

Digital Economy as a Moderator: Examining the Impact of Economic Development on Carbon Emissions

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Abstract

Under the Paris Climate Accord, China has pledged to reduce carbon emissions by 2030 to help limit global temperature rise within 2°C. Using panel data for 2011–2019 and system GMM estimation, this study examines the Environmental Kuznets Curve (EKC) in the Chinese context and identifies both the direct and moderating effects of the digital economy. The results show that (i) the digital economy exerts a direct mitigating effect on carbon emissions, yet its interaction with GDP per capita is positive, indicating that in more digitalized regions the marginal impact of economic growth on emissions is stronger; and (ii) the relationship between GDP per capita and carbon emissions is U-shaped, with most regions situated on the rising limb, which explains the overall increase in emissions associated with GDP growth during the sample period. These findings suggest that the inverted-U EKC is not universally applicable, and that consumption upgrading and urbanization are key mechanisms driving emission dynamics. Therefore, achieving the Sustainable Development Goals requires policies tailored to development stages and regional heterogeneity. Aligning digital transformation with green growth is essential to balance economic advancement, evolving consumption, and environmental sustainability on China's path to low-carbon development.

Keywords

GDP Per Capita; Carbon Emission; U-Shaped Environment Kuznets Curve (EKC); Digital Economy; Consumption Upgrade; Urbanization Proces.

1. Introduction

China's rapid economic growth has driven a sustained rise in GDP, yet resource constraints and environmental pressures have increased in tandem, with carbon emissions remaining elevated and broadly trending upward. For example, in 2019 the manufacturing sector consumed approximately 2.586 billion tons of standard coal-about 55% of national terminal energy use-and accounted for roughly 36% of energy-related CO₂ emissions. Figure 1 depicts the spatial evolution of carbon emissions from 2000 to 2019: eastern coastal provinces and major metropolitan areas exhibit higher emission levels and faster growth, underscoring pronounced regional heterogeneity[1, 3]. As one of the world's major contributors to global emissions, China urgently needs to identify the mechanisms linking economic growth and carbon emissions in a systematic manner to support the achievement of sustainable development goals[15, 22, 25].

Furthermore, the digital economy has rapidly expanded, providing new momentum for growth. According to the China Academy of Information and Communications Technology, the digital sector reached RMB 39.2 trillion in 2020-over one third of national GDP-and its contribution to GDP rose from 27.0% in 2015 to 38.6% in 2019[27]. As digital technologies become increasingly integrated with the real economy, the digital economy has emerged as a key driver of growth model transformation and resource-allocation efficiency[6]. However, its

implications for the relationship between economic development and carbon emissions remain insufficiently articulated. Existing studies primarily emphasize the direct, emissions-mitigating effects of digital tools via efficiency gains and energy transition, while evidence on the interaction between digitalization and GDP per capita-and the associated heterogeneity across industries and regions-remains mixed[5]. Moreover, the linkage between the digitalization process and the Environmental Kuznets Curve (EKC) framework is not yet well established: in the early stages of digitalization, asymmetries between infrastructure buildout and efficiency improvements may lead to a temporary rise in emissions[8]. Consequently, it is necessary-in the Chinese context-to disentangle the digital economy's direct influence on emissions and its moderating influence on the growth-emissions relationship.

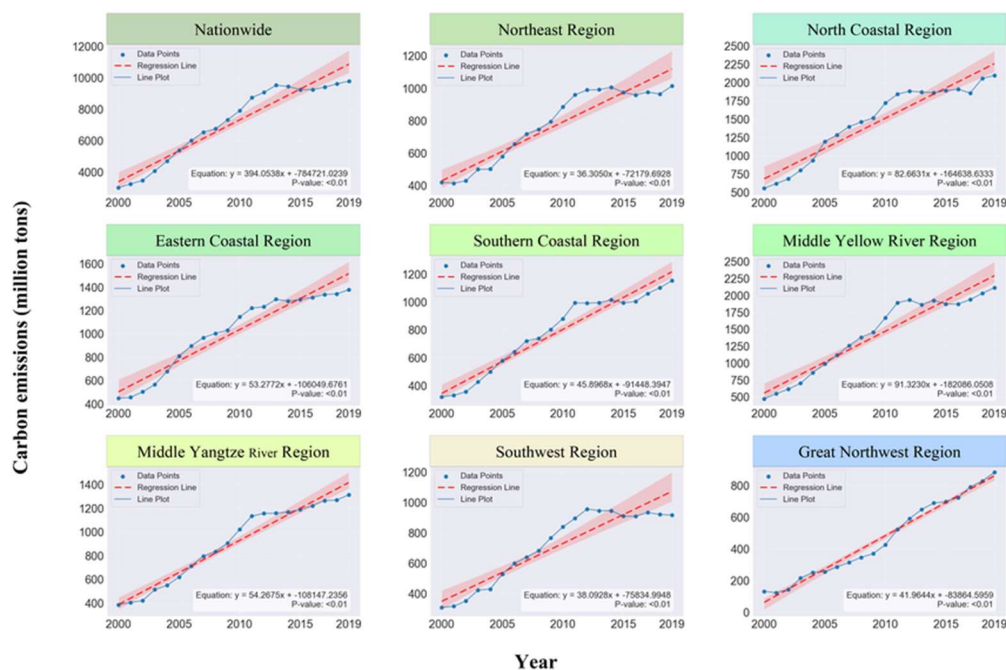


Figure 1. Spatial evolution of carbon emissions in China (2000–2019)

Using information drawn from 194 Chinese prefecture-level cities spanning 2011 to 2019, this study employs the system GMM approach to analyze the dynamic relationships among carbon emissions, GDP per capita, and the level of digital economic development, and derives policy implications accordingly. It addresses three core questions: (1) How does economic expansion affect carbon emission levels? (2) Does the digital economy moderate the relationship between China's economic development and carbon emissions, and through what mechanisms? (3) Do nonlinearities-for example, a quadratic term for digitalization-alter the way in which economic growth influences carbon emissions?

2. Literature Review

Since the 2010s, rapid global economic growth has been accompanied by mounting carbon emission pressures, with per capita GDP regarded as a major driver of emission dynamics[7, 9]. At the same time, the rise of digital technologies such as electronics, the Internet of Things, and artificial intelligence has positioned the digital economy as a critical factor influencing energy efficiency and carbon emissions. Scholars have increasingly focused on the interaction between these two dimensions, with particular attention to how economic growth contributes to rising emissions and how the digital economy, through technological innovation and industrial

upgrading, may either facilitate emission reductions or, under certain conditions, exacerbate them.

2.1. Theoretical Framework and Hypotheses

China ranks among nations with both robust economic growth and elevated carbon emissions. According to World Bank statistics, China's CO₂ emissions reached 9809.2 million tons in 2019. Zhu et al. [28] collected data from 2011 to 2019 in 278 cities in China, concluding that digitalization significantly curbed carbon emissions overall and revealed a certain degree of "decoupling" between economic growth and emissions. Similarly, Xiang et al. [26] emphasized that digitalization plays a positive role by simultaneously promoting resource optimization and innovation, though excessive GDP growth may lead to resource misallocation and weaken environmental benefits.

A considerable body of literature also employs the Environmental Kuznets Curve (EKC) framework to explain the nonlinear relationship between the economy and the environment. The classical EKC posits an inverted U-shaped relationship: pollution intensifies in the early stages of economic growth but declines once a high level of development is reached. However, findings remain inconsistent [13, 14]. Some studies find a U-shaped relationship between GDP and carbon emissions, in which middle-income countries exhibit lower emission levels, whereas both highly developed and less developed regions show higher emissions [30]. Moreover, Jobert et al. [12] noted that the EKC lacks robustness in most countries, as its validity largely depends on differences in energy efficiency and stages of development.

While the conventional Environmental Kuznets Curve (EKC) hypothesis predicts an inverted U-shape, the empirical results in this paper indicate a U-shaped relationship. This suggests that in China, emissions initially decline with rising incomes, reflecting early efficiency gains and regulatory improvements, but subsequently increase as urbanisation and consumption upgrading intensify demand for energy-intensive goods and services. Unlike the standard EKC narrative, this pattern reflects structural characteristics of China's growth trajectory, including rapid urban expansion and lifestyle transitions. Clarifying this mechanism is essential, as it highlights that the U-shaped curve is not an anomaly but a context-specific outcome of China's development path, differing from earlier inverted-U evidence.

2.2. Mechanisms of Impact

2.2.1. Industrial Structure Transformation

The digital economy promotes the transformation of industrial structures from resource-intensive to technology-driven, thereby enabling, to some extent, the decoupling of economic expansion from carbon emissions [16]. Industrial upgrading not only enhances energy utilization but also improves resource allocation efficiency. However, in the early stages of digital transformation, infrastructure development and rising energy demand may generate short-term emission pressures. To address these complexities, Liu and Saraiva [18] proposed a GMM-SAR framework suitable for handling heteroskedasticity and large-scale data, providing methodological support for examining the relationship between industrial structure and carbon emissions. Overall, scholars generally agree that the digital economy plays a positive role in promoting industrial upgrading and low-carbon transition, while also acknowledging the costs and risks associated with the initial stages of transformation.

2.2.2. Technology and Efficiency

The widespread application of digital tools such as big data and artificial intelligence has improved resource allocation efficiency and facilitated the adoption of renewable energy [23]. As GDP rises, the marginal impact of per capita GDP on carbon emissions tends to decline. However, some studies reveal a rebound effect: efficiency gains reduce costs but simultaneously stimulate consumption, thereby offsetting part of the emission reduction

benefits [24]. Moreover, policy contexts may alter the relationship between the digital economy and emissions; for instance, anti-corruption policies have been found to strengthen the positive impact of digitalization on carbon emissions. In contrast, evidence from Europe and Latin America highlights that green investment and renewable energy promotion can both support economic growth and reduce emissions [19, 20]. Taken together, these studies suggest that the effects of technological progress vary across economies and policy environments, serving either as a driver of emission reduction or as a source of new challenges.

2.3. Non-Linear Effects and Regional Disparities

Empirical analyses reveal non-linear impacts of the per capita GDP on emissions. The magnitude in reducing carbon emissions varies across regions, depending on digital maturity and local industrial characteristics. In urban centers, advanced economic development plus digital adoption shows clear benefits, whereas in less-developed areas, challenges such as infrastructure gaps and high upfront energy costs persist [17]. Furthermore, Zhu et al. [28] and Xiang et al. [26, 31] likewise held China as an example, significant regional heterogeneity in their research. Eastern and coastal regions with advanced digital infrastructure and higher green energy efficiency benefit more from emission reductions than central or western regions. Spillover effects are noted, where digital economy advancements in one region positively or negatively influence neighboring regions.

2.4. Challenges and Gaps

The convergence across these studies underscores how per capita GDP impacts regarding carbon emissions as well as the transformative potential presented by digital economic development when promoting sustainability. However, realizing its full potential requires addressing disparities in digital infrastructure, fostering innovation, and mitigating unintended consequences like increased energy consumption and regional inequalities. Future policies should therefore be tailored to local conditions, focusing on improving green energy efficiency, promoting digital inclusiveness, and maximizing emission reduction through renewable energy and differentiated strategies. While prior research has revealed a possible U-shaped relationship between China's per capita GDP and carbon emissions, a common bias persists in assuming that GDP growth necessarily leads to higher emissions. To address this, the present study incorporates multiple control variables to examine the nonlinear relationship between GDP squared and carbon emissions, thereby providing evidence for formulating context-specific sustainable development policies.

3. Hypothesis

Hypothesis 1: The higher GDP per capita will lead to a higher carbon emissions level in China.

Hypothesis 2: The most developed areas may have similarly high levels of carbon emissions as less developed areas, while moderately developed areas tend to have lower levels of carbon emissions. This could result in a U-shaped association linking GDP per person with carbon emissions in China.

Hypothesis 3: The moderating role of the digital economy involves two competing mechanisms. On one hand, digitalisation can weaken the growth–emissions link by enabling efficiency gains, smarter energy use, and dematerialisation. On the other hand, it can strengthen the link by stimulating consumption demand, expanding logistics, and increasing energy-intensive data infrastructure. In China's context, where digitalisation coincides with rapid consumption upgrading and extensive urbanisation, the reinforcing mechanism is more likely to dominate. Therefore, we hypothesise that digitalisation will amplify, rather than mitigate, the impact of economic growth on emissions.

4. Data and Methods

4.1. Data and Variable Description

The variables selected in this study cover economic development, digital economy, energy use, industrial structure, and demographic characteristics. The balanced panel dataset consists of 1746 observations from 194 prefecture-level cities in China during 2011–2019. Table 1 provides detailed definitions and corresponding data sources. Descriptive statistics are available from the authors upon request.

Table 1. Variable definitions and data sources

Variable type	Variable	Definition	Source
Dependent	Carbon Emissions (<i>CO₂lncarbon</i>)	Log of carbon emissions at prefecture-level cities	China Carbon Accounting Database
Independent	GDP Per Capita (<i>lgdp</i>)	Log of GDP per capita	China Statistical Yearbook
Moderating	Digital economy level (<i>digital_1</i>)	PCA-based composite index of digital economy	Peking Univ. Digital Inclusive Finance Index; China Communications Industry Statistical Yearbook
Control	Energy Efficiency (<i>lnee</i>)	Log of energy consumption per unit of output	China Energy Statistical Yearbook
	Energy Consumption (<i>lnec</i>)	Log of total energy consumption	China Energy Statistical Yearbook
	Technological Progress (<i>tc</i>)	Number of patent applications	China Statistical Yearbook
	Population (<i>popu_new</i>)	Total population	China Statistical Yearbook
	Regional Area (<i>area</i>)	Size of administrative area	China Administrative Division Yearbook
	Industrialized Level (<i>ids</i>)	Log of enterprises above designated size	National Bureau of Statistics
	Informatization (<i>tele</i>)	Fixed telephone users per 100 people	China Communications Industry Statistical Yearbook
	Foreign Capital Utilization (<i>fdi</i>)	FDI as a proportion of GDP	China Statistical Yearbook; Ministry of Commerce
	Environmental Infrastructure Development (<i>eid</i>)	Green area as proxy	China Urban Construction Statistical Yearbook
	Industrial Structure (<i>inds</i>)	Ratio of secondary to tertiary sector output	China Statistical Yearbook

4.2. Model Setting

4.2.1. Linear Model

This study applies a dynamic panel model estimated using the Arellano-Bond generalized method of moments (GMM) [2] to analyze the determinants of carbon emissions[10]. The dependent variable is the logarithm of CO₂ emissions (*CO₂lncarbon*), with the one-period lagged term (*l.CO₂lncarbon*), GDP per capita (*lgdpp*), and digital economy index (*digital_1*) as the core explanatory variables, alongside the control variables discussed above. To address endogeneity,

higher-order lags of carbon emissions serve as instruments. The error term excludes omitted time- or individual-specific factors to ensure instrument validity. The model assumes weak exogeneity of explanatory variables, no second-order autocorrelation, and valid moment conditions, consistent with the Arellano-Bond framework. The specific model form is:

$$CO_2 \ln carbon_{i,t} = \beta_0 CO_2 \ln carbon_{i,t-1} + \beta_1 \ln gdpp_{i,t} + \beta_2 digital_{i,t} + \beta' Control_{i,t} + u_{it} \quad (1)$$

4.2.2. Nonlinear Models

1) Quadratic Extension

Following Aiken and West [1] and the GMM estimation approach [2], we extend the linear model by adding the squared term of GDP per capita to test for a potential U-shaped relationship between GDP and carbon emissions, and to identify the turning point if confirmed. Model 2 form is:

$$CO_2 \ln carbon_{i,t} = \beta_0 CO_2 \ln carbon_{i,t-1} + \beta_1 \ln gdpp_{i,t} + \beta_2 (\ln gdpp_{i,t})^2 + \beta_3 digital_{i,t} + \beta' Control_{i,t} + u_{it} \quad (2)$$

2) Moderating and Marginal Effects

According to the model of Cao et al. [4] and the GMM estimation [2], we introduce an interaction term between GDP per capita and the digital economy to assess how digitalization moderates the GDP–emissions nexus. The marginal effects of GDP at different levels of digitalization (minimum, mean, and maximum) are calculated following Bahri et al. [3]. Model 3 form is:

$$CO_2 \ln carbon_{i,t} = \beta_0 CO_2 \ln carbon_{i,t-1} + \beta_1 \ln gdpp_{i,t} + \beta_2 digital_{i,t} + \beta' Control_{i,t} + \beta_3 (\ln gdpp_{i,t} \times digital_{i,t}) + u_{it} \quad (3)$$

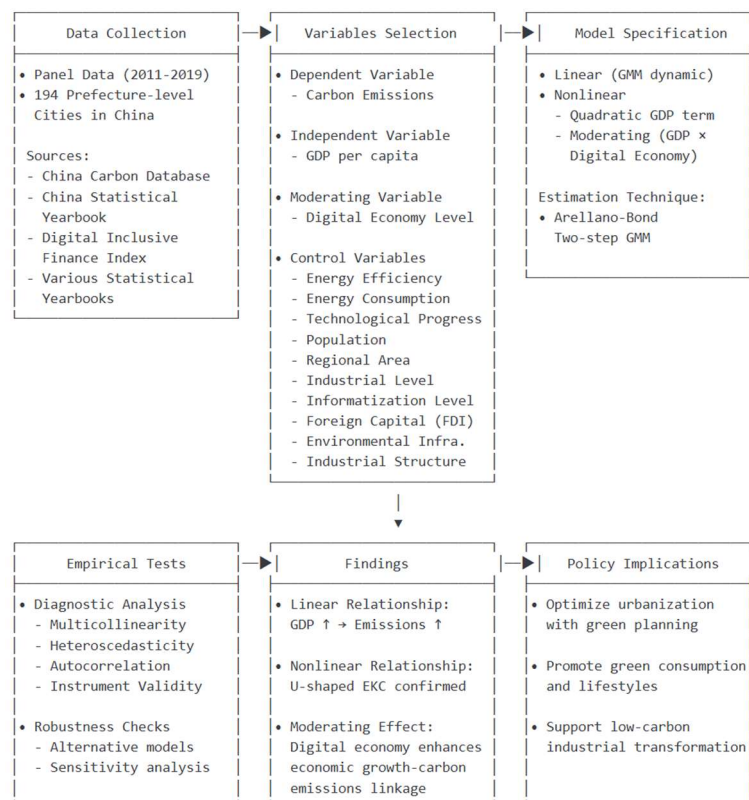


Figure 2. Methodological framework of this study

Figure 2 illustrates the methodological framework, outlining the process from data collection to estimation and highlighting the linear, nonlinear, and moderating analyses.

5. Results and Discussion

5.1. The Linear Model

5.1.1. Descriptive Statistics and Diagnostic Tests

Firstly, the model is analyzed by descriptive data, and Table 2 below is obtained. Robustness checks indicate no multicollinearity ($VIF < 10$) and no significant heteroskedasticity (White and IM tests); detailed statistics appear in the Appendix.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
CO ₂ lncarbon.	1,746	3.405	0.895	0.496	6.126
L1.	1,336	3.450	0.884	0.566	6.078
lgdp	1,746	10.791	0.571	8.842	13.056
digital_1	1,746	0.589	0.051	0.508	0.903
inds	1,746	1.296	0.623	0.193	8.802
area	1,746	9.328	0.792	7.015	12.474
ids	1,746	6.866	1.005	3.296	9.309
fdi	1,746	0.298	0.273	0	1.876
tele	1,746	16.957	7.744	1.045	67.508
eic	1,746	13.860	4.747	2.4	75.05
lnec	1,746	4.855	1.181	0.432	8.311
popu_new	1,746	49.043	34.431	1.95	341.6
lntc	1,746	8.469	1.647	1.386	12.474

5.1.2. Estimation Results

Next, we run the model and get the following results:

Table 3. GMM Regression Results

Variable	Coef.	Std. Err.	z	P> z
L1.	0.365	0.328	1.12	0.265
lgdpp	0.729**	0.301	2.42	0.015
digital_1	-3.518	3.858	-0.91	0.362
inds	0.084	0.121	0.70	0.485
area	0.976***	0.371	2.63	0.008
ids	-0.071	0.320	-0.22	0.828
fdi	-0.072	0.331	-0.22	0.828
tele	-0.056	0.336	-0.17	0.868
eic	-0.016	0.026	-0.61	0.539
lnec	0.026	0.024	1.02	0.307
popu_new	-0.009	0.007	-1.39	0.164
lntc	-0.228*	0.118	-1.93	0.054
cons	-13.784***	4.120	-3.35	0.001
AR(1)	z = -3.00 (p = 0.003)			
AR(2)	z = 2.95 (p = 0.003)			
Sargan test	$\chi^2(15) = 27.83$ (p = 0.023)			
Difference-in-Sargan test	$\chi^2(9) = 14.24$ (p = 0.114); $\chi^2(6) = 13.59$ (p = 0.035)			

Table 3 reports the dynamic panel estimation results using one-step system GMM. Per capita GDP significantly raises emissions (coef. = 0.729, $p < 0.05$), highlighting the environmental cost of growth. The digital economy is negative but insignificant (coef. = -3.518), indicating unrealized mitigation potential. The Arellano–Bond test shows expected AR(1) correlation but also significant AR(2) ($p = 0.003$), suggesting possible issues with instrument specification. The Sargan test ($p = 0.023$) indicates potential overidentification, while the difference-in-Sargan test ($p = 0.114$; $p = 0.035$) provides partial support for instrument exogeneity. Overall, the model offers economic interpretability, though instrument number and selection may affect robustness and require further refinement.

5.2. The Nonlinear Model

5.2.1. Result of Quadratic Extension

Model 2 introduces the quadratic term (*lgdp_square*) to capture a potential U-shaped linkage between the explanatory and outcome variables. Pre-estimation diagnostics (White and IM tests) suggest no major heteroscedasticity or skewness, with only mild kurtosis issues. Overall, the error distribution is acceptable for estimation.

Table 4. GMM Regression Results

Variable	Coef.	Std. Err.	z	P> z
L1.	0.962***	0.005	183.81	0.000
lgdpp	-1.394***	0.192	-7.26	0.000
lgdpp_square	0.066***	0.009	7.43	0.000
digital_1	-0.672***	0.100	-6.72	0.000
inds	-0.020***	0.005	-3.88	0.000
area	0.032***	0.006	5.75	0.000
ids	-0.017**	0.008	-2.29	0.022
fdi	-0.011	0.009	-1.17	0.190
tele	-0.006	0.006	-0.97	0.331
eic	-0.000	0.000	-0.90	0.369
lnec	0.022***	0.005	5.02	0.000
popu_new	-0.001	0.002	-0.73	0.455
lntc	-0.012***	0.003	-3.55	0.000
cons	7.553***	1.078	7.01	0.000
AR(1)	z = -4.84 Pr > z = 0.000			
AR(2)	z = 1.51 Pr > z = 0.131			
Sargan test	chi2(164) = 221.85 Prob > chi2 = 0.002			
Hansen test	chi2(164) = 177.08 Prob > chi2 = 0.230			

Note: Difference-in-Hansen tests generally support instrument exogeneity.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The above Table 4 shows the results of the system GMM estimation model and related diagnostic tests. The coefficient of GDP per capita becomes negative ($\beta = -1.394$, $p < 0.01$), while the quadratic term is positive ($\beta = 0.066$, $p < 0.01$). This finding implies a U-shaped pattern: carbon emissions first decrease as GDP per capita grows, but begin to climb again once a threshold of economic development (GDP per capita = 43,914 yuan) is crossed. This result also supports hypothesis 2. The level of digital economy consistently exhibits a negative correlation with carbon emissions ($\beta = -0.672$, $p < 0.01$), strengthening its role in emission mitigation. In terms of diagnostic tests, The Arellano–Bond tests confirm significant AR(1) but no AR(2) ($p =$

0.131), satisfying system GMM requirements. The Sargan test ($p = 0.002$) suggests possible overidentification, whereas the Hansen test ($p = 0.230$) supports instrument validity. Difference-in-Hansen results largely confirm the exogeneity of lagged instruments. Overall, the estimates are credible, though potential instrument proliferation may affect robustness. Model findings are generally credible, but the excessive use of instrumental variables may bring certain uncertainties to the interpretation of the results.

5.2.2. Results of Moderating and Marginal Effects

The Table 5 shows the dynamic panel estimation results and diagnostic tests based on the two-stage system GMM estimation. The estimation results indicate that the interaction term between GDP per capita and the digital economy is positive and highly significant ($\beta = 0.395$, $p < 0.01$), lending support to Hypothesis 3. This suggests that as digitalization advances, the reinforcing effect of economic growth on carbon emissions becomes stronger. The marginal effect analysis further confirms this pattern: the impact of GDP on emissions rises steadily across different levels of digital economy development, from $\beta = 0.379$ ($p < 0.01$) at the minimum level, to $\beta = 0.436$ ($p < 0.01$) at the mean, and to $\beta = 0.650$ ($p < 0.01$) at the maximum. These results imply that higher levels of digital economy, while potentially improving efficiency, also intensify the emission-increasing effect of economic growth. The diagnostics indicate that AR(1) is significant while AR(2) is not, supporting instrument validity. Hansen and difference-Hansen tests confirm instrument exogeneity, though the Sargan test suggests potential overidentification. Overall, the estimates are credible, but caution is warranted regarding instrument proliferation.

Table 5. GMM Regression Results

Variable	Coef.	Std. Err.	z	P> z
L1.	0.968***	0.005	188.98	0.000
lgdpp	0.040***	0.009	4.02	0.000
digital_1	-0.783***	0.136	-5.75	0.000
d_lgdppdig	-0.395***	0.092	-4.31	0.000
inds	-0.014***	0.005	-2.81	0.005
area	0.036***	0.006	6.50	0.000
ids	-0.021***	0.005	-3.89	0.000
fdi	-0.012	0.008	-1.57	0.117
tele	-0.006	0.006	-0.96	0.337
eic	-0.000	0.000	-0.93	0.351
lnec	0.016***	0.005	3.37	0.001
popu_new	0.000	0.002	0.21	0.833
lntc	0.015***	0.004	3.84	0.000
cons	-0.196*	0.116	-1.69	0.092
AR(1)	z = -4.84 Pr > z = 0.000			
AR(2)	z = 1.54 Pr > z = 0.124			
Sargan test	chi2(164) = 223.61 Prob > chi2 = 0.001			
Hansen test	chi2(164) = 183.08 Prob > chi2 = 0.146			
Diff-Hansen	largely confirms instrument exogeneity			

6. Conclusion and Policy Implications

As China's economy has grown rapidly, its global GDP status has strengthened. Yet, escalating resource consumption and environmental issues-especially the surge in carbon emissions-have become global concerns. On this basis, this article applies panel data from 194 Chinese

prefecture-level cities (2011–2019), constructing a GMM framework to empirically examine how GDP per capita, the digital economy, and carbon emissions interact over time, and draws the following conclusions: The analysis confirms a U-shaped relationship between GDP per capita and carbon emissions, consistent with China's dual-stage development trajectory: initial efficiency gains reduce emissions, but subsequent urbanisation and consumption upgrading drive them upward. While consumption and urbanisation variables were not directly modelled here, they provide a theoretically grounded explanation for the observed U-shape and should be incorporated in future research. These complexities may stem from consumption upgrades and urbanization, which increase the demand for energy-intensive products and services, while urbanization further amplifies energy use intensity and carbon emissions [8]. Especially in the middle and high income stage, the impact of the change of residents' lifestyle on the environment cannot be ignored. In addition, the degree of the digital economy's moderating effect has strengthened: where digitalization is more advanced, economic growth exerts a greater influence on emissions. Therefore, future digital transformation must align more closely with environmental priorities via supportive policies and technological advances. Future studies can further explore the influence of other potential variables (such as cultural factors, international trade) regarding how economic expansion influences environmental outcomes.

6.1. Optimize Urbanization Process and Promote Green City Planning

The technology upgrading and rationalization brought about by the stage of urbanization can improve more efficient use of resources; however, as urbanization intensifies, energy costs tend to rise [21]. Accordingly, advocating for compact city development in urban growth is essential, reduce resource waste through efficient land use, prioritize the construction of green buildings, and implement renewable energy supply systems such as solar and geothermal heating. Meanwhile, it is necessary to optimize the urban public transport system, and to expand the coverage of subways and electric buses, and bike-sharing and pedestrian-friendly urban design should be promoted to reduce the use of private cars.

6.2. Promote Green Consumption Patterns and Enhance Citizen's Environmental Consciousness

Due to the large amount of carbon emissions from urbanization, this is considered to be a major factor leading to serious climate change problems. In order to solve this problem, various low-carbon green development plans have been launched at the global city level [11]. Promote the upgrading of green consumption patterns by imposing taxes on energy-intensive goods such as luxury goods or disposable products to curb demand for products with high carbon emissions and promote shifting consumer patterns toward low-carbon lifestyles. At the same time, energy-saving and environmentally friendly products, such as eco-friendly vehicles and energy-efficient appliances can be incentivized through subsidies or tax breaks to motivate the adoption of low-carbon products. Additionally, strengthening green certification and labeling systems can assist consumers in identifying sustainable products more effectively.

6.3. Support the Transformation of Industrial Structure and Promote the Development of Low-carbon Industries

Because of the large area of China, the industrial structure and technology are very different from each other. It is important to explore the long-term structural drivers to achieve carbon reduction. According to Roberts and Grimes [32], economic development level is the major determining factor of carbon emissions. If so, it is expected that the continuous transformation of Chinese industrial structure will be a structural factor influencing carbon emissions [29]. In the context of consumption upgrading, we will use the economies of scale brought by urbanization to promote development of services and the digital economy should be advanced,

supporting broader digital technology use in sectors such as retail and logistics, thereby boosting resource use efficiency. At the same time, we will encourage traditional high-polluting encourage high-polluting industries to upgrade into cleaner, value-added sectors, and to step up support to R&D and use of clean energy, energy saving and energy efficient materials.

References

- [1] Aiken, L. S., & West, S. G. (1991). *Multiple Regression: Testing and Interpreting Interactions*. Sage Publications. <https://us.sagepub.com/en-us/nam/multiple-regression/book3045>
- [2] Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58(2), 277–297. <https://doi.org/10.2307/2297968>
- [3] Bahri, E. N. A., Nor, A. H. S. M., Nor, N. H. H. M., & Sarmidi, T. (2017). Foreign direct investment, financial development and economic growth: A panel data analysis. *Jurnal Pengurusan*, 51(1), 11–24. <https://doi.org/10.17576/pengurusan-2018-51-02>
- [4] Cao, L., Wang, Y., Yu, J., Zhang, Y., & Yin, X. (2024). The impact of digital economy on low-carbon transition: What is the role of human capital? *Finance Research Letters*, 69, 106246. <https://doi.org/10.1016/j.frl.2024.106246>
- [5] Chen, J., Li, W., Liu, Y., & Wu, B. (2024). Digital economy, transformation of factor effects, and urban carbon emissions: A test based on regulatory and threshold effects. *Journal of Beijing Jiaotong University (Social Sciences Edition)*, 23(2), 137–151.
- [6] Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., & Pan, Y. (2022). How does digital economy affect carbon emissions? Evidence from global 60 countries. *Science of The Total Environment*, 852, 158401. <https://doi.org/10.1016/j.scitotenv.2022.158401>
- [7] Fan, Y., & Wang, W. (2011). An empirical study on the driving effect of China's economic growth on carbon emission. *Journal of Guizhou University of Finance and Economics*, (03), 7–13.
- [8] Fang, C., Liu, H., & Wang, S. (2021). The coupling curve between urbanization and the eco-environment: China's urban agglomeration as a case study. *Ecological Indicators*, 130, 108107. <https://doi.org/10.1016/j.ecolind.2021.108107>
- [9] Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement. *NBER Working Paper Series*, No. 3914. <https://doi.org/10.3386/w3914>
- [10] Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029–1054. <https://doi.org/10.2307/1912775>
- [11] Huang, Z., Fan, H., & Shen, L. (2019). Case-based reasoning for selection of the best practices in low-carbon city development. *Frontiers of Engineering Management*, 6(3), 416–432.
- [12] Jobert, T., Karanfil, F., & Tykhonenko, A. (2012). Environmental Kuznets Curve for carbon dioxide emissions: Lack of robustness to heterogeneity? Working Paper.
- [13] Jobert, T., & Lanoie, P. (2012). Does the Environmental Kuznets Curve really exist? *Environmental Economics and Policy Studies*, 14(3), 141–157. <https://doi.org/10.1007/s10018-012-0035-6>
- [14] Kirikkaleli, D., & Kalmaz, D. B. (2020). Testing the moderating role of urbanization on the environmental Kuznets curve: Empirical evidence from an emerging market. *Environmental Science and Pollution Research*, 27(30), 38169–38180. <https://doi.org/10.1007/s11356-020-09831-1>
- [15] Kon, Y. Q., Chin, M. Y., & Ong, S. L. (2023). The threshold level of economic growth in BRI and non-BRI developing countries for better environmental quality. *Institutions and Economies*, 1–25.
- [16] Li, Z., & Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: Evidence from city-level empirical data in China. *Journal of Cleaner Production*, 351, 131570. <https://doi.org/10.1016/j.jclepro.2022.131570>
- [17] Li, Z. (2023, August). The Impact of Digital Economy Development on Carbon Emissions: A Multi-dimensional Study Based on Threshold Effect. In *Proceedings of the 2nd International Academic Conference on Blockchain, Information Technology and Smart Finance (ICBIS 2023)* (pp. 1229–

- 1243). Atlantis Press. <https://www.atlantis-press.com/proceedings/icbis-23/125989746atlantis-press.com>
- [18] Liu, X., & Saraiva, P. (2019). GMM estimation of spatial autoregressive models in a system of simultaneous equations with heteroskedasticity. *Econometric Reviews*, 38(4), 359–385. <https://doi.org/10.1080/07474938.2017.1308087>
- [19] Lyeonov, S., Pimonenko, T., Bilan, Y., Štreimikienė, D., & Mentel, G. (2019). Assessment of green investments' impact on sustainable development: Linking gross domestic product per capita, greenhouse gas emissions and renewable energy. *Energies*, 12(20), 3891. <https://doi.org/10.3390/en12203891>
- [20] Patiño, L. I., Padilla, E., Alcántara, V., & Raymond, J. L. (2020). The relationship of energy and CO₂ emissions with GDP per capita in Colombia. *Atmosphere*, 11(8), 778. <https://doi.org/10.3390/atmos11080778>
- [21] Tang, Y., Zhu, H., & Yang, J. (2022). The asymmetric effects of economic growth, urbanization and deindustrialization on carbon emissions: Evidence from China. *Energy Reports*, 8, 513–521. <https://doi.org/10.1016/j.egy.2022.05.076>
- [22] Wang, H., Lu, X., Deng, Y., Sun, Y., Nielsen, C. P., Liu, Y., ... & McElroy, M. B. (2019). China's CO₂ peak before 2030 implied from characteristics and growth of cities. *Nature Sustainability*, 2(8), 748–754. <https://doi.org/10.1038/s41893-019-0339-6>
- [23] Wang, Q., & Li, L. (2021). The effects of population aging, life expectancy, unemployment rate, population density, per capita GDP, urbanization on per capita carbon emissions. *Sustainable Production and Consumption*, 28, 760–774. <https://doi.org/10.1016/j.spc.2021.06.029>
- [24] Wang, Q., Sun, J., Pata, U. K., Li, R., & Kartal, M. T. (2024). Digital economy and carbon dioxide emissions: Examining the role of threshold variables. *Geoscience Frontiers*, 15(3), 101644. <https://doi.org/10.1016/j.gsf.2023.101644>
- [25] World Commission on Environment and Development (WCED). (1987). *Our Common Future*. Oxford University Press. <https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf>
- [26] Xiang, X., Yang, G., & Sun, H. (2022). The impact of the digital economy on low-carbon, inclusive growth: Promoting or restraining. *Sustainability*, 14(12), 7187. <https://doi.org/10.3390/su14127187>
- [27] Yi, M., Liu, Y., Sheng, M. S., & Wen, L. (2022). Effects of digital economy on carbon emission reduction: New evidence¹ from China. *Energy Policy*, 171, 113271. <https://doi.org/10.1016/j.enpol.2022.113271>
- [28] Yu, Z., Liu, S., & Zhu, Z. (2022). Has the digital economy reduced carbon emissions? Analysis based on panel data of 278 cities in China. *International Journal of Environmental Research and Public Health*, 19(18), 11814. <https://doi.org/10.3390/ijerph191811814>
- [29] Zhou, X., Zhang, J., & Li, J. (2013). Industrial structural transformation and carbon dioxide emissions in China. *Energy Policy*, 57, 43–51. <https://doi.org/10.1016/j.enpol.2012.09.025>
- [30] Zhong, K., Fu, H., & Li, T. (2022). Can the digital economy facilitate carbon emissions decoupling? An empirical study based on provincial data in China. *International Journal of Environmental Research and Public Health*, 19(11), 6800. <https://doi.org/10.3390/ijerph19116800>
- [31] Zhu, Z., Liu, B., Yu, Z., & Cao, J. (2022). Effects of the digital economy on carbon emissions: Evidence from China. *International Journal of Environmental Research and Public Health*, 19(15), 9450. <https://doi.org/10.3390/ijerph19159450>
- [32] Roberts, J. T., & Grimes, P. E. (1997). Carbon intensity and economic development 1962–1991: A brief exploration of the environmental Kuznets curve. *World Development*, 25(2), 191–198.