urbanisation level, and regional innovation capacity into the model, the following conclusions emerge. Total carbon emissions are featured in columns (2), (5), and (8), with total carbon emissions and per-capita carbon emissions serving as the dependent variables, and the inverse of total carbon emissions. It is observed that even after the inclusion of intermediary variables, a nonlinear relationship persists between economic development and both total and per capita carbon emissions in the Yellow River Basin. The coefficients, both positive and negative, are reduced, suggesting that industrial structure, urbanisation level, and regional innovation capacity act as moderators. This further substantiates the validity of hypothesis 2.

Table 4

Mediation effect results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Industrial structure			Urbanisation level			Regional innovation capability		
	is	$\ln ce$	$\ln pca$	ub	$\ln ce$	$\ln pca$	iv	$\ln ce$	$\ln pca$
$\ln de$	0.374*** (5.94)	0.104*** (3.54)	0.0816** (2.75)	0.0488** (9.10)	0.0677* (2.30)	0.0520* (1.73)	0.263* (2.40)	0.129*** (4.37)	0.109** (3.63)
$\ln de^2$	–0.0758** (–4.64)	–0.022* (–2.99)	–0.0185* (–2.42)	–0.0089*** (–6.36)	–0.0163* (–2.19)	–0.0136* (–1.79)	–0.0729* (–2.55)	–0.0267*** (–3.47)	0.0232* (–2.95)
$\ln pa$		0.0780** (5.66)	0.0850** (6.08)						
$\ln dy$					1.336** (8.39)	1.259* (7.74)			
$\ln pgdp$								0.0163* (1.99)	0.0136* (1.63)
Control	control	control	control	control	control	control	control	control	control
Fixed time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$cons$	–1.123 (–0.74)	3.776** (5.44)	0.987 (1.40)	–0.661*** (–5.12)	4.572* (6.62)	1.724* (2.44)	2.426 (0.92)	3.698*** (5.24)	0.833 (1.16)

Regional heterogeneity

This study focuses on the Yellow River Basin, encompassing its upper, middle, and lower reaches, with the goal of investigating the impact of economic development on carbon emissions. Analysis of the data in Table 5 reveals that the relationship between the level of economic development, total carbon emissions, and per capita carbon emissions in the Yellow River Basin follows a nonlinear U-shaped curve. A comparison across the basin indicates that economic development has a stronger effect on total and per-capita carbon emissions in the middle and lower reaches than in the upper reach. The estimated effects are similar in the middle and lower reaches.

The middle and lower reaches of the Yellow River contain many densely populated urban areas, a larger proportion of heavy industry within their industrial structures, and higher energy consumption. Compared to the upper reaches, this region experiences greater pressure for development transformation, making in-depth research on it particularly significant. In the current developmental phase, the industrial and technological shifts

spurred by digitalisation necessitate substantial capital and energy investments by enterprises, resulting in significant carbon emissions. Consequently, it can be deduced that the initial stages of economic development in the Yellow River Basin have exerted a more substantial influence on carbon emissions in the middle and lower reaches.

Table 5

Results of regional heterogeneity analysis

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln ce$			$\ln pca$		
	Upstream	**Middle reaches**	**Downstream**	**Upstream**	**Middle reaches**	**Downstream**
$\ln de$	0.368*** (9.466)	0.626*** (10.726)	0.641*** (15.235)	0.380*** (9.521)	0.640*** (10.595)	0.501*** (12.439)
$\ln de^2$	–0.079*** (–7.967)	–0.246*** (–9.883)	–0.247*** (–13.983)	–0.081*** (–7.949)	–0.251*** (–9.702)	–0.194*** (–11.690)
$cons$	8.173*** (128.413)	8.767*** (130.143)	8.791*** (178.648)	2.712*** (41.477)	3.084*** (44.186)	2.302*** (48.911)
Control variable	control	control	control	control	control	control
Fixed time	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes	Yes	Yes

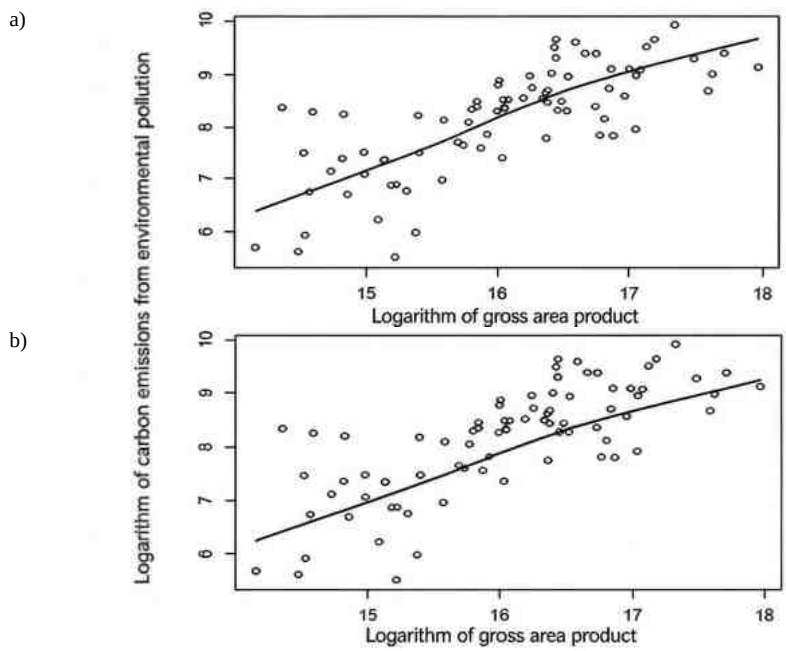


Fig. 2. Curve-fitting plots: a) total carbon emissions, b) per-capita carbon emissions versus logarithm of gross area product

As shown in Figure 2, in general, observations from regional units in close proximity tend to be similar. In the spatial analysis, the Moran index was calculated for industrial wastewater discharge and gross regional product, and a certain degree of spatial autocorrelation was found. An absolute z-score above 2.58 or a *p*-value below 0.01 provides evidence against the null hypothesis of spatial randomness at the 1 % significance level.

Discussion

By empirically analysing the panel data of 69 cities in the Yellow River Basin from 2011 to 2021, this study finds that there is a significant inverted U-shaped nonlinear relationship between economic growth and carbon emissions. Specifically, economic growth pushes up carbon emissions in the initial stage, mainly due to the expansion of traditional heavy industries and the reliance on high-carbon energy sources; however, as the economy develops further and the industrial structure is transformed, carbon emissions gradually tend to decrease. This finding supports the ”Environmental Kuznets Curve” (EKC) hypothesis, that is, the early stage of economic development is accompanied by environmental degradation, and with technological progress, industrial upgrading and environmental awareness, environmental quality is improved. In addition, the empirical analysis also reveals the mediating effects of industrial structure, urbanisation level and regional innovation capacity between economic growth and carbon emissions. Economic development indirectly contributes to the reduction of carbon emissions by optimising industrial structure, promoting urbanisation and enhancing innovation capacity.

In particular, the optimisation of industrial structure helps to reduce resource consumption and energy waste, while the advancement of urbanisation improves energy efficiency and promotes the construction of green infrastructures, and the enhancement of regional innovation capacity promotes the widespread application of low-carbon technologies. Therefore, this study shows that economic growth not only affects the environment through direct energy consumption and carbon emissions, but also acts indirectly on carbon emissions by changing industrial structure and enhancing innovation capacity. In addition, regional heterogeneity analysis further reveals that economic development in the middle and lower reaches of the Yellow River Basin contributes significantly more to carbon emissions than in the upper reaches, which is mainly related to the higher level of industrialisation, higher energy consumption, and higher reliance on carbon emissions in these regions.

Conclusion

Using panel data for 69 prefecture-level administrative units in China’s Yellow River Basin over 2011-2021, this study estimated the nonlinear effect of economic development on carbon emissions and its transmission channels. Three findings emerge. First, both total and per-capita emissions follow an inverted U-shaped path: with full controls, the coefficients on economic development and its squared term are 0.119 and –0.025 for total emissions and 0.104 and –0.023 for per-capita emissions, all significant at the 5 % level or better. The pattern survives one-period lagging of the regressors, 1 % two-sided winsorisation, and exclusion of the Qinghai subsample, and is consistent with the Environmental Kuznets Curve hypothesis. Second, industrial structure, urbanisation and regional innovation capacity act as partial transmission channels: economic development

significantly shapes each of them, and the emission coefficients attenuate once these mediators enter the model, indicating that the downward arm of the curve operates through structural upgrading and innovation rather than growth alone. Third, the effect is markedly stronger in the middle and lower reaches - densely urbanised and more heavily industrialised - than in the upper reaches, supporting spatially differentiated policy: accelerated industrial restructuring and low-carbon innovation downstream, and prevention of an emission-intensive development path upstream. The 2011-2021 window, reliance on statistical-yearbook data and the identifying assumptions of the panel design limit generalisation; longer series and alternative causal-inference strategies are natural extensions.

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