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Yixin Wang , Shu-Kam Lee , Kai-Yin Woo *

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The Digital Economy and Carbon Emissions in China: A Moderated EKC Analysis Incorporating Green Finance, Local Fiscal Pressure, and Climate Policy Uncertainty

Yixin Wang, Shu-Kam Lee and Kai-Yin Woo *

Hong Kong Shue Yan University, Hong Kong, China
* Correspondence: kywoo@hksyu.edu

Abstract

The digital economy, while a pivotal engine for growth, presents a dual challenge in the context of climate goals. Utilizing panel data from 267 Chinese cities covering the period from 2011 to 2022, this study investigates the nonlinear relationship between the digital economy and carbon dioxide emissions, testing its conformity with the Environmental Kuznets Curve (EKC) hypothesis. Moving beyond a static verification, this research introduces a dynamic framework by examining how three exogenous shock variables—green finance, local government fiscal pressure, and climate policy uncertainty—reshape the EKC curve. Specifically, construct an extended EKC model with interaction terms to empirically assess how these exogenous shock variables shift the inflection point horizontally and vertically and alter the curve's slope. Our findings reveal that these factors significantly influence both the timing and peak level of emissions, as well as the efficiency of decarbonization before and after the turning point. This study provides a nuanced understanding of the digital economy's environmental impact, offering policymakers critical insights to navigate the green transition in the digital era.

Keywords: digital economy; carbon emission; environmental Kuznets curve; inflection point; fixed effect; China

JEL code: O10, O44, Q50

1. Introduction

For decades, China's rapid economic growth was propelled by large-scale industrial investment, export-oriented manufacturing and urban real-estate expansion [1]. Yet demographic headwinds, diminishing marginal returns to capital, and a sluggish global recovery have sharply curtailed the expansionary power of these engines. To sustain further economic development and strengthen China's global competitiveness, the country must pivot to an entirely new track—one that transcends the exhausted dividends of the old growth model. That new track is the digital economy.

The digital economy, a new economic form that uses digitalized knowledge and information as key production factors, modern information networks as carriers, and digital technology-driven innovation [2], is profoundly reshaping the global economic landscape. Through the dual pathways of "digital industrialization" and "industrial digitalization" [3], it promotes industrial structure optimization and total factor productivity growth, fosters regional coordination and corporate innovation, while providing consumers with more convenient and personalized experiences. Globally, major economies such as the United States, the European Union, and Japan have incorporated the digital economy into their national strategies, introducing multiple policies to drive

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its development. In China, the scale of the digital economy reached 53.9 trillion yuan in 2023, accounting for 42.8% of GDP1, making it a vital engine for high-quality economic development [4]. Developing the digital economy has become a global consensus, with countries actively exploring development paths suited to their national conditions to seize opportunities and competitive advantages in the era of the digital economy.

Faced with the acute conflict between ecological preservation and economic growth, China is grappling with severe multidimensional environmental pressures, particularly air pollution—in 2023, 136 cities failed to meet national air quality standards, with 31% exceeding PM2.5 limits2. High-concentration pollution events are closely linked to carbon dioxide emissions, which not only intensify climate change but also increase environmental governance and industrial transition costs. To address this, China has set dual-carbon goals and established a national carbon emissions trading market, while promoting low-carbon city pilots to drive emission reductions through market mechanisms and comprehensive urban governance. However, the root cause of high emissions lies in a traditional growth model reliant on fossil fuels, which also exacerbates energy security risks. Therefore, shifting away from this model is imperative, and the green, innovation-driven digital economy has emerged as a key pathway to break the impasse and achieve deep emission reductions alongside high-quality development.

Based on the above context, this study utilizes data from 267 Chinese cities from 2011 to 2022 to investigate the relationship between the digital economy and carbon emissions from the perspective of the Environmental Kuznets Curve (EKC). Furthermore, it incorporates the exogenous shock variables of green finance, local government fiscal pressure, and climate policy uncertainty into the analytical framework, examining their impact on the inflection point position and the slope of the curve. Compared to existing research, this study offers several contributions:

First, this study verifies the inverted U-shaped relationship between the digital economy and per capita carbon emissions from the perspective of the Environmental Kuznets Curve, enriching the connotation of EKC theory in the digital era and delving into the relationship between the digital economy and carbon emissions. This provides insights for China’s pursuit of high-quality economic development and a green, low-carbon transition. Second, this paper innovatively introduces three exogenous shock variables: local government fiscal pressure, green finance, and climate policy uncertainty, revealing their moderating effects on the inverted U-shaped relationship between the digital economy and carbon emissions. Third, this research examines how these three exogenous shock variables influence the position of the inflection point and the slope of the inverted U-shaped curve between the digital economy and carbon emissions, offering new perspectives on the dynamic evolution of the traditional EKC theory.

The remainder of this paper is structured as follows. Section 2 presents theoretical analysis and research hypotheses. Section 3 describes the research methodology, including the empirical model, variable definitions, and descriptive statistics. Section 4 reports empirical results, covering baseline regression findings, moderating effect analysis, heterogeneity tests, robustness, and endogeneity testing. Finally, Section 5 concludes by summarizing the main findings, proposing policy implications, and discussing the study’s limitations.

2. Literature Review

As society’s attention to environmental protection grows increasingly, the environmental benefits of the digital economy—especially its connection with carbon emissions—are attracting more and more people’s attention. However, the relationship between the digital economy and carbon emissions is not simply clear-cut; instead, it presents complex and controversial characteristics.

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[1] The data are all sourced from the “China Digital Economy Development Research Report” and the “China Digital Economy Development White Paper”, both published by the China Academy of Information and Communications Technology.

[2] China Ecological Environment Status Bulletin 2024

Most researchers hold the view that the digital economy is capable of cutting down carbon emissions in an effective manner [5–8]. First off, the growth of the digital economy has enhanced the way governments carry out environmental supervision. With big data, cloud computing, and other technologies, the government can collect and analyze environmental data in real time to achieve dynamic monitoring of changes in carbon dioxide emissions, which improves regulatory efficiency while enhancing the ability to accurately locate and track the source of carbon emissions, making environmental regulation more timely and effective [9]. Second, the digital economy acts as a dual catalyst: it diffuses advanced digital technologies into traditional industries, steering them toward intelligent, automated, and information-rich operations that raise resource- and energy-efficiency while curbing waste and carbon emissions [10–12]; concurrently, it can cultivate and develop emerging industries, such as artificial intelligence and new energy vehicles, which are themselves characterized by low carbon and environmental protection. Third, the spread of digital media makes the exchange of information more convenient, which is conducive to accelerating the dissemination of environmental protection concepts and environmental information, enhancing the public's awareness of environmental protection, and helping to strengthen the communication between the public and the government, facilitating the public's supervision of the environment [13]. Moreover, digital finance is lowering the cost and entry barriers of financial services while sharpening the efficiency of conventional banking, channeling capital toward the modernization of legacy industries and accelerating green-finance innovation—both of which translate into measurable cuts in carbon emissions [14].

Yet, a counterview argues that the digital economy may aggravate carbon emissions [15,16]. Evidence shows that, in many developing nations, limited capacity to absorb new technologies and inadequate adoption of green technologies prevent digitization from lowering CO_2 emissions at all [17]. Danish et al. (2018) illustrate with N-11 data that ICT expansion raises carbon output due to energy-inefficient hardware, high power demand, material consumption, and mounting e-waste, thereby degrading environmental quality [18]. Similarly, Lee et al. (2014) show for ASEAN nations that ICT growth boosts GDP yet simultaneously drives up CO_2 emissions [19]. Evidence further shows that, even in developed economies, the digital economy may also undermine environmental goals. Park et al. (2018), analyzing European data, reveal that rising internet penetration drives up carbon emissions by boosting electricity demand [20]. Raheem et al. (2019) corroborate this finding with G7 evidence, demonstrating that expanded internet use heightens CO_2 output [21]. Focusing on China, Zhang et al. (2022) employ provincial panel data and find that the digital economy raises carbon dioxide emissions [22]. First, the build-out of digital infrastructure boosts resource consumption and thereby CO_2 emissions [23]. Second, because China's digital economy is still in its infancy—marked by immature technologies, unclear transformation strategies, and low sectoral digital penetration—the resulting environmental gains remain limited [24].

Therefore, the relationship between the digital economy and carbon emissions may not be a simple linear relationship but shows an inverted U-shaped nonlinear relationship. That is, with the continuous development of the digital economy, carbon dioxide emissions may exhibit a trend of an inverted U-shaped curve, rising first and then falling [25,26].

3. Theoretical Analysis and Hypothesis

3.1. Environmental Kuznets Curve: The Inverted U-Shape Relationship Between the Digital Economy and Carbon Dioxide Emission

The environmental Kuznets curve is a classic model that is often referred to as an inverted U-shaped relationship between environmental pollution and economic growth [27,28]. When a country's level of economic development is low, the level of environmental pollution is also low. However, as per capita income increases, there is a tendency for environmental pollution to gradually increase. When per capita income increases to a certain level, with the further increase of per capita income, the trend of environmental pollution gradually decreases, and the quality of the environment gradually improves [25].

Given that the digital economy is now a well-established engine of growth, this study investigates whether it follows the Environmental Kuznets Curve (EKC) hypothesis, like per capita GDP, that is, as the digital economy develops, carbon emissions will first rise and then fall [29].

At the early stage of the development of the digital economy, with the expansion of the scale of the digital economy, carbon dioxide emissions may show a sustained upward trend. First, the rapid increase in Internet penetration has significantly increased electricity consumption and energy demand [30]. While China currently has a high proportion of coal power, the rise in electricity consumption also leads to an increase in coal consumption, thereby increasing carbon and pollution emissions [31]. Secondly, at this stage, the development of the digital economy also entails large-scale infrastructure construction, such as data centers and 5G base stations. In the production, construction and operation stages of these infrastructures, they consume a large amount of energy leading to an increase in carbon emissions [32]. Third, in this stage many traditional enterprises began to carry out digital transformation, on the one hand, the enterprise digital production needs to reset production equipment, on the other hand, the combination of digitalization and traditional industry makes the enterprise profit increase thus prompting enterprises to carry out large-scale production, but has not yet formed the economy of scale, and thus brings more energy demand and industrial pollution emissions [33]. Fourth, although the development of the digital economy will bring technological progress, the benefits of technological innovation have a certain lag [11]. Consequently, CO_2 emissions continue to climb during this stage of digital-economy growth.

However, when the digital economy develops to a certain level, its carbon emissions will hit a peak. Beyond this point, the environmental benefits of the digital economy will gradually emerge as it continues to develop [34].

Firstly, the environmental benefits of technological progress, driven by the development of the digital economy, are beginning to emerge. The advancement of digital technology not only enhances production and energy utilization efficiency but also reduces resource consumption and pollution emissions. Furthermore, it gives rise to numerous low-carbon and environmental protection technologies, which are conducive to reducing carbon emissions and improving environmental pollution [35]. Secondly, at this stage, the development of emerging digital industries gradually matured. The digital transformation of traditional industries has been gradually completed [36]. As a result, enterprise production began to form economies of scale, and pollution emissions from large-scale production were gradually reduced. Production efficiency improved, and the energy utilization rate was also continuously enhanced. Environmental pollution emissions have begun to be gradually reduced [37]. Thirdly, in this stage, the digital economy has a higher level of development, the application of digital technology is gradually extensive, big data, cloud computing, block chain and other technologies are more popular, and the government is beginning to realize the importance of environmental protection, the role of the digital economy in the regulation and control of pollution is gradually appearing [38]. Ultimately, with the continuous development of the digital economy, the quality of the environment is expected to continue improving, environmental pollution will be gradually reduced, and carbon dioxide emissions will also decrease.

Therefore, we can put forward a hypothesis:

H1. *The relationship between the digital economy and carbon dioxide emissions conforms to the traditional EKC, exhibiting an inverted U-shape that increases initially before decreasing.*

3.2. Local Government Fiscal Pressure

Local government finance is a key determinant of how regional resources are allocated and how policies are designed and implemented; fiscal pressure compels local authorities to channel their limited resources into areas that promise the greatest returns or demand the most urgent attention. Both the infrastructure construction of the digital economy (e.g., 5G networks, smart cities) and environmental governance require financial support from the government [39,40]. When the government faces fiscal pressure, the path of its impact shows complexity and a multifaceted nature.

First, the impact of local government fiscal pressure on the timing of the turning point is uncertain. On the one hand, fiscal pressure may advance the turning point. When facing significant fiscal strain, local governments may prioritize allocating more financial resources to emerging industries and the upgrading of traditional sectors to ensure sustainable economic development and industrial transformation [41]. Particularly in areas related to the digital economy, given to its broad prospects and high potential returns, governments tend to provide greater fiscal support [42]. This not only accelerates the rapid development of the digital economy but also facilitates the earlier realization of its environmental benefits through the innovative application of digital technologies. However, on the other hand, greater fiscal pressure may delay the arrival of the inflection point. Under substantial fiscal stress, governments are more likely to adopt expenditure-reduction strategies to alleviate pressure [43], which could lead to reduced investment in environmental governance and digital economy development, along with relaxed environmental regulations [44,45]. This is because these sectors often have long investment return cycles and offer little short-term relief for fiscal difficulties [46]. Instead, local governments tend to prioritize allocating limited resources to traditional industries such as real estate and manufacturing, which can quickly generate tax revenue and employment [47]. This would slow the development of the digital economy and the improvement of environmental quality, thereby shifting the inflection point to the right.

Second, an increase in local government fiscal pressure is likely to lead to an upward shift of the inflection point. This is because heightened fiscal pressure often triggers expansionary fiscal behavior. In pursuit of short-term tax revenue growth and economic stimulation, local governments tend to relax environmental supervision for high-energy-consuming industries [48]. Concurrently, amid fiscal constraints, they may cut subsidies for the digital economy and green technologies [49]. On one hand, the rapid release of high-carbon production capacity directly increases carbon emissions. On the other hand, the digital economy, still in its scale-expansion phase, has not yet fully realized its emission reduction potential. Instead, its own demand for high-energy-consumption infrastructure, such as data centers and 5G base stations, contributes to higher carbon emissions. The combined effect of these two forces means that, at the same level of digital economic development, the peak of carbon emissions is pushed to a higher level, resulting in an upward shift of the inverted U-shaped curve’s inflection point.

Third, the increase in local government fiscal pressure will cause the slope of the inverted U-shaped curve of the digital economy and carbon emissions to change. On the left side of the inflection point, under the circumstances of tight local financial resources, governments tend to prioritize safeguarding current tax revenues and employment, leading to relaxed regulation of high-emission enterprises [45]. This encourages firms to expand production capacity in pursuit of higher profits. As a result, for each unit of expansion in the digital economy, the elasticity of energy demand and carbon emissions becomes amplified, causing the “scale effect” to outweigh the “technology effect,” thereby steepening the slope of the curve. On the right side of the inflection point, as the digital economy enters a mature stage, the marginal benefits of digital emission-reduction technologies decline. Combined with reduced fiscal support from local governments, the reduction in carbon emissions per unit of digital economic development narrows, leading to a flattening of the overall curve.

Based on this, we can put forward the following hypothesis:

H2. *Local governments’ fiscal pressure will cause the inflection point between the digital economy and per capita emissions to move rightward and upward, and will lead to a steeper curve on the left side of the inflection point and a gentler curve on the right side.*

3.3. Green Finance

In the present era, rapid economic growth has made environmental problems increasingly severe, and green finance—serving as a vital link between economic development and environmental protection—has become more important than ever. Green finance is one of the most effective ways for China to achieve its “dual carbon” goal and promote green innovation. On the one hand, green finance will promote the redistribution of capital. Enterprises with better environmental performance can secure longer-term, larger-scale, and lower-cost external financial support. In contrast, enterprises with higher pollution and carbon emissions will face higher financing thresholds and costs [50,51]. On the other hand, for enterprises that undertake green technological innovation and transformation, green finance will provide more financial support [52]. Therefore, the improvement of green finance development can broaden the financing channels for traditional enterprises, provide more abundant funds, and inspire enterprises to devote themselves to technological innovation, thereby accelerating the pace of upgrading traditional industries [53], and prompt enterprises to embark on the road of digital transformation of the industry at an earlier time. At the same time, the vigorous development of green finance has significantly promoted green technological innovation among enterprises [54], thereby enhancing the efficiency of energy utilization and reducing both energy consumption and environmental pollution. Therefore, the development of green finance is undoubtedly a significant exogenous factor influencing the inflection point of the digital economy and carbon emissions.

First, green finance may shift the inflection point between the digital economy and carbon emissions to the left, meaning it accelerates the arrival of this turning point. Green finance facilitates capital reallocation [55], enabling firms with strong environmental performance to access long-term, large-scale funding at lower financing costs, while high-pollution, high-carbon enterprises face higher financing barriers and costs. This incentivizes businesses to transition toward environmentally friendly practices. Secondly, while encouraging this transition, green finance also provides enterprises with capital for green technology innovation [56], enhancing energy efficiency and reducing energy consumption and carbon emissions. Third, the financial support from green finance not only alleviates corporate funding pressures and promotes technological innovation but also enables traditional firms to undertake digital transformation [53]. This simultaneously boosts corporate environmental performance and fosters digital development, thereby contributing to the earlier arrival of the inflection point in the relationship between the digital economy and environmental pollution.

Second, the development of green finance may push the peak of the digital economy-carbon emissions curve upward. Achieving the “dual carbon” goals requires a transition in energy and industrial structures. Green finance supports the development of large-scale new energy infrastructure—such as wind power, photovoltaics, ultra-high voltage grids—and the rise of emerging industries [57]. However, the construction of this infrastructure and the growth of related industries are themselves energy- and carbon-intensive processes, consuming substantial amounts of steel, cement, and energy. Before these green industries can fully replace traditional high-carbon sectors, economic growth remains partially dependent on the existing system. Consequently, this large-scale construction phase generates significant additional emissions. Meanwhile, the carbon reduction effects of the digital economy have not yet fully materialized. The combined effect of these two factors is likely to push the peak carbon emissions level higher.

Third, as green finance develops, the slope of the inverted U-shaped curve may increase; that is, the curve on the left side of the inflection point is steeper, while the curve on the right side is flatter. On the left side of the inflection point, green finance drives large-scale construction of green infrastructure. However, under the current energy structure, the manufacturing and construction processes of these facilities remain highly energy- and carbon-intensive [58,59]. As a result, total carbon emissions rise at an accelerated rate, leading to a steeper slope. On the right side of the turning point, as the digital economy enters a mature stage, the marginal benefits of digital emission reduction gradually diminish. Although green finance continues to provide financial support, its role is limited, and further improving emission reduction technologies through green finance becomes more difficult and costly. Consequently, the pace of carbon emission decline slows, causing the curve to flatten.

Based on this, we assume:

H3. *The development of green finance will cause the inflection point between the digital economy and per capita emissions to move leftward and upward, and will lead to a steeper curve on the left side of the inflection point and a gentler curve on the right side.*

3.4. Climate Policy Uncertainty

In modern society, economic development is deeply influenced by political factors, and frequent policy changes often pose significant obstacles to economic growth. Currently, climate change has become a global focus, with countries actively formulating climate policies to address this challenge. China has been continuously introducing relevant policies since 2007 and has solemnly pledged to achieve carbon peaking before 2030 and carbon neutrality before 2060. However, it cannot be ignored that the formulation and implementation of these climate policies have, to some extent, increased climate policy uncertainty [60,61], which has subsequently become a key factor affecting economic development. Higher climate policy uncertainty exacerbates energy price volatility [62], raises corporate compliance and financing costs, dampens firms' willingness and capacity to engage in digital and green technology innovation [63], and also delays corporate transformation processes [64]. Conversely, lower climate policy uncertainty indicates relatively stable climate policies and a more predictable external environment for corporate investment. Such stability not only encourages more innovation but also motivates firms to increase investment in upgrading production equipment [65]. Therefore, climate policy uncertainty may significantly influence the relationship between the digital economy and carbon emissions.

First, increased climate policy uncertainty may shift the inflection point between the digital economy and carbon emissions to the right, meaning it delays the arrival of this turning point. This occurs because heightened uncertainty regarding long-term carbon prices, emission standards, and policy directions creates a wait-and-see attitude among market participants, reducing their willingness to make long-term investments in digital and green low-carbon technologies [66]. This weakens the digital economy's role in driving industrial upgrading and transformation while reinforcing the lock-in effect of existing high-carbon models. As a result, it slows down both the digital and intelligent transformation of the economic structure and the process of carbon emission reduction, ultimately leading to a rightward shift of the inflection point.

Second, increased climate policy uncertainty may push the peak of the digital economy–carbon emissions curve upward. This is because greater uncertainty makes companies concerned about potential fluctuations in future climate policies and regulations [67], leading them to delay green transition and maintain existing high-carbon production models to secure short-term profits. Against this backdrop, the expansion of the digital economy still largely relies on the traditional energy system. As a result, the same level of digital economic development leads to higher carbon emissions, causing the inflection point of the inverted U-shaped curve to shift upward.

Third, climate policy uncertainty may alter the shape of the curve. On the left side of the inflection point, climate policy uncertainty can trigger a "last-chance effect" among firms. On one hand, fearing that high-carbon projects may be halted, they accelerate investments in such projects to circumvent potential future policy restrictions [68]. On the other hand, policy uncertainty makes them hesitant to invest in low-carbon technologies, which require long investment cycles, high costs, and offer slow returns, thereby delaying the low-carbon transition [61]. The combined effect of these two behaviors leads to a faster increase in carbon emissions, reflected in a steeper slope of the curve. On the right side of the inflection point, deep emission reductions require disruptive technologies and systemic transformations, investments that heavily depend on long-term stable policy signals. Increased climate policy uncertainty discourages firms from investing heavily in comprehensive low-carbon upgrades [40], prompting them to opt for lower-cost, more conservative marginal improvements, such as maintaining existing equipment and making minor efficiency enhancements. This significantly slows the rate of emission reduction and lacks strong new drivers to accelerate the decline. As a result, the absolute value of the slope decreases in this phase, and the curve becomes flatter.

Based on this, we assume:

H4. *Climate policy uncertainty will cause the inflection point between the digital economy and per capita emissions to move rightward and upward, and will lead to a steeper curve on the left side of the inflection point and a gentler curve on the right side.*

4. Research Methodology

4.1. Research Models

4.1.1. The Inverted U-Shaped Relationship Between the Digital Economy and Carbon Emissions from the Perspective of EKC

According to the traditional EKC theoretical framework, the model is constructed as follows:

$\mathrm{PCO2} = \alpha_0 + \alpha_1\mathrm{DIG} + \alpha_2\mathrm{DIG}^2 + \varepsilon$ (1)

where the explained variable is the per capita carbon dioxide emissions, denoted by PCO2; the explanatory variable is the level of development of the digital economy, denoted by DIG. And DIG^2 is the square term of the digital economy. ε is the error term.

By taking the derivative of equation (1), we can obtain equation (2):

$\frac{\mathrm{dPCO2}}{\mathrm{dDIG}} = \alpha_1 + 2\alpha_2\mathrm{DIG}$ (2)

Then, let equation (2) equal to 0, and we can obtain the inflection point $\mathrm{DIG}_1{}^*$:

$\mathrm{DIG}_1{}^* = -\frac{\alpha_1}{2\alpha_2}$(3)

where $\mathrm{DIG}_1{}^*$ is the inflection point of the inverted U-shaped curve relationship between the digital economy and per capita CO2 emissions.

Plugging $\mathrm{DIG}*_1$ back into the equation (2) gives the corresponding carbon emission level $\mathrm{PCO2}_1{}^*$:

$\mathrm{PCO2}_1{}^* = \alpha_0 - \frac{\alpha_1{}^2}{4\alpha_2}$(4)

where $\mathrm{PCO2}_1{}^*$ is the peak of the inverted U-shaped relationship between the digital economy and per capita carbon emissions.

The slope represents the marginal effect of the digital economy on carbon emissions—that is, the change in carbon emissions induced by a unit increase in the digital economy. It is defined as:

$\mathrm{Slope} = \frac{\mathrm{dPCO2}}{\mathrm{dDIG}} = \alpha_1 + 2\alpha_2\mathrm{DIG}$(5)

The absolute value of the slope, which is $|\alpha_1 + 2\alpha_2\mathrm{DIG}|$, measures the marginal carbon change (whether increase or decrease) resulting from a unit change in digital output. A larger absolute value indicates a steeper inverted U-shaped curve. Conversely, a smaller absolute value reflects a flatter curve.

4.1.2. The Shift of the Inflection Point and the Change of the Slope of the EKC Caused by Exogenous shocks

To investigate whether exogenous shocks cause a shift in the inflection point and a change in the steepness of the environmental Kuznets curve, the model is specified as follows:

$\mathrm{PCO2} = \alpha_0 + \alpha_1\mathrm{DIG} + \alpha_2\mathrm{DIG}^2 + \alpha_3\mathrm{Z} + \alpha_4\mathrm{Z} \times \mathrm{DIG} + \alpha_5\mathrm{Z} \times \mathrm{DIG}^2 + \varepsilon$(6)

where Z is the exogenous shock variable.

Referring to the method of Haans et al. (2016) [69], the location of the inflection point can be obtained by deriving the core variable digital economy (DIG) in model (6). The inflection point is assumed to be $\mathrm{DIG}_2{}^*$.

We perform the first-order condition on equation (6):

$\frac{\mathrm{dPCO2}}{\mathrm{dDIG}} = \alpha_1 + 2\alpha_2\mathrm{DIG} + \alpha_4 Z + 2\alpha_5 Z \times \mathrm{DIG}$(7)

Let equation (7)equal to 0, and solve for DIG yields the inflection point:

$\mathrm{DIG}_2{}^* = \frac{-\alpha_1-\alpha_4 Z}{2\alpha_2+2\alpha_5 Z}$(8)

where $\mathrm{DIG}_2{}^*$ is the inflection point of the relationship between the digital economy and the inverted U-shaped curve of carbon emissions per capita, for which there is an exogenous shock effect. At this point, the inflection point is affected by the exogenous shock variable Z. To further analyze how changes in the exogenous shock variables will have an impact on the inflection point, we take the partial derivative of Z in equation (7), which can be obtained as follows:

$$\frac{\mathrm{dDIG}_2{}^*}{\mathrm{dZ}} = \frac{-\alpha_4(2\alpha_2+2\alpha_5 Z)-2\alpha_5(-\alpha_1-\alpha_4 Z)}{(2\alpha_2+2\alpha_5 Z)^2}$$

$= \frac{2\alpha_5\alpha_1-2\alpha_2\alpha_4}{(2\alpha_2+2\alpha_5 Z)^2}$ (9)

In equation (9), the denominator is the squared term, which is strictly non-negative, so the effect of a change in the exogenous shock variable on the inflection point is determined by examining the positive or negative sign of the numerator $2\alpha_5\alpha_1-2\alpha_2\alpha_4$. If the numerator is positive, the inflection point will move to the right as the exogenous shock increases. If the numerator is negative, the inflection point will move to the left as the exogenous shock variable increases.

In the Environmental Kuznets Curve (EKC) hypothesis, the horizontal coordinate of the inflection point indicates the level of per capita income at which environmental pollution reaches its peak. Beyond this point, as per capita income continues to rise, environmental conditions begin to improve. The vertical coordinate of the inflection point, that is, the position of the peak, reveals the maximum level of pollution. A higher peak implies a greater maximum pollution level, more severe cumulative environmental damage, and increased pressure and higher costs for future environmental governance. Conversely, a lower peak indicates that the maximum pollution level is suppressed earlier, allowing environmental benefits to be realized sooner and reducing the pressure of later environmental governance.

Exogenous shocks not only cause the inflection point to shift horizontally—altering the threshold at which environmental pollution transitions from increasing to decreasing as per capita income rises—but also lead to vertical shifts in the inflection point. That is, when the threshold is reached, the peak level of environmental pollution may change. If an exogenous shock shifts the inflection point upward, the peak level of pollution at the inflection point becomes higher, thereby increasing the pressure for future environmental governance. If, however, an exogenous shock causes the inflection point to shift downward, the peak level of pollution at the inflection point is reduced, thus alleviating the pressure for environmental management in the future.

Plugging $\mathrm{DIG}_2{}^*$ back into the equation(6) gives the corresponding carbon emission level $\mathrm{PCO2}_2{}^*$:

$\mathrm{PCO2}_2{}^* = \alpha_0+\alpha_3 Z-\frac{(\alpha_1+\alpha_4 Z)^2}{4(\alpha_2+\alpha_5 Z)}$ (10)

To further examine how the exogenous shock variable Z affects the movement of the $\mathrm{PCO2}_2{}^*$, we take the partial derivative of Equation (10) with respect to Z, which yields:

$\frac{\mathrm{dPCO2}_2{}^*}{\mathrm{dZ}} = \alpha_3-\frac{\alpha_4(\alpha_1+\alpha_4 Z)}{2(\alpha_2+\alpha_5 Z)}+\frac{\alpha_5(\alpha_1+\alpha_4 Z)^2}{4(\alpha_2+\alpha_5 Z)^2}$ (11)

If $\frac{\mathrm{dPCO2}_2{}^*}{\mathrm{dZ}} < 0$, it indicates that as Z increases, gradually decreases, meaning the exogenous shock reduces the peak level of per capita carbon emissions. If $\frac{\mathrm{dPCO2}_2{}^*}{\mathrm{dZ}} > 0$, it implies that as Z increases, $\mathrm{PCO2}_2{}^*$ also gradually increases, meaning the exogenous shock raises the peak level of per capita carbon emissions.

The slope of the inverted U-shaped curve can be derived by taking the first-order derivative of Equation (6) :

$\mathrm{Slope} = \alpha_1+2\alpha_2\mathrm{DIG}+\alpha_4 Z+2\alpha_5 Z\times\mathrm{DIG}$ (12)

To examine how the slope of the inverted U-shaped curve is influenced by the exogenous shock Z, we take the first-order partial derivative of the slope with respect to Z:

$\frac{\mathrm{dSlope}}{\mathrm{dZ}} = \alpha_4+2\alpha_5\mathrm{DIG}$(13)

If the value of $\frac{\mathrm{dSlope}}{\mathrm{dZ}}$ is greater than 0, the slope increases with an increase in Z; If $\frac{\mathrm{dSlope}}{\mathrm{dZ}}$ equals 0, the slope remains unchanged with variations in Z; If $\frac{\mathrm{dSlope}}{\mathrm{dZ}}$ is less than 0, the slope decreases with an increase in Z. Therefore, the value of $\frac{\mathrm{dSlope}}{\mathrm{dZ}}$ is primarily influenced by α_4, α_5 and the value of DIG.

4.1.3. Econometric Methods

The study was analyzed using panel data and fixed effects model. The models are as follows:

$$\mathrm{PCO2}_{it} = \alpha_0 + \alpha_1\mathrm{DIG}_{it} + \alpha_2\mathrm{DIG}^2{}_{it} + \alpha_3\mathrm{control}_{it} + \theta_t + \delta_i + \varepsilon_{it} \quad (14)$$

$$\mathrm{PCO2}_{it} = \alpha_0 + \alpha_1\mathrm{DIG}_{it} + \alpha_2\mathrm{DIG}^2{}_{it} + \alpha_3 Z + \alpha_4 Z \times \mathrm{DIG}_{it} + \alpha_5 Z \times \mathrm{DIG}^2{}_{it} + \alpha_6\mathrm{control}_{it} + \theta_t + \delta_i + \varepsilon_{it} \quad (15)$$

where $\mathrm{PCO2}_{it}$ denotes per capita carbon dioxide emissions, DIG_{it} denotes the level of development of the digital economy, Z denotes Exogenous Shock variables, $\mathrm{control}_{it}$ denotes Control variables, θ_t and δ_i denote time and city fixed effects, respectively.

4.2. variables and Data

The sample of this study is 267 prefecture-level cities in China from 2011 to 2022. The sample period, 2011-2022, is chosen because in 2011, the Chinese government released the 12th Five-Year Plan, which officially listed the digital economy as a strategic emerging industry, marking the beginning of digital economy policy. In 2022, the full-scale launch of China's "East Data West Computing" project and the implementation of the "1+N" policy system for carbon peaking will mark the beginning of integrating digital technology with carbon emission control. On the other hand, China's carbon emissions hit their fastest growth rate between 2011 and 2013, after which they entered a plateau phase. In 2021, the country made commitments to achieve "carbon peak" and "carbon neutrality". This path shows a relatively close alignment with the cycle of the digital economy evolving from its development stage to a green transformation phase. As such, selecting the 2011-2022 period can better capture the shifts in the relationship between the digital economy and carbon emissions.

4.2.1. Dependent Variable: Per Capita Carbon Dioxide Emissions, PCO2

Grounded in the Environmental Kuznets Curve (EKC) hypothesis, which posits a link between per capita income and environmental pollution, this study uses per capita CO_2 emissions (PCO2) as the explained variable to align the empirical analysis with the theoretical cornerstone. Per capita carbon emission will be measured as total CO_2 emissions (tons) divided by the permanent residents. permanent residents' data are taken from the China City Statistical Yearbook and provincial statistical yearbooks, while CO_2 emission data are obtained from the Emissions Database for Global Atmospheric Research (EDGAR).

4.2.2. Independent Variable: The Level of Development of the Digital Economy, Dig

Currently, most studies on measuring the digital economy use the digital economy index. Considering the relatively few data indicators available at the municipal level and considering the availability of relevant data at the city level, the study decides to draw on the methodology of [70] to construct the digital economy index, which consists of five dimensions: internet penetration, relevant employees, relevant outputs, cell phone penetration, and digital inclusive financial development. broadband subscriptions per 100 residents, the share of urban employees in computer services and software, per-capita telecom revenue, mobile-phone accounts per 100 residents, and the China Digital Inclusive Finance Index. Raw data for the first four are drawn from the China Urban Statistical Yearbook; the last index is jointly released by Peking University's Digital Finance Research Center and Ant Group.

The study will adopt the entropy method, following the approach of [30], to construct the digital economy index. This method is selected primarily because it provides an objective weighting mechanism that effectively addresses the multidimensional and complex nature of the digital economy. By scientifically determining weights based on the dispersion of each indicator's data, the method assigns higher importance to indicators with greater variation across samples: the more an indicator's values differ among observations, the lower its entropy value, the greater its informative value, and consequently, the higher its assigned weight. This approach eliminates biases arising from researchers' subjective judgments, ensures rigor in index construction and reliability in results, thereby enabling a more accurate revelation of the true relationship between the digital economy and carbon emissions.

4.2.3. Exogenous Shock Variables, Z

The exogenous shock variables in this study are the level of green finance development, local government fiscal pressure, and climate policy uncertainty.

Local government fiscal pressure

Regarding the measurement of local government fiscal pressure, this study refers to the study by Bai et al. (2019), which characterizes fiscal pressure as the difference between local government fiscal expenditure and fiscal revenue, expressed as a proportion of fiscal revenue. Larger values indicate higher fiscal pressure [71]. The data is mainly sourced from China's provincial and municipal statistical yearbooks.

Green finance

Regarding the measurement of green finance, the study plan to refer to the methods of Zhou & Chen(2023), Zhou et al. (2023), and Liu & He (2021) to construct the indicators, primarily based on seven key components: green credit (total amount of Credit allocated to environmental protection projects in the city/the total amount of Credit in the province), green securities (the total issuance of green bonds/total issuance of all bonds), green insurance (the green insurance component/total premium revenue), green investment (the investment in environmental pollution control/GDP), green support (fiscal environmental protection expenditure/fiscal general budget expenditure), green funds (the total market capitalization of green funds/total market capitalization of all funds), and green equity (the total amount of carbon trading, energy rights trading, and emission rights trading/the total amount of equity market trading, measures green equity)[51,54,72].

The above data are primarily sourced from the China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, China Financial Yearbook, China Agricultural Statistical Yearbook, China Industrial Statistical Yearbook, as well as provincial and municipal statistical yearbooks and environmental bulletins.

Climate Policy Uncertainty

Regarding the quantitative assessment of climate policy uncertainty, the study refers to the city-level Climate Policy Uncertainty (CCPU) index in China constructed by Ma et al. (2023b) [73]. The methodology for constructing this index is as follows: First, considering credibility, influence, and internationalization, six representative mainstream domestic media newspapers— "People's Daily", "Guangming Daily", "Economic Daily", "Global Times", "Science and Technology Daily", and "China News Service"—are selected as the primary information sources for building the Chinese CCPU index. Second, utilizing the MacBERT deep learning model, textual content is automatically identified and analyzed to accurately extract core vocabulary closely related to climate policy and uncertainty. Third, the number of news articles containing the keywords within a specific time period is counted and divided by the total number of articles published by the newspapers during that period to obtain the initial raw data. Finally, following the method of Baker et al. (2016), the CCPU index is constructed by standardizing the data [74].

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4.2.4. Control Variables

To mitigate the estimation bias caused by omitted variables, the study plans to control a series of variables that have an impact on carbon emissions, mainly including economic development (PGDP), urbanization (URBAN), Regional infrastructure development (ROAD), the degree of openness (TRADE), and technological progress (APATENTS). To mitigate heteroscedasticity, economic development, regional infrastructure, and technological progress are log-transformed. All the above data come from China's provincial and city statistical yearbooks.

According to the Environmental Kuznets Curve theory, the study included economic development (PGDP) as a control variable, which is measured by per capita GDP, as its omission would cause systemic emission reduction effects to be absorbed into the digital economy coefficient, biasing the turning point estimation [73,75]. The degree of openness (TRADE), measured by the ratio of total import and export trade to GDP, is included because it influences carbon emissions via the "pollution haven" effect or technology transfer, and omitting it would distort the estimated turning point and peak of the digital economy's impact [76,77]. Regional infrastructure (ROAD), represented by regional road mileage (km), directly increases transport and industrial carbon emissions, and failing to control for it would misattribute this effect to the digital economy [79]. Urbanization (URBAN), measured by the proportion of urban residents in the total population, drives carbon emissions through construction, public service expansion, and consumption upgrades, making it essential to control for its influence [30]. Technological progress (APATENTS), proxied by the number of patent applications, reduces carbon emissions through efficiency gains and clean energy substitution; excluding it would overestimate the digital economy's net effect [78].

Table 1. Definition of variables.

Variable	Definition
Dependent variable	Per capita carbon dioxide emissions (PCO2)
Independent variable	Digital Economy (DIG): digital economy index
Z variables	Green Finance (GF): green finance index
	Local Government Fiscal Pressure (LFP): The ratio of the difference between the local government's fiscal expenditure and fiscal revenue to the total fiscal revenue
	Climate Policy Uncertainty (CPU): Climate Policy Uncertainty index
Control variables	Economic development (PGDP): per capita GDP
	Openness (TRADE): The ratio of the total value of imports and exports to GDP
	Infrastructure (ROAD): The total kilometers of roads in the region
	Urbanization (URBAN): The ratio of the permanent resident population in towns to the total permanent resident population
	Technological progress (APATENTS): the number of patent applications

4.3. Descriptive statistics of variables

Table 2 presents the descriptive statistics of 267 cities in China from 2011 to 2022.

Table 2. Descriptive statistics.

VarName	Obs	Mean	Median	SD	Min	Max
lnPCO2	3204	8.765	8.797	0.865	6.712	10.961
DIG	3204	0.135	0.108	0.086	0.049	0.563
lnPGDP	3204	10.811	10.786	0.542	9.642	12.061
TRADE	3204	0.183	0.085	0.271	0.003	1.568
lnROAD	3204	9.328	9.435	0.642	7.277	10.478
URBAN	3204	0.574	0.553	0.144	0.299	0.949

lnAPATENTS	3204	7.993	7.889	1.564	4.554	11.759
GF	3204	0.336	0.359	0.104	0.082	0.532
LFP	3204	1.802	1.350	1.539	0.020	7.646
CPU	3204	1.421	1.386	0.554	0.345	2.856

5. Empirical Results

5.1. Results of Benchmark Regressions

Table 3 presents the regression results of the digital economy and its squared term on per capita carbon dioxide emissions. Column (1) shows the regression results with only the digital economy and its squared term, while columns (2) to (6) display the results after gradually adding control variables. Table 3 indicates that the digital economy (DIG) and its squared term (DIG2) are consistently significant at the 1% level, with DIG always positive and DIG2 always negative. This confirms an inverted U-shaped relationship between the digital economy and per capita carbon emissions. Specifically, at lower levels of digital economic development, its growth leads to an increase in carbon dioxide emissions. However, when the development level of the digital economy exceeds the turning point, further advancement of the digital economy promotes a reduction in carbon dioxide emissions.

Table 3. Benchmark regression result of the inverted-U shape curve.

Variables	**(1)** **lnPCO2**	**(2)** **lnPCO2**	**(3)** **lnPCO2**	**(4)** **lnPCO2**	**(5)** **lnPCO2**	**(6)** **lnPCO2**
DIG	0.800***	0.624***	0.621***	0.561**	0.535**	0.531**
	(3.42)	(2.72)	(2.72)	(2.47)	(2.35)	(2.32)
DIG2	-1.787***	-1.542***	-1.540***	-1.443***	-1.358***	-1.353***
	(-4.56)	(-4.03)	(-4.02)	(-3.81)	(-3.55)	(-3.53)
lnPGDP		0.092***	0.092***	0.086***	0.088***	0.085***
		(4.99)	(4.99)	(4.84)	(4.94)	(4.74)
lnROAD			-0.010	-0.006	-0.007	-0.006
			(-0.32)	(-0.19)	(-0.22)	(-0.20)
URBAN				0.318***	0.306***	0.301***
				(3.74)	(3.61)	(3.56)
TRADE					0.065*	0.061*
					(1.84)	(1.73)
lnAPATENTS						0.010
						(1.09)
Constant	8.703***	7.728***	7.816***	7.670***	7.654***	7.602***
	(379.97)	(38.68)	(23.78)	(23.54)	(23.46)	(23.10)
Observations	3,204	3,204	3,204	3,204	3,204	3,204
R-squared	0.981	0.981	0.981	0.981	0.981	0.981
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

According to the regression results in Table 4, the coefficient of DIG is 0.531, and the coefficient of DIG2 is -1.353. Using equation (3), $\mathrm{DIG_1}^{*}= -\frac{\alpha_1}{2\alpha_2}$, the symmetrical axis DIG*, which represents the inflection point of the inverted U-shaped curve between the digital economy and carbon emissions, is calculated as 0.196. When the development level of the digital economy exceeds 0.196, the impact of the digital economy on carbon emissions shifts from promoting to inhibiting.

Additionally, based on the regression results in Table 3, with α_0 is 7.602, $\alpha_1$is 0.531, and α_2 is -1.353, equation (4) $PCO2_1{}^* = \alpha_0 - \frac{\alpha_1{}^2}{4\alpha_2}$ is used to calculate $\ln PCO2_1{}^*$ as 7.654. Thus, the peak per capita carbon emissions $PCO2_1{}^*$ is determined to be 2109.065 kg per person. This means that when per capita carbon emissions reach 2109.065 kg per person, they attain their maximum value. Thereafter, with further development of the digital economy, the marginal effect of the digital economy on carbon emissions turns from positive to negative.

Using the slope equation (5): Slope = $\frac{dPCO2}{dDIG} = \alpha_1 + 2\alpha_2 DIG$, and substituting $\alpha_1 = 0.531$, $\alpha_2 = -1.353$, the slope is derived as slope= $\frac{dPCO2}{dDIG} = 0.531 - 1.353DIG$. When DIG < 0.196, $\frac{dPCO2}{dDIG} > 0$, indicating a positive slope. During this phase, as the digital economy develops, per capita carbon emissions gradually increase. However, the absolute value of the slope gradually decreases, meaning the curve becomes flatter. This implies that the incremental increase in per capita carbon emissions resulting from each additional unit of digital economy development diminishes. When DIG = 0.196, the slope equals 0, and per capita carbon emissions reach their peak. When DIG > 0.196, $\frac{dPCO2}{dDIG} < 0$, indicating a negative slope. In this phase, as the digital economy develops, per capita carbon emissions gradually decrease. Moreover, the absolute value of the slope gradually increases, meaning the curve becomes steeper. This implies that the incremental decrease in per capita carbon emissions resulting from each additional unit of digital economic development accelerates.

Table 4. U-test result.

Variable	Control	Lower Bound	Upper Bound	Extreme Point
Dig	NO	0.627***	-1.210***	0.224
Dig	YES	0.399**	-0.992***	0.196

Subsequently, a U-test was conducted on the model, and the results are presented in Table 4. Whether control variables were included or not, the digital economy was significant at both the 1% and 5% significance levels. Furthermore, the lower bound was significantly positive, and the upper bound was significantly negative, indicating a significant inverted U-shaped relationship between the digital economy and carbon emissions.

Therefore, the conclusion of this study is consistent with the findings of Wang et al. (2023) and Ma et al. (2025b) [25,26]. There exists an inverted U-shaped relationship between the digital economy and carbon emissions, meaning that the relationship between the digital economy and carbon emissions satisfies the environmental Kuznets curve theory, thus supporting Hypothesis 1. In the early stage of the digital economy, the development of the digital economy mainly relied on an energy structure dominated by coal. The environmental benefits of digital technology had not yet emerged, and the government's environmental policies and supervision were insufficient. As a result, the infrastructure construction and industrial expansion would increase energy consumption and carbon dioxide emissions. After the digital economy enters a mature stage, the environmental benefits of digital technology become evident. Production and energy utilization efficiency improve, scale effects are formed, and government environmental supervision is strengthened. Eventually, as the digital economy further develops, carbon emissions gradually decrease.

5.2. Benchmark Regression Result of Exogenous Shock

The study examines how changes in exogenous shock variables affect the shift of the inflection point and the slope of the curve. This research selects local fiscal pressure, green finance, and climate policy uncertainty as the exogenous shock variables. Table 5 presents the regression results. Column (1) shows the regression results after including the variable for local government fiscal pressure (LFP). Column (2) presents the results incorporating the interaction term between the digital economy and local government fiscal pressure (DIG_LFP) and the interaction term between the squared term of the digital economy and local government fiscal pressure (DIG2_LFP), in addition to the variables in Column (1). Column (3) displays the regression results after adding the variable for green finance (GF). Column (4) reports the results, including the interaction term between the digital economy and green finance (DIG_GF) and the interaction term between the squared term of the digital economy and green finance (DIG2_GF), in addition to the variables in Column (3). Column (5) provides the regression results after incorporating the variable for climate policy uncertainty (CPU). Column (6) shows the results, including the interaction term between the digital economy and climate policy uncertainty (DIG_CPU) and the interaction term between the squared term of the digital economy and climate policy uncertainty (DIG2_CPU), in addition to the variables in Column (5).

Table 5. Benchmark regression result of exogenous shock.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	lnPCO2	**lnPCO2**	**lnPCO2**	**lnPCO2**	**lnPCO2**	**lnPCO2**
DIG	0.518**	0.839***	0.541**	0.346	0.526**	0.565**
	(2.28)	(2.77)	(2.37)	(1.53)	(2.30)	(2.45)
DIG2	-1.290***	-2.474***	-1.364***	-1.054***	-1.346***	-1.526***
	(-3.41)	(-2.95)	(-3.57)	(-2.89)	(-3.52)	(-3.80)
LFP	0.022***	0.018*				
	(2.59)	(1.78)				
DIG_LFP		0.463**				
		(2.00)				
DIG2_LFP		-1.254**				
		(-2.13)				
lnPGDP	0.107***	0.103***	0.084***	0.079***	0.080***	0.079***
	(5.67)	(5.52)	(4.72)	(4.46)	(4.49)	(4.42)
lnROAD	-0.009	-0.011	-0.005	-0.026	-0.008	-0.009
	(-0.29)	(-0.36)	(-0.15)	(-0.85)	(-0.26)	(-0.31)
URBAN	0.319***	0.318***	0.297***	0.259***	0.302***	0.298***
	(3.86)	(3.86)	(3.51)	(3.09)	(3.57)	(3.53)
TRADE	0.059*	0.057*	0.063*	0.036	0.061*	0.060*
	(1.70)	(1.66)	(1.79)	(1.13)	(1.71)	(1.70)
lnAPATENTS	0.011	0.011	0.012	0.008	0.009	0.009
	(1.12)	(1.20)	(1.30)	(0.85)	(0.98)	(0.98)
GF		0.103***	0.225**	0.330***		
		(5.52)	(2.41)	(3.49)		
DIG_GF				-3.721**		
				(-2.51)		
DIG2_GF				0.883		
				(0.37)		
CPU					0.011**	0.011**
					(2.12)	(2.17)
DIG_CPU						-0.238
						(-1.27)
DIG2_CPU						0.648*
						(1.70)
Constant	7.331***	7.464***	7.503***	7.934***	7.657***	7.739***
	(22.59)	(22.76)	(22.54)	(23.45)	(23.39)	(23.37)
Observations	3,204	3,204	3,204	3,204	3,204	3,204
R-squared	0.981	0.981	0.981	0.982	0.981	0.981
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

5.2.1. Local Government Fiscal Pressure

According to Column (2) in Table 5, when the exogenous shock variable is Local Government Fiscal Pressure (LFP), α_1, α_2 are statistically significant at the 1% level, α_3 is significant at the 10% level, and α_4, α_5 are significant at the 5% level. With coefficients of α_1 = 0.839, α_2 = -2.574 α_4 = 0.463, α_5 = -1.254, according to equation (9) $\frac{dDIG_2*}{dZ} = \frac{2\alpha_5\alpha_1 - 2\alpha_2\alpha_4}{(2\alpha_2 + 2\alpha_5 Z)^2}$ can calculate that $2\alpha_5\alpha_1 - 2\alpha_2\alpha_4$ =0.187, which is greater than zero. Therefore, it can be concluded that the increase in local government fiscal pressure has driven the right shift of the inflection point of the digital economy and carbon emissions. Under the circumstances of significant fiscal pressure, the government, in order to alleviate fiscal pressure, stabilize tax revenue and employment, will slow down investment in digital and green industries with longer payback cycles, and prioritize the development of traditional industries with faster returns, thereby delaying the appearance of the turning point.

Substituting the coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ ， into equation (11) $\frac{dPCO2_2*}{dZ} = \alpha_3 - \frac{\alpha_4(\alpha_1 + \alpha_4 Z)}{2(\alpha_2 + \alpha_5 Z)} + \frac{\alpha_5(\alpha_1 + \alpha_4 Z)^2}{4(\alpha_2 + \alpha_5 Z)^2}$ yields $\frac{dPCO2_2*}{dZ} = 0.018 + \frac{1.039 + 1.061Z + 0.269Z^2}{4(-2.474 - 1.254Z)^2}$, Since Z represents local government fiscal pressure, ranging from 0.020 to 7.646, $\frac{dPCO2_2*}{dZ} > 0$. Thus, increased local government fiscal pressure pushes the peak of the inverted U-shaped curve between the digital economy and carbon emissions upward. In the early stage of the development of the digital economy, environmental benefits have not yet emerged, but the energy consumption of related infrastructure construction is relatively high. At this time, with the government's financial resources being relatively tight, local governments tend to relax environmental control over high-carbon industries, which leads to an increase in carbon emissions at the same level of digital economic development. As a result, the peak per capita carbon emissions will increase, and the inflection point will shift upward.

Substituting α_4, α_5 into equation (13) $\frac{dSlope}{dZ} = \alpha_4 + 2\alpha_5 DIG$, the slope can be derived, which is $\frac{dSlope}{dZ} = 0.463 - 2.508DIG$. Setting $\frac{dSlope}{dZ}$ equal to zero yields a critical DIG value of 0.185. When the digital economy development index（DIG） is less than 0.185, the slope gradually increases with rising local government fiscal pressure. If the digital economy development level has not reached the turning point, the curve becomes steeper. If it has passed the turning point, the left side of the curve becomes steeper, and the right side becomes flatter. When the digital economy development index is greater than 0.185, the slope gradually decreases with rising local government fiscal pressure. If the digital economy development level has not reached the turning point, the curve becomes flatter. If it has passed the turning point, the left side of the curve becomes flatter, and the right side becomes steeper. When the digital economy development level is exactly 0.185, local government fiscal pressure does not affect the change in slope.

When DIG is 0.185, it is already very close to the inflection point of the digital economic development level. When the development level of the digital economy is below the inflection point, on the one hand, the benefits of the digital economy in reducing carbon emissions have not yet emerged. As the digital economy develops, per capita carbon emissions increase. On the other hand, the relatively high financial pressure on local governments will prompt the government to relax environmental regulations and reduce subsidies for the development of the green economy and the digital economy. Under the combined effect of these two aspects, the carbon emissions brought about by each unit of digital economic development will be greater, and the slope of the curve will be steeper. When the development level of the digital economy exceeds the inflection point, the digital economy is relatively mature at this time, and the environmental protection effect brought by the development of the digital economy has also emerged. However, the marginal benefit of digital technology in reducing carbon emissions will gradually decrease, and under the circumstances of greater financial pressure on local governments, government subsidies will gradually decrease. Therefore, the reduction in carbon emissions per unit of digital output has narrowed, and the overall curve has slowed down.

5.2.2. Green Finance

According to Column (4) in Table 5, when the exogenous shock variable is green finance (GF), α_2, α_3 are statistically significant at the 1% level, α_4 is significant at the 5% level, while α_1, α_5 are not significant. After introducing green finance as an exogenous shock variable, the coefficient of the linear term of the digital economy (DIG) is not significant, whereas the coefficient of the quadratic term (DIG2) is significantly negative. This indicates that, after controlling for nonlinear and interaction terms, the digital economy exhibits a nonlinear impact on per capita carbon emissions, with no direct linear effect. Secondly, the coefficient of the interaction term between the linear term of the digital economy and green finance (DIG_GF) is significantly negative, suggesting that green finance significantly moderates the impact of the linear component of the digital economy on carbon emissions. However, while the coefficient of the quadratic term of the digital economy (DIG2) itself is significantly negative, its interaction term with green finance (DIG2_GF) is not significant. This implies that the inherent inverted U-shaped nonlinear relationship between the digital economy and per capita carbon emissions exists independently, and the exogenous shock of green finance does not affect this nonlinear relationship.

Since the coefficients of α_1, α_5 are not significant, they are treated as zero in the calculation. With $\alpha_2 = -1.054, \alpha_3 = 0.330$ $\alpha_4 = -3.721$, using equation (9) $\frac{\mathrm{dDIG_2}*}{\mathrm{dZ}} = \frac{2\alpha_5\alpha_1 - 2\alpha_2\alpha_4}{(2\alpha_2 + 2\alpha_5 \mathrm{Z})^2}$, we can calculate $2\alpha_5\alpha_1 - 2\alpha_2\alpha_4 = -7.844$ which is less than zero. Therefore, it can be concluded that green finance shifts the turning point between the digital economy and carbon emissions to the left, meaning that the development of green finance promotes an earlier arrival of the turning point in the relationship between the digital economy and carbon emissions. Green finance, by guiding the flow of funds, provides more support for the development of environmental protection enterprises and restricts highly polluting enterprises, promotes technological innovation, accelerates the transformation and upgrading of industries, and brings the turning point forward.

Substituting the coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ nto equation (11) $\frac{\mathrm{dPCO2_2}*}{\mathrm{dZ}} = \alpha_3 - \frac{\alpha_4(\alpha_1 + \alpha_4 Z)}{2(\alpha_2 + \alpha_5 Z)} + \frac{\alpha_5(\alpha_1 + \alpha_4 Z)^2}{4(\alpha_2 + \alpha_5 Z)^2}$, yields $\frac{\mathrm{dPCO2_2}*}{\mathrm{dZ}} = 0.330 + 6.568Z$. Since Z represents the green finance index, and its value is greater than zero, $\frac{\mathrm{dPCO2_2}*}{\mathrm{dZ}} > 0$. Therefore, the development of green finance pushes the peak of the inverted U-shaped curve between the digital economy and carbon emissions upward. The development of green finance will encourage the construction and development of new energy infrastructure. Before the completion of these infrastructures and the rise of related industries, a large amount of energy will be consumed. On the other hand, before green industries are completely replaced, economic development still relies on existing traditional industries. Therefore, the combined effect of these two aspects will push the peak of carbon emissions to a higher level.

Substituting α_4, α_5 into equation (13) $\frac{\mathrm{dSlope}}{\mathrm{dZ}} = \alpha_4 + 2\alpha_5 \mathrm{DIG}$, yields $\frac{\mathrm{dSlope}}{\mathrm{dZ}} = 0.463$. Therefore, as green finance develops, the slope gradually increases. Before the turning point, the slope is positive. With the development of green finance, the slope becomes larger, meaning the curve becomes steeper. After the turning point, the slope is negative. With the development of green finance, the slope increases and becomes less negative, meaning the absolute value of the slope decreases, and thus the curve becomes flatter. Before the inflection point, green finance will promote the large-scale construction of green infrastructure, thereby causing a large amount of energy consumption. Therefore, the development of green finance will lead to an increase in per capita carbon emissions per unit of digital economic development, and the curve will become steeper. After the inflection point, although the green capacity of green finance investment becomes the main body, which helps to reduce carbon emissions, the marginal benefits of carbon reduction will decline, and the difficulty and cost of further developing emission reduction technologies will be higher. Therefore, the curve will tend to flatten.

5.2.3. Climate Policy Uncertainty

According to Column (6) in Table 5, when the exogenous shock variable is Climate Policy Uncertainty (CPU), α_2 is statistically significant at the 1% level, $\alpha_5$is significant at the 10% level, α_1, α_3 are significant at the 10% level, while α_4 is not significant. With α_1 = 0.565, α_2 = $-1.526, \alpha_3$ = 0.011, α_5 = -1.254= 0.648, equation (9) $\frac{dDIG_2*}{dZ} = \frac{2\alpha_5\alpha_1-2\alpha_2\alpha_4}{(2\alpha_2+2\alpha_5Z)^2}$ calculates $2\alpha_5\alpha_1 - 2\alpha_2\alpha_4$ =0.732, which is greater than zero. Therefore, it can be concluded that increased climate policy uncertainty shifts the turning point between the digital economy and carbon emissions to the right, meaning that heightened climate policy uncertainty delays the arrival of this inflection point. The increase in climate policy uncertainty will enhance the wait-and-see mentality of market entities, leading to a decrease in their willingness to invest in digital and low-carbon technologies, thereby delaying the development of the digital industry and causing the turning point to be delayed.

Substituting the coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ ， α_5 into equation (11) $\frac{dPCO2_2*}{dZ} = \alpha_3 - \frac{\alpha_4(\alpha_1+\alpha_4 Z)}{2(\alpha_2+\alpha_5 Z)} + \frac{\alpha_5(\alpha_1+\alpha_4 Z)^2}{4(\alpha_2+\alpha_5 Z)^2}$, yields $\frac{dPCO2_2*}{dZ} = 0.011 + \frac{0.207}{4(0.648Z-1.526)^2}$. Since the denominator is a squared term and strictly greater than zero, $\frac{dPCO2_2*}{dZ} > 0$. Therefore, an increase in climate policy uncertainty pushes the peak of the inverted U-shaped curve between the digital economy and carbon emissions upward. The increase in the uncertainty of climate policies will cause enterprises to delay their green transformation and maintain their existing production models due to concerns over the instability of climate policies. Some may even expand production in the short term for profit, which will lead to an increase in the peak carbon emissions and an upward shift in the inflection point.

Substituting α_4 ， α_5 into equation (13) $\frac{dSlope}{dZ} = \alpha_4 + 2\alpha_5 DIG$, yields $\frac{dSlope}{dZ} = 1.296DIG$ ， . Since the digital economy index is positive, $\frac{dSlope}{dZ} > 0$. Therefore, as climate policy uncertainty increases, the slope gradually increases. Before the turning point, the slope is positive. With increasing climate policy uncertainty, the slope becomes larger, meaning the curve becomes steeper. After the turning point, the slope is negative. With increasing climate policy uncertainty, the slope increases and becomes less negative, meaning the absolute value of the slope decreases, and thus the curve becomes flatter. Before the inflection point, on one hand, concerns that high-carbon-emissions projects may be halted in the future due to climate policy changes that drive firms to expand current production. On the other hand, uncertainty about future policies leads to hesitation in investing in low-carbon and digital technologies. The combined effect of these two factors increases the carbon emissions per unit of the digital economy, making the curve steeper. After the inflection point, climate policy uncertainty makes firms reluctant to further upgrade low-carbon and digital technologies, preferring instead to maintain existing equipment and make minor improvements. Since technologies are subject to diminishing marginal returns, the reduction in carbon emissions per unit of the digital economy gradually slows, causing the curve to flatten.

5.3. Heterogeneity Test

Table 6. Heterogeneity analysis results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	East	**Middle**	**West**	**Coastal**	**Non-Coastal**	**High_ Urban**	**Low_ Urban**
DIG	0.498	0.106	1.196**	0.509*	0.541	0.373	1.310*
	(1.56)	(0.20)	(2.19)	(1.80)	(1.40)	(1.32)	(1.79)
DIG2	-1.110**	-1.714	-2.329**	-1.114**	-1.689**	-0.978**	-4.412**
	(-2.25)	(-1.29)	(-2.47)	(-2.42)	(-2.34)	(-2.24)	(-2.02)
lnPGDP	-0.007	0.129***	0.071**	0.010	0.098***	0.102***	0.029
	(-0.25)	(3.79)	(2.00)	(0.38)	(4.03)	(3.75)	(0.99)
lnROAD	0.026	-0.016	-0.019	0.030	-0.035	-0.028	-0.024
	(0.93)	(-0.28)	(-0.36)	(0.98)	(-0.81)	(-0.82)	(-0.39)

URBAN	0.148	0.580***	0.202*	0.136	0.401***	0.202	0.013
	(1.43)	(2.86)	(1.69)	(1.36)	(3.02)	(1.34)	(0.08)
TRADE	0.080	0.074	-0.000	0.087	0.006	0.014	0.115***
	(1.25)	(1.43)	(-0.01)	(1.60)	(0.18)	(0.31)	(2.92)
lnAPATENTS	-0.002	0.003	0.018	0.006	0.009	0.000	0.005
	(-0.15)	(0.17)	(1.07)	(0.57)	(0.64)	(0.03)	(0.34)
Constant	8.442***	7.215***	7.842***	8.130***	7.757***	7.964***	8.302***
	(20.58)	(11.11)	(12.30)	(19.00)	(15.74)	(17.92)	(11.99)
Observations	1,176	1,176	852	1,320	1,884	1,593	1,601
R-squared	0.981	0.972	0.988	0.982	0.981	0.985	0.979
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Note：Robust t-statistics in parentheses：*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3.1. Heterogeneity of Regions

To examine whether the inverted-U relationship between the digital economy and per capita carbon emissions varies across regions, the study split the 267 cities into eastern, central, and western areas following NBS definitions. Columns (1)– (3) of Table 6 show an inverted-U relationship for all three regions, but with differing significance. The western sub-sample is significant at the 5% level for both terms. In the eastern region, the linear term (DIG) is insignificant while the squared term (DIG2) is significant at 5%, implying a purely non-linear effect. For the central region, neither term is significant. These differences reflect dissimilar development stages, industrial structures, digital capacities, and environmental regulation stringency. Eastern cities—already ahead of the turning-point—face strong green regulation, so the linear upward effect is diluted. Central cities remain locked in heavy industry with laxer regulation and weaker digital foundations, flattening the curve [11].

5.3.2. Heterogeneity of Coastal–Non-Coastal Divide

To examine whether the relationship between the digital economy and per capita carbon emissions in both coastal and inland cities conforms to an inverted U-shaped pattern, the study categorized the 267 cities into coastal and non-coastal regions based on whether they belong to a coastal province and conducted regression analyses on them. The regression results are shown in columns (4) to (5) of Table 6. Both regions exhibit a non-linear relationship consistent with an inverted U-shape. In coastal regions, the linear term of the digital economy is statistically significant at the 10% significance level, while the squared term of the digital economy is significant at the 5% level. In non-coastal regions, the linear term of the digital economy is not significant, but the squared term is significant at the 5% level. This can be attributed to the fact that coastal regions, compared to inland areas, possess more advanced and well-developed digital economy infrastructure, have an industrial structure predominantly based on the tertiary sector, and exhibit a higher degree of openness to the outside world. As a result, the inverted U-shaped relationship is more significant in these areas. In contrast, inland regions, characterized by a higher proportion of heavy industry, slower development of the digital economy, and lagging environmental regulations, demonstrate weaker significance in this relationship compared to coastal regions.

5.3.3. Heterogeneity of Urbanization

To examine whether the relationship between the digital economy and per capita carbon emissions conforms to an inverted U-shaped relationship across different levels of urbanization, the study categorized the 267 cities into high and low urbanization groups and conducted regression analyses. The results, presented in columns (6) to (7) of Table 6, indicate that both groups exhibit a non-linear relationship consistent with an inverted U-shape. In cities with low urbanization levels, the linear term of the digital economy is statistically significant at the 10% significance level, while the squared term is significant at the 5% level. In contrast, in highly urbanized cities, the linear term of the digital economy is not significant, whereas the squared term is significant at the 5% level. This can be explained by the fact that a higher level of urbanization is generally associated with a more advanced economic development stage. Highly urbanized cities possess more developed digital economy infrastructure and are more advanced in innovation and green technologies, enabling comprehensive carbon emission reduction [26]. As a result, the emission reduction effect captured by the squared term is stronger, while the linear effect is absorbed.

5.4. Robustness and Endogeneity Testing

Table 7. Robustness and Endogeneity Testing Results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	lnPCO2	**lnPCO2**	**DIG**	**DIGSQ**	**lnPCO2**
L1_DIG			0.500***	0.075	
			(0.098)	(0.066)	
L1_DIGSQ			-0.060	0.374**	
			(0.204)	(0.155)	
DIG	0.513*	0.458*			1.099*
	(1.88)	(1.88)			(0.656)
DIG2	-1.079**	-1.381***			-2.454**
	(-2.53)	(-3.41)			(1.100)
lnPGDP	0.054***	0.087***	0.006*	-0.002	0.084**
	(2.69)	(4.69)	(0.003)	(0.002)	(0.020)
lnROAD	-0.063	-0.005	-0.013***	-0.006**	-0.024
	(-1.56)	(-0.17)	(0.005)	(0.003)	(0.031)
URBAN	0.268**	0.293***	0.012	-0.003	0.284***
	(2.20)	(3.43)	(0.013)	(0.009)	(0.099)
TRADE	0.138***	0.080**	-0.031*	-0.025*	0.037
	(3.18)	(1.96)	(0.018)	(0.013)	(0.041)
lnAPATENTS	11.410***	0.012	-0.001	-0.000	0.009
	(3.53)	(1.19)	(0.001)	(0.001)	(0.011)
Constant	8.406***	7.550***			
	(22.76)	(22.30)			
Observations	2,136	3084	2937	2937	2937
R-squared	0.989	0.980			0.029
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note：Robust t-statistics in parentheses：*** p<0.01, ** p<0.05, * p<0.1.

5.4.1. Deleting Cities Lagging in the Digital Economy

Given that cities differ in both the timing and the stage of digital-economy development, we followed the approach of Ma et al. (2025) and dropped all cities in Qinghai and Gansu provinces, where the digital economy started late and has remained underdeveloped [26]. Column (1) of Table 7 shows that the inverted-U relationship between the digital economy and per capita carbon emissions remains significant, reconfirming our baseline findings.

5.4.2. Altering the Sample Period

The years 2011–2012 were the infancy of China’s digital economy, when relevant statistics were first released and measurement standards were still evolving; we therefore exclude them. The period 2021–2022 coincides with the vigorous implementation of the “dual-carbon” targets, during which

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local governments imposed abrupt, command-and-control emission cuts that overlapped with—and were hard to disentangle from—the gradual, market- and technology-driven effects of the digital economy. In addition, this two-year span covers the post-COVID recovery, featuring disrupted global supply chains, stimulus packages, and unusual price volatility. For these reasons, we retain only 2013–2020 and re-estimate the model. Column (2) of Table 7 reports a significant inverted-U pattern, corroborating our earlier conclusion.

5.4.3. Endogeneity Test

Recognizing the potential bidirectional causality between the digital economy and per capita carbon emissions, this study addresses endogeneity concerns to ensure the reliability of findings. On one hand, the digital economy influences carbon emissions—initially increasing them due to reliance on traditional energy sources and large-scale infrastructure development, but later curbing them through the environmental benefits of advanced technologies. On the other hand, carbon emissions may also drive digital economy development, particularly through policy pressures and market demand, which can incentivize and stimulate digital transformation. To mitigate endogeneity, we adopt the approach of Wang (2023) and use the one-year lags of both the digital-economy index and its squared term as instruments [32]. Two-stage least-squares estimates are presented in columns (3)–(5) of Table 7. The positive coefficient on the lagged linear term and the negative coefficient on the lagged quadratic term are both statistically significant, consistent with an inverted-U shape and confirming the robustness of our results.

6. Conclusions

6.1. Summary of the Findings

The digital economy is becoming increasingly important as a new driver of economic growth. At the same time, the urgency of realizing the goal of “carbon peaking and carbon neutrality” is also increasing. In this context, it is of great theoretical and practical significance to explore the environmental effects of the development of the digital economy, especially its dynamic relationship with carbon emissions. This study employs a fixed effects model to conduct an empirical investigation using panel data from 267 Chinese cities spanning the period 2011-2022, examining the relationship between the digital economy and per capita carbon emissions. From the perspective of the Environmental Kuznets Curve, this paper aims to explore whether the digital economy, similar to per capita GDP, exhibits an inverted U-shaped relationship with per capita carbon emissions. Furthermore, it investigates whether exogenous shocks can shift the position of the inflection point in the relationship between the digital economy and per capita carbon emissions, as well as whether such shocks alter the slope of the curve. The main findings are summarized as follows:

There exists an inverted U-shaped relationship between the digital economy and per capita carbon emissions. Using panel data covering 267 Chinese cities from 2011 to 2022, this study empirically shows that as the digital economy expands, per capita emissions first rise and then decline. A U-test confirms the robustness of this inverted U-shape, and additional checks—dropping cities with underdeveloped digital sectors and varying the sample period—yield consistent results, indicating that the digital economy, like per capita GDP, follows the Environmental Kuznets Curve. Given that there might be a bidirectional causal relationship between the digital economy and per capita carbon emissions, the linear and quadratic terms of the digital economy are lagged one period and re-estimated with two-stage least squares; the inverted U-shape remains intact. Heterogeneity analyses further reveal that the inverted U-shape is more significant in eastern and western regions than in the central region, more significant in coastal than in non-coastal cities, and more significant in low-urbanization than in high-urbanization areas.

The study subsequently examined the impact of exogenous shock variables on both the position of the turning point and the slope of the curve between the digital economy and per capita carbon emissions. The analysis focused on three exogenous shock variables: local government fiscal pressure, green finance, and climate policy uncertainty.

First, an increase in local government fiscal pressure shifts the inflection point rightward and upward, while steepening the curve initially and flattening it later. This occurs because fiscal strain prompts governments to relax environmental regulations and favor high-carbon industries, leading to an initial reliance on scale effects that drive up emissions, followed by diminishing marginal returns in emission reduction technologies that slow the decline. Second, the development of green finance shifts the inflection point leftward but upward, while progressively steepening the curve. The leftward shift stems from green capital reallocation triggering the emission reduction effects of digital technologies earlier, whereas the upward shift results from substantial embedded carbon emissions during the early stages of green infrastructure construction. The curve steepens in the early phase due to the combination of high emissions and flattens later due to technological bottlenecks and rising marginal costs. Third, rising climate policy uncertainty also shifts the inflection point rightward and upward, while steepening the early segment of the curve and flattening the later segment. This is because companies delay green transitions and reinforce carbon lock-in due to policy ambiguity, leading to a “last-chance effect” that accelerates high-carbon investments in the early stage, while the absence of long-term signals restricts post-inflection efforts to marginal improvements, thereby slowing the pace of emission reduction.

6.2. Policy Recommendation

The conclusions of this research have the following implications:

Firstly, the government should strengthen the green and low-carbon orientation of digital infrastructure. This can be achieved by implementing investment subsidies and electricity price incentives to reduce construction and operational costs, thereby accelerating the realization of environmental benefits. Concurrently, it is crucial to promptly establish and enforce energy consumption and carbon emission limit standards for data centers, 5G base stations, and industrial internet platforms. Transforming technological carbon reduction capabilities into industry access thresholds will guide green transformation from the source.

Secondly, a specialized support system should be constructed from the perspective of green finance. The central bank could introduce preferential loan interest rates for digital carbon reduction projects and create a fast-track channel for issuing related bonds, simplifying approval procedures. Additionally, establishing a dedicated risk capital pool to appropriately underwrite potential loan default risks would incentivize more capital to flow into the field of digital carbon reduction.

Thirdly, local governments should optimize the linkage mechanism between fiscal policies and performance evaluations. On one hand, continuous support through subsidies, interest rate discounts, and electricity price reductions will lower enterprise transformation costs and help them achieve break-even point earlier. On the other hand, linking government performance assessments, fiscal transfers, and debt quotas directly to carbon reduction intensity will guide fiscal resources automatically towards projects with the lowest carbon reduction cost per unit and the highest long-term returns. This approach will significantly shift the inflection point of the inverted U-shaped curve between the digital economy and carbon emissions to the left.

Finally, to address climate policy uncertainty, the government could explore establishing compensation mechanisms for costs related to stranded assets or carbon quota resets triggered by sudden policy changes, thereby reducing investment hesitancy among enterprises. Companies, in turn, could adopt a “modular policy-scenario portfolio” strategy, breaking projects into reversible, quick-return initial stages. Decisions to expand or exit can then be made as policy signals become clearer, ensuring short-term returns while maintaining flexibility for deep decarbonization decisions.

6.3. Limitations

This study has several limitations. First, in constructing the digital economy index, limited by data availability and consistency at the city level, the study only selected proxy indicators from five dimensions: internet penetration, relevant employees, relevant outputs, mobile phone penetration, and the development of digital inclusive finance. This framework fails to encompass emerging key areas such as e-commerce transactions, data element circulation, platform economic activity, the depth of digital finance, and green computing power. This dimensional compression may weaken the accuracy of depicting the "true" level of digital economic development, consequently introducing potential measurement errors in estimating the position and slope of the EKC turning point. Second, the sample of this study covers only 267 prefecture-level cities in China. While this allows for capturing the inverted U-shaped relationship between the digital economy and carbon emissions at the regional level, as well as the impact of exogenous shocks on the turning point and slope, this scope is confined within a single institutional context and development stage, limiting the ability to capture heterogeneity. Given the rapid global diffusion of the digital economy, future research could construct cross-national city panels or adopt a multi-regional comparative framework to test the robustness of the EKC curve across different policy environments, cultural contexts, and resource endowments, thereby enhancing the external validity of the findings. Third, there are limitations regarding the considered exogenous shocks. The selected exogenous shock variables—green finance and local government fiscal pressure—are deeply rooted in China's specific institutional background and developmental stage characteristics. Although these variable choices effectively explain the EKC inflection point shifts within the Chinese context, they consequently restrict the universality of the research conclusions. Their explanatory power may be limited in countries with different institutional frameworks and development levels. Future studies could select other exogenous shock variables with greater general applicability. Fourth, when exploring the relationship between the digital economy and per capita carbon emissions, the research is only based on the inverted U-shaped EKC theory. However, with the development of the economy, some more developed countries and regions have already presented N-shaped EKC curves. Therefore, in future research exploring the relationship between the digital economy and carbon emissions, the N-shaped relationship between the two can be taken into consideration.

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