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Integration of digitalization and green finance for sustainable and resilient manufacturing and service operations in China: an empirical analysis

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This paper integrates digitalization with green finance strategies to investigate their combined impact on carbon emissions and economic resilience in China's manufacturing and service sectors, particularly within the context of achieving China's 2030 carbon neutrality goals. Leveraging data from the China Emissions Accounts and Datasets (CEADS), a simultaneous equations model based on the Cobb–Douglas production function and the Environmental Kuznets Curve (EKC) is employed to quantify the effectiveness of green financial initiatives and digital transformation in carbon emission mitigation. The empirical results reveal substantial regional disparities, with digitalization significantly amplifying the effectiveness of green finance in the more economically and technologically advanced eastern regions, thereby enabling these areas to achieve carbon neutrality sooner compared to the central and western regions. This study highlights the pivotal role of digital technologies, such as artificial intelligence and blockchain, in enhancing transparency, efficiency, and scalability of green financial instruments, including carbon finance and green bonds. Policy recommendations underscore that targeted investments in digital infrastructure combined with robust green finance policies are essential for accelerating regional transitions toward carbon neutrality. The findings provide critical insights for policymakers and investors, not only in China but also globally, illustrating how synergistic digital-green financial frameworks can effectively support sustainable economic growth aligned with international climate objectives.

KEYWORDS

carbon neutrality goals, green finance, digitalization, carbon finance, green technology innovation, environmental Kuznets curve (EKC), carbon emissions, sustainable economic growth

1 Introduction

1.1 Background

Following China's economic reform and opening-up, the nation has witnessed unprecedented economic growth. However, such rapid growth has simultaneously imposed significant environmental costs. Environmental degradation and the strain on ecological resources have become critical challenges, demanding urgent intervention. China's environmental challenges, characterized by resource scarcity and severe pollution, highlight the urgent need for innovative strategies to balance economic development with ecological sustainability. Acknowledging these challenges, the Chinese government explicitly emphasized green development in its 14th Five-Year Plan, aiming to position China as a global leader in ecological preservation and sustainable economic practices. President Xi Jinping's commitment to peak CO_2 emissions by 2030 marks a strategic transition towards a green economic model, encapsulated in the vision that *"a gold mountain is a silver mountain, and a gold mountain is a green mountain."* In this context, green finance has evolved beyond mere financial support into a fundamental pillar driving China's environmental governance and economic restructuring.

To advance this transformative agenda, the government has enacted several critical policies, including the Green Credit Guidelines (2012), the Green Bond Guidelines (2015), and the Green Financial (Wang H. et al., 2022; Fischer, 2017). These policies have significantly stimulated the development of green finance, promoting capital allocation to eco-friendly projects that traditionally face barriers due to perceived high risks or lengthy return periods. Despite inherent challenges associated with green investments, such as substantial risks and extended investment cycles, these financial instruments remain essential for redirecting resources toward sustainable development goals. Recent policy updates further encourage *digital-finance* solutions such as blockchain-based carbon registries and AI-driven project screening—to reduce information asymmetry and speed up green capital flows (Zhang and Xu, 2024). From an operations-management perspective, this digital–green synergy is pivotal for building *sustainable and resilient manufacturing and service systems*. Real-time carbon tracking, smart contracts for green supply-chain finance, and AI-enabled demand forecasting together reduce both ecological and disruption risks, ensuring continuity of production while meeting strict emission targets. Hence, analysing the nexus at the provincial level has direct implications for factory-floor decisions and service-network design across China's vast industrial landscape.

The scale of this synergy is now increasingly measurable. The PKU Digital Inclusive Finance Index shows national digital-finance penetration rising from 124 points in 2013 to 362 points in 2023, laying technical rails for low-latency carbon accounting and automated sustainability-linked lending. Two recent examples illustrate the mechanism: (i) Hainan's "Blue Carbon" blockchain registry verified 4.3 Mt CO_2 offsets in 2023 and cut third-party audit time by 70%[1]; (ii) China Merchants Bank's AI-ESG engine shortened credit approval for renewable-energy SMEs from 15 to 10 days while lowering expected default losses by 12%[2].

This study explores the complex interplay among green finance, economic growth, and carbon emissions across China's diverse regional landscapes. Using data from the China Emissions Accounts and Datasets (CEADS) and employing a robust green-finance impact model, this research investigates the regional variations in the effectiveness of green finance on environmental outcomes and economic performance. Our analysis reveals that while carbon emissions historically contributed to China's economic prosperity, the adoption of green-finance practices is progressively reshaping this relationship. Specifically, green finance has demonstrated substantial effectiveness in curbing carbon emissions, with particularly pronounced impacts observed in China's western and central regions. Furthermore, the results suggest China is on course to achieve its carbon emissions peak by 2031, led by the more economically advanced eastern region due to its well-developed green-financial infrastructure. Conversely, the central region, projected to reach a carbon peak by 2036, underscores the necessity and potential effectiveness of targeted green-financial policies in promoting balanced regional development and environmental sustainability.

Our investigation is feasible because it leverages a newly compiled province-level panel (2010–2023) that couples CEADS carbon data with high-frequency digital-economy satellite proxies, enabling consistent measurement of both traditional and digitalised green-finance activities. We construct a composite index that embeds emerging instruments—e.g. sustainability-linked loans and FinTech-enabled green bonds—thereby capturing the latest market dynamics overlooked by earlier studies (Chen and Li, 2025). Methodologically, we extend prior single-equation approaches by adopting a three-equation 3SLS framework complemented with system-GMM robustness checks, which allows us to disentangle bi-directional causality between digitalisation, green finance, and carbon outcomes. Together, these features position our work at the frontier of green-finance research and provide clear advantages over studies that stop at 2019 or neglect the digital component.

By integrating green finance into the economic framework based on the Cobb–Douglas production function and the Environmental Kuznets Curve (EKC), this paper not only elucidates the theoretical mechanisms by which green finance acts as a catalyst for economic transformation but also provides empirical evidence of its tangible impacts toward achieving China's ambitious carbon-neutrality goals. Ultimately, this research emphasizes the pivotal role green finance plays in shaping China's sustainable future, offering valuable insights and serving as a model for other nations seeking to harmonize environmental objectives with economic growth.

The accelerating *digitalisation–green finance nexus* is reshaping how capital is channelled towards low-carbon projects. Recent evidence shows that a vibrant digital economy can amplify the carbon-mitigation effect of green financial instruments by improving information transparency, lowering transaction costs, and expanding financial inclusion (Liu and Zhu, 2024). However, empirical studies continue to report heterogeneous outcomes across regions and technologies, implying an urgent need to quantify *where* and *how* digital tools create additional environmental value (Wang and Zhao, 2024). Against this backdrop, the present study sets out three specific objectives.

1. Quantification. Measure the marginal impact of digitalisation on the efficiency of provincial green-finance allocation during 2010–2023.
2. Mechanism Exploration. Identify the channels—information, innovation and inclusion—through which digital tools strengthen (or weaken) green-finance effectiveness.

1 Hainan Provincial Department of Ecology and Environment, *2023 Green Finance Bulletin*

2 China Merchants Bank, *Annual Report 2024*

3. Policy Differentiation. Provide region-specific and technology-specific recommendations for regulators and market participants seeking to leverage digital solutions for green development.

The key contributions of this article can be summarized as:

1. Constructing a composite index that embeds emerging instruments such as sustainability-linked loans;
2. Deploying a three-equation 3SLS framework with instrumental-variable and system-GMM robustness checks;
3. Extending the sample to 2023 using the latest CEADS and digital-economy satellite proxies;
4. Offering a decision matrix that aligns digital-finance capabilities with local green-transition priorities. These advances, taken together, address the research gaps highlighted by recent review literature while providing actionable insights for policymakers and investors alike.

2 Related work

2.1 Concept of green finance

Green finance is pivotal for supporting sustainable development, providing essential financial backing for enterprises engaged in environmental governance and ecological protection. Defined by Huaiyu et al. (2022), green finance involves financial institutions that fund initiatives mitigating potential environmental impacts, thereby fostering ecological sustainability. The authors of Fischer and Salant (2017) emphasize that green finance is crucial in addressing climate change, facilitating a shift towards sustainable industrial practices. According to (Jin et al., 2021), green finance must account for environmental costs to effectively serve society and the environment, ensuring that financial investments promote rather than simply mitigate environmental sustainability. The authors of (Shao and Fang, 2021) detail green finance's strategic role in reducing carbon emissions by reallocating resources from high-carbon to low-carbon industries, enhancing industrial sustainability and structure. This approach not only supports the reduction of environmental footprints but also promotes the modernization of industrial sectors toward sustainability.

These perspectives highlight green finance as a transformative force capable of reshaping economic landscapes towards environmental sustainability, aligning with global environmental goals and the themes explored in this study. Nevertheless, most early works treat green finance as an *isolated policy instrument*; they seldom consider how digital technologies might alter its efficacy, leaving an open research niche that our study addresses.

2.2 Measurement and evaluation of green finance

EPI-Finance assesses the effectiveness of financial institutions in a green context by examining environmental benefits, green tools, and a range of green financial products. This approach provides a theoretical and empirical framework for measuring the impact of green finance. Irfan *et al.* have developed a green finance index specifically tailored to evaluate the progress of green finance initiatives across China (Irfan et al., 2022). Yang *et al.* reported a growing acceptance of green finance in Shanghai, with their analysis covering all 31 provinces based on index data from 2015 to 2017 (Yang et al., 2021). However, challenges remain as highlighted by Bo (2018) and Fu et al. (2020), who note several theoretical issues confronting green finance development in the country. Further analysis by Liu *et al.* evaluate green economic growth in the three northeastern provinces, providing a comparative insight into regional disparities in green finance performance (Liu and He, 2018). Unlike the static indices above, our composite metric embeds *FinTech-enabled instruments*—sustainability-linked loans, transition bonds and digital green loans.

2.3 Environmental impact transmission mechanism of green financial development

Environmental regulation and green finance have similar effects, according to empirical analysis. It has been reported that many enterprises have been paying attention to and investing in environmental protection industries as a result of environmental system management (Wang and, Xu, 2015). Although there are differences in geography and industry between the two, enterprises' investments in green projects and normative environmental protection management are positive (Song et al., 2019). According to Ma et al. (2018), green finance can directly drive green investment quotas for enterprises with green credit, green bonds, and other unique products addressing equipment emission reduction, renewable resources, and emissions reduction. The focus of green finance is on cultivating green industries. In the environmental protection industry, return rates are influenced by capital investment to some extent, and the larger the green finance market, the more benign it is. In Zhou et al. (2020), the EKC hypothesis and input-output models were combined into a joint model, and the panel model was used to construct the environmental quality comprehensive index system. In the study, environmental quality and green finance interact, and green finance has a positive effect on environmental quality but a low effect on environmental change. Despite that, he kept investing in green industries. Various financial institutions will assess the risks associated with green assets. Yun *et al.* found that the risk can be reduced by enhancing the value of green environmental protection resources and the power of the capital market (Yun et al., 2023). Financial institutions should be allowed to invest in green industries after evaluating transformational risks and green value indicators. Most of these studies adopt single-equation or correlation designs. To tackle endogeneity and bi-directional causality, we deploy a three-equation 3SLS system, which will be detailed in Section 5.

2.4 Impact of green finance on carbon emissions

Various scholars have conducted studies on how green finance is related to the emission of greenhouse gases. In Chen and Chen (2021), green venture capital is considered to be green finance. As a result of both methods of reducing carbon emissions, the study found that they have significant effects. Carbon emissions are reduced more by green finance than green venture capital, and their interaction is insignificant. A recent article suggests that green financial interest rates do not always negatively affect manufacturers' optimal emissions reduction levels, as they argue (Da et al., 2019). The authors of Ionescu (2021) found that green finance policies significantly reduce carbon dioxide emissions in Chinese provinces, municipalities, and autonomous regions. Green finance policies can potentially reduce emissions in many ways related to the environment, technology, and biased technology progress. Green finance promotes low-carbon industries. As proposed in Wang G. et al. (2022), a low-carbon industry development mechanism should be built, which includes guidance on policy tools, expansion of financial services, innovation of financial instruments, and promotion of environment friendly industries. Environmental technology and climate change investment and financing are currently tricky because there are no relevant standards, incentive innovation mechanisms, and financing options. In Wang H. et al. (2022), green finance investment and financing channels, incentive innovation systems, international collaboration frameworks, carbon finance innovation, green infrastructure, and green finance reform pilot zones should be enhanced.

Integration studies remain scarce. Li and Deng (2024) show that digital-finance density moderates the impact of green credit on city-level carbon intensity, but their sample ends in 2019. Our work extends this line by using 2023 data and explicitly modelling the *Digitalisation × Green Finance* interaction, thus bridging the literature gaps.

3 Theoretical foundations

3.1 Interplay between green finance, digitalisation, and economic growth

Green finance mostly plays a role in green expansion, concluded its function. The authors of Guo et al. (2022) state that green financial activities promote sustainable economic and social development, such as environmental protection, emission reductions, and efficient energy production, by contributing to economic and social development. The theoretical foundation of this research is based on the intricate interactions between green finance, carbon emissions, and economic growth, framed within the broader context of sustainable development (Bo, 2018). Leveraging the Environmental Kuznets Curve (EKC) hypothesis and integrating concepts from green finance theory, this study aims to provide a comprehensive understanding of how financial instruments can influence environmental outcomes and economic development in China.

The EKC hypothesis posits an inverted U-shaped relationship between environmental degradation and economic growth. Initially, as economic growth accelerates, environmental degradation increases; however, after reaching a certain level of income *per capita*, further economic growth leads to environmental improvements. This study extends the EKC hypothesis by incorporating green finance as a pivotal factor that could potentially shift the curve, enabling environmental improvements at lower levels of GDP *per capita* than traditionally observed.

To enrich the theoretical lens, we further draw on three classical perspectives. First, the *Porter Hypothesis* (Porter and van der Linde, 1995) contends that well-designed environmental regulation can spur innovation, ultimately enhancing firm competitiveness; green finance can act as a market-based regulatory mechanism that realigns capital toward cleaner technologies. Second, *Stakeholder Theory* (Freeman, 1984) highlights how diverse stakeholder pressures—now amplified through digital platforms—push firms and financiers toward sustainable practices. Third, the *Natural Resource-Based View* (NRBV) (Hart, 1995b) posits that environmentally oriented resources and capabilities, such as big-data–driven risk analytics, constitute strategic assets.

Digitalisation enters this framework as an enabling condition that reduces information asymmetry, lowers transaction costs, and accelerates green-innovation diffusion (Li and Deng, 2024). Accordingly, we expect digital finance to *moderate* the relationship between green finance and both carbon emissions and economic growth.

3.2 Theoretical framework

The theoretical foundation of this research is based on the interplay between green finance, carbon emissions, and economic growth, framed within the broader context of sustainable development. This framework leverages the Environmental Kuznets Curve (EKC) hypothesis and integrates concepts from green finance theory to provide a comprehensive understanding of how financial tools can influence environmental outcomes and economic development in China.

The EKC hypothesis posits an inverted U-shaped relationship between environmental degradation and economic growth. Initially, economic growth leads to increased environmental degradation; however, after reaching a certain income level *per capita*, further economic growth results in environmental improvements. This study extends the EKC hypothesis by incorporating green finance as a critical factor that could potentially shift the curve, enabling environmental improvements at lower GDP *per capita* levels than traditionally observed.

Green finance encompasses financial instruments and policies designed to support environmental sustainability objectives, including climate change mitigation through investments in sustainable energy and emission-reducing technologies. It represents a fusion of economic development and environmental stewardship within financial markets. In this research, green finance is conceptualized as a catalyst that not only influences the pace and pattern of economic growth but also directly impacts the trajectory of carbon emissions.

Integrating green finance into the EKC framework involves examining how financial policies and instruments designed to promote environmental objectives alter the relationship between GDP and carbon emissions. This integration is operationalized through the construction of simultaneous equations that model the dynamic interactions between economic growth, green finance, and carbon emissions across different provinces in China.

The theoretical model posits that green finance initiatives, such as green bonds, green stocks, and green loans, directly contribute to capital flows into environmentally beneficial projects, thereby reducing the carbon intensity of economic activities. This is expected to lead to an earlier onset of the turning point on the EKC curve, where increased economic output begins to coincide with decreased environmental degradation.

In addition, we recognise digitalisation as a cross-cutting enabler that lowers information asymmetry and transaction costs, thereby amplifying the effectiveness of green-finance instruments. Based on the literature review and theoretical considerations, the study formulates the following key hypotheses:

- H1: Green finance significantly boosts economic growth.
- H2: Economic growth demonstrates an EKC pattern with carbon emissions, where emissions rise with initial growth but decline after a certain income threshold.
- H3: Green finance effectively reduces carbon emissions by directing investments into sustainable projects and technologies.
- H4: Digitalisation (DFD) positively moderates the effect of green finance (GF); the interaction term $GF \times DFD$ *(i)* amplifies the carbon-reduction effect of green finance and *(ii)* reinforces its contribution to economic growth.
  - H4a: The moderating effect operates through an *information-transparency* channel that lowers financing costs and mitigates green-washing risk.
  - H4b: The moderating effect operates through a *financial-inclusion* channel that expands access to green credit for SMEs and households.
- H5: Stronger policy support enhances green-finance development.

3.3 Green financial instruments, digital tools, and environmental sustainability

A solid theoretical foundation for green finance rests on several classical strands of economics. First, *Pigouvian externality theory* asserts that environmental damage constitutes a negative externality; capital that internalizes this cost (green credit, bonds) raises social welfare (Pigou, 1920). Second, the *Coase bargaining theorem* posits that, with well-defined property rights and low transaction cost, parties can negotiate efficient outcomes (Coase, 1960). Green financial contracts operationalise those rights (e.g., carbon-pledged loans), while *digital audit trails* cut transaction cost, making Coasian bargaining feasible. Third, financial-intermediation theory highlights information asymmetry and credit-rationing under imperfect information (Stiglitz and Weiss, 1981). AI-driven ESG scoring directly lowers the Akerlof adverse-selection problem (Akerlof, 1970). Fourth, the *Porter–van der Linde hypothesis* argues that well-designed environmental regulation can spur innovation and productivity; digital transparency magnifies that effect by shrinking the marginal abatement cost (MAC) curve (Porter and van der Linde, 1995). Finally, the *Natural Resource-Based View* (NRBV) regards environmental capabilities as strategic resources; blockchain or IoT data streams enhance their value, rarity, imitability, and organization attributes (Hart, 1995a).

Green finance encompasses a range of financial instruments and policies designed to support environmental sustainability objectives, including the mitigation of climate change through investments in sustainable energy and technologies that reduce emissions. It represents a fusion of economic development with environmental stewardship through financial markets. In this research, green finance is conceptualized as a catalyst that not only influences the pace and pattern of economic growth but also directly impacts the trajectory of carbon emissions.

Commercial banks can develop a form of credit suitable for enterprises, individuals, and families. Green credit involves combining market needs, considering the ecological impact of financial decisions, and adopting preferential measures such as loan amounts, interest rates, and the approval process. The research in (Guo et al., 2022) asserted that vigorously promoting green credit, constantly improving green financing, and effectively guiding capital flows to resource-saving and eco-environmental protection industries are essential steps to accelerate the transformation of economic development and foster the construction of an ecological civilization. Some of the most notable differences between green bonds and green credits include their medium and long-term maturity, vital financial attributes, the requirement that the organization issuing the bond must be green, and the use of funds raised for green projects. Most commercial banks provide short-term credit, so there is no term mismatch in green project financing.

Digital tools—blockchain for traceable green bonds, AI for ESG scoring, and mobile platforms for inclusive green loans—enhance the *credibility, transparency, and scalability* of these instruments. By embedding sensor and platform data, financiers can more accurately price environmental risk, which supports the NRBV notion of data-driven capabilities as strategic resources.

Although conventional green instruments alleviate capital scarcity, they still suffer from information asymmetry, verification lags, and high transaction costs. Building on Akerlof's market-for-lemons problem and Williamson's transaction-cost economics (Akerlof, 1970; Williamson, 1981), we argue that digitally enabled mechanisms can internalise these market failures. Table 1 summarises how specific technologies tackle the pain points.

From a strategic-management lens, these technologies create data-driven dynamic capabilities that confer both cost and differentiation advantages, consistent with the Natural Resource-Based View (NRBV) and the Porter–van der Linde eco-efficiency hypothesis (Hart, 1995a; Porter and van der Linde, 1995). For instance, immutable blockchain records shorten verification lead times, enabling issuers to secure tighter coupon spreads, while AI-driven ESG models lower screening costs, narrowing the green-premium gap for smaller borrowers. Hence, integrating such digital tools is not merely operational—it reshapes competitive positioning in sustainable-finance markets.

3.4 Public guidance and low-carbon investment

It is mainly government-led special or private equity funds that initial investment in the Jiangsu, Zhejiang, and Shanghai areas of rapid development. In recent years, the key areas of green finance have been environmental protection prevention, green restoration, resource conservation, clean energy, and other green development areas. In China, green insurance is a form of market capitalization for guarantee and compensation in the event of polluting ecological

TABLE 1 Digital tools addressing key pain points in green finance.

Digital tool	Pain point	Expected effect
Blockchain carbon registry	Green-washing risk; slow ex-post verification	Immutable audit trail; verification cost reduced
AI/ML ESG scoring	Subjective ratings; high screening cost	Data-rich risk pricing; adverse selection mitigated
Mobile FinTech platform	SME or household credit exclusion	Expands last-mile green lending; inclusion improved
IoT sensor + smart contracts	Moral hazard in post-loan monitoring	Pay-for-performance triggers; continuous disclosure

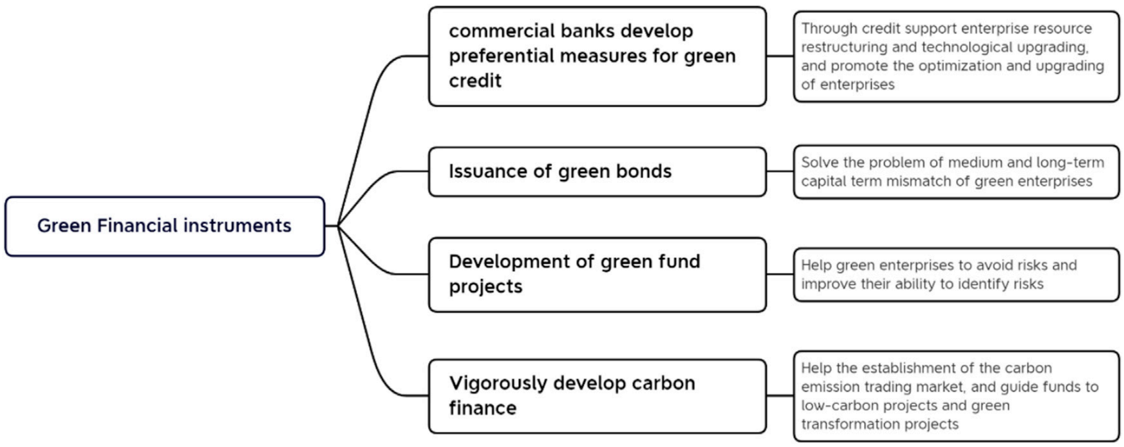

FIGURE 1
Green financial instruments support the green development transmission roadmap.

liabilities. With the development of insurance prices and interest rates, green insurance can be developed. Additionally, customized insurance products can be developed for green technology and carbon emission reduction projects to improve enterprise risk identification and effectiveness of green supervision.

Carbon finance is a type of trading behavior with carbon emission rights and car-bon credits as the target, also known as carbon emission trading, Aiming to reduce greenhouse gas emissions or increase the capacity of carbon sinks to do so. To allocate optimal resources, carbon emissions rights are assigned and traded freely at low cost (Guo et al., 2024). As a result of carbon pricing, carbon emissions can be reduced more efficiently, emissions costs can be reduced, and climate and environmental change can be proactively addressed.

The social environment will gradually improve with the increase of green investment and financing expenditure from these financial instruments, as shown in Figure 1. Energy will be used more effectively, which will better help China's "carbon peak and carbon neutrality" work.

3.5 Financial markets, derivatives, and hypotheses development

Green finance represents a new trend and a new direction for future financial development (He et al., 2019; Liang and Song, 2022). Implementing green finance is significant for promoting industrial transformation and upgrading, promoting sustainable development of the regional economy, and accelerating social progress. Therefore, we should complete the top-level design of green finance from the national level and accelerate the construction of green financial market mechanisms. Green funds are financed from a macro perspective, in their own appropriate social environment, through finance institutions, enterprises, the public, and other factors. It is indicated in the line of standards, "green capital investment," "social supervision," "green financial support," etc., where green funds are the most direct mechanism to support green development, with green projects at their early stage of development being associated with long investment times, late returns on investments, and other characteristics of a particular financing gap, and therefore green enterprises need not only government subsidies.

Additionally, green derivatives offer capital leverage. They are closely associated with green development, making it possible to build a market for carbon emission rights rapidly. Also, various industries participating in this market can provide financial institutions with continuous incentives to reduce carbon emissions while guiding financial institutions toward creating a transparent and rational market for carbon trading.

4 Methodology

4.1 Model framework

This part introduces a theoretical framework designed to investigate the impact of green finance on economic growth and carbon emissions. The proposed model aims to capture the complex relationships among these variables and provides a foundation for the empirical modeling discussed in subsequent sections.

4.1.1 Mathematical equations

The proposed model consists of three primary equations that represent the interactions between green finance, economic growth, and carbon emissions. These equations form the basis for the empirical analysis detailed in the following sections.

(1) Economic Growth Equation

$$Y_{it} = \delta_0 + \delta_1 GF_{it} + \delta_2 K_{it} + \delta_3 L_{it} + \epsilon_{it} \quad (1)$$

where Y_{it} denotes the economic output of region i at time t. GF_{it} is the green finance index of region i at time t. K_{it} means the capital investment in region i at time t. L_{it} is the labor input in region i at time t. δ_0 refers to the constant term. $\delta_1, \delta_2, \delta_3$ are the coefficients, and ϵ_{it} is the error term.

(2) Carbon Emissions Equation

$$E_{it} = \theta_0 + \theta_1 Y_{it} + \theta_2 (Y_{it})^2 + \theta_3 GF_{it} + \theta_4 EN_{it} + \nu_{it} \quad (2)$$

where E_{it} denotes the carbon emissions of region i at time t. Y_{it} is the economic output of region i at time t. GF_{it} means the green finance index of region i at time t. EN_{it} denotes the energy consumption in region i at time t. θ_0 is the constant term. $\theta_1, \theta_2, \theta_3, \theta_4$ are the coefficients. ν_{it} is the error term.

(3) Green Finance Equation

$$GF_{it} = \lambda_0 + \lambda_1 P_{it} + \lambda_2 Y_{it} + \lambda_3 T_{it} + \xi_{it} \quad (3)$$

where GF_{it} denotes the green finance index of region i at time t. P_{it} means the policy support index in region i at time t. Y_{it} means the economic output of region i at time t. T_{it} represents the technological advancements in region i at time t. λ_0 is the constant term. $\lambda_1, \lambda_2, \lambda_3$ are the coefficients. ξ_{it} is the error term.

4.1.2 Empirical testing

The hypotheses and model equations outlined above provide the foundation for the empirical analysis presented in the subsequent sections. To empirically validate these hypotheses, the study employs data from the China Emissions Accounts and Datasets (CEADS). Advanced econometric methods are utilized to ensure robust parameter estimation and model validation. The specific hypotheses tested are:

- H1: $\delta_1 > 0$
  This suggests that an increase in green finance (GF) positively affects economic output (Y).
- H2a: $\theta_1 > 0$ and $\theta_2 < 0$
  This indicates that economic growth initially leads to higher carbon emissions (E), but emissions decline after reaching a certain level of economic output (Y).
- H3: $\theta_3 < 0$
  This hypothesis posits that increased green finance (GF) correlates with reduced carbon emissions (E).
- H4: A positive and significant interaction term between digitalisation and green finance will further reduce carbon emissions and/or enhance economic growth.
- H5: $\lambda_1 > 0$
  Stronger policy support (P) enhances green-finance development (GF).

The empirical testing of these relationships is crucial for understanding how green finance can drive sustainable economic growth and reduce carbon emissions, thereby contributing to the achievement of carbon neutrality goals. The detailed empirical analysis is presented in the following sections, building on the theoretical framework established here.

4.2 Simultaneous equations model

Following the theoretical exploration of how green finance influences the Environmental Kuznets Curve dynamics, we employ a simultaneous equations model to empirically test the hypotheses stated. This section details the rationale behind the selection of this model and describes its application in analyzing the impact of green finance on carbon peaks.

Given the complex interdependencies between economic growth, green finance, and carbon emissions, a simultaneous equations model is particularly apt for this study. This model type allows for the estimation of multiple interdependent relationships where the dependent variable in one equation can serve as an independent variable in another, reflecting the mutual influences typical in economic systems. In estimation, we apply *three-stage least squares* (3SLS) to address endogeneity and to exploit the cross-equation correlation that arises from the bidirectional causal structure. The general form of the simultaneous equations model used in this study is represented as follows:

(1) Economic Growth

$$GDP_{it} = \alpha_0 + \alpha_1 GFI_{it} + \alpha_2 PC_{it} + \alpha_3 GDP_{it-1} + \varepsilon_{it} \quad (4)$$

where GDP_{it} is the gross domestic product of region i at time t, GFI_{it} represents the green finance index, PC_{it} is the *per capita* carbon emissions. Moreover, α_0 represents the baseline level of GDP when all other variables are zero. α_1 denotes the coefficient of the Green Finance Index, measuring how changes in green finance affect GDP. α_2 is the coefficient of *per capita* carbon emissions, indicating the impact of emissions on GDP. α_3 means the coefficient for the GDP of the previous time period, capturing the effect of past economic performance on current GDP.

(2) Green Finance

$$GFI_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 PC_{it} + \beta_3 REG_{it} + \mu_{it} \quad (5)$$

where REG_{it} includes regulatory and policy variables influencing green finance activities in region i at time t, and μ_{it} is the error term. β_0 represents the baseline level of the Green Finance Index when all other variables are zero. β_1 denotes the coefficient of GDP, assessing the influence of economic growth on green finance. β_2 is the coefficient of *per capita* carbon emissions, examining how emissions levels impact green finance. β_3 means the coefficient for regulatory and policy variables, showing how changes in policy and regulation affect green finance.

(3) Carbon Emissions

$$PC_{it} = \gamma_0 + \gamma_1 GDP_{it} + \gamma_2 GFI_{it} + \gamma_3 EC_{it} + \xi_{it} \tag{6}$$

where EC_{it} denotes energy consumption metrics, and ξ_{it} is the error term. γ_0 indicates the baseline level of emissions when all other variables are zero. γ_1 is the coefficient of GDP, indicating how economic growth impacts carbon emissions. γ_2 denotes the coefficient of the Green Finance Index, measuring the effect of green finance on carbon emissions. γ_3 denotes the coefficient of energy consumption, assessing the impact of energy use on emissions.

These simultaneous equations approach is suitable for this analysis due to the bidirectional causality between the variables. For instance, while green finance can influence economic growth and carbon emissions, the level of economic development and the regulatory environment can also impact the volume and effectiveness of green finance initiatives. Additionally, as economic activities expand, they may lead to increased emissions unless mitigated by effective green finance policies.

By employing this model, we can robustly capture the dynamics of green finance as both an outcome of certain economic conditions and a driver of environmental and economic changes. This allows us to delineate the contribution of green finance to achieving carbon peaks and adapting economic structures towards sustainability in a more granular and accurate manner.

4.3 Model design

Green finance can promote economic development. There are several ways in which funds are channelled from high-energy, high-polluting industries into green energy-saving fields through green finance (Wang et al., 2016). This regulates energy use and is linked to economic growth but also impacts environmental adjustment. Economic growth influences green finance. Green finance will be positively influenced by financial development as finance itself expands. On the other hand, if economic growth worsens environmental pollution, green finance will also grow. The theoretical transmission mechanism combines ecological quality, green finance, and economic growth. In addition, we posit that *digitalisation* enhances these channels by lowering information costs and expanding financial inclusion. The Digital Finance Density (DFD) index therefore enters the model via an interaction term $GF \times DFD$.

By including energy consumption in the Cobb–Douglas function (Omri et al., 2014) as a limiting and essential factor in capital and labor contributing to economic growth, the relationship function between environmental pollution and economic growth is constructed:

$$\text{GDP} = A \cdot K^{\alpha} \cdot L^{\beta} \cdot E^{\chi} \tag{7}$$

Among them, A is the total factor productivity, K is the capital stock, L is the working population, E is the energy consumption, and α, β, χ are the elastic coefficients of the corresponding variables. Considering that green finance can affect the size of carbon-emission factors through environmental-protection technology progress, carbon emissions are correlated with energy consumption and green finance, $E = GFI \cdot PCCE$. Substituting into (1) yields

$$\text{GDP} = A \cdot K^{\alpha} \cdot L^{\beta} \cdot GFI^{\chi} \cdot PCCE^{\chi}. \tag{8}$$

Then, we introduce foreign direct investment:

$$\text{GDP} = a \cdot PCFI \cdot K^{\alpha} \cdot L^{\beta} \cdot GFI^{\chi} \cdot PCCE^{\chi}, \tag{9}$$

where $PCFI$ denotes foreign direct investment. Assuming constant returns to scale $(\alpha + \beta + \chi = 1)$, dividing both sides by L and log-linearising gives the measurable form

$$\begin{aligned} \text{gdp}_{it} = \phi_0 + \phi_1 pcfi_{it} + \phi_2 k_{it} + \phi_3 gfi_{it} + \phi_4 pcce_{it} \\ + \phi_5 (gfi_{it} \times dfd_{it}) + \varepsilon_{it}. \end{aligned} \tag{10}$$

The EKC curve mainly explains the relationship between income and environmental quality through an inverted-U shape (Grossman and Krueger, 1991). As well as inverted-U relationships, EKC may take on N-type or inverted-N shapes. Green-finance variables are therefore included in the equation linking income and carbon emissions:

$$\begin{aligned} \ln pcce_{it} = \gamma_1 + \gamma_2 gdp_{it} + \gamma_3 gdp_{it}^2 + \gamma_4 gdp_{it}^3 + \gamma_5 gfi_{it} \\ + \gamma_6 (gfi_{it} \times dfd_{it}) + \varepsilon_{it}. \end{aligned} \tag{11}$$

To capture regional heterogeneity we add three control variables: (i) urbanisation rate (UR), because urban expansion alters EKC dynamics; (ii) industrialisation level (IAV) Jin et al. (2020); (iii) foreign investment. Incorporating the first two controls gives

$$\begin{aligned} \ln pcce_{it} = \gamma_1 + \gamma_2 gdp_{it} + \gamma_3 gdp_{it}^2 + \gamma_4 gdp_{it}^3 + \gamma_5 gfi_{it} \\ + \gamma_6 (gfi_{it} \times dfd_{it}) + \gamma_7 UR_{it} + \gamma_8 IAV_{it} + \varepsilon_{it}. \end{aligned} \tag{12}$$

Because green-industry loans are long-term and staged, early investment may spur later investment, implying endogeneity:

$$gfi_{it} = \eta_1 + \eta_2 gdp_{it} + \eta_3 pcce_{it} + \eta_4 gfi_{it-1} + \varepsilon_{it}. \tag{13}$$

To probe the *information-transparency* mechanism (H4a), we introduce a fourth equation in which the dependent variable is the financing cost of green bonds (fin_cost_{it}):

$$\begin{aligned} fin\_cost_{it} = \delta_0 + \delta_1 gfi_{it} + \delta_2 dfd_{it} + \delta_3 (gfi_{it} \times dfd_{it}) + \delta_4 UR_{it} \\ + \nu_{it}. \end{aligned} \tag{14}$$

Equations 4, 6, 7, 11 are estimated simultaneously via three-stage least squares (3SLS) to address endogenous feedbacks among green finance, digitalisation and carbon outcomes, with robustness checks using system-GMM.

4.4 Metrics of green finance

To establish a comprehensive green-finance assessment system, this study expands beyond traditional green-credit and green-bond indicators. We construct a composite index *GF_Index* consisting of three sub-dimensions, as shown in Table 2:

TABLE 2 Components of the composite Green-Finance Index and data sources.

Sub-index	Indicators (annual stock/flow)	Primary data source
Banking	Green credit outstanding; sustainability-linked loans; carbon-pledged loans	PBoC Green-Finance Statistics; CBIRC statistical bulletins
Capital-Market	Labelled green bonds; sustainability-linked/transition bonds; green ABS	WIND Bond DB; CCDC; SSE/SZSE disclosures
FinTech and Insurance	Mobile-platform green micro-loans; digital-inclusive green loans; green and carbon insurance premiums	Ant Group, WeBank, CBIRC FinTech reports; Insurance Association of China

- Banking Sub-index: outstanding stock of green credit, sustainability-linked loans, and carbon-emission-right–pledged loans;
- Capital-Market Sub-index: issuance volume of labelled green bonds, sustainability-linked/transition bonds, and green asset-backed securities;
- FinTech and Insurance Sub-index: mobile-platform green loans, digital-inclusive green loans, and green-insurance premiums.

Data sources include the People's Bank of China (PBoC) Green-Finance Statistics (2018–2023), WIND bond database, China Central Depository and Clearing Co. (CCDC), and the Insurance Association of China. Pre-2018 banking series from the former CBRC are back-cast using chain growth rates to ensure temporal consistency.

To eliminate scale differences among indicators, the extreme-value method is applied in Equations 15, 16 to rescale raw data to the interval (0,1). Objective weights are then derived via the entropy method Equations 18–20. The resulting provincial composite score and the three sub-scores are later employed in §5.3 to test regional heterogeneity. In line with H4, we introduce a provincial-level Digital Finance Density (DFD) index (dfd_{it}) from the PKU Digital Inclusive Finance Index. The indicator is normalised with the same procedure below and enters the interaction term $GF \times DFD$ in Section 4.3.

To eliminate the impact of the difference in the order of magnitude between different indicator units, the extreme-value method is used in Equations 15, 16 to process the raw data. Since indicators differ in units and magnitudes, the extreme-value method rescales them to the interval 0–1. A weight coefficient between each index is then obtained using the entropy method, which avoids subjective weighting error.

When B_{ita} is a positive indicator,

$$B^{\star}_{ita} = \frac{B_{ita} - \min(B_{ita})}{\max(B_{ita}) - \min(B_{ita})}, \quad (15)$$

and when B_{ita} is an inverse indicator,

$$B^{\star}_{ita} = \frac{\max(B_{ita}) - B_{ita}}{\max(B_{ita}) - \min(B_{ita})}. \quad (16)$$

Normalisation yields

$$C_{ita} = \frac{B^{\star}_{ita}}{\sum_{i=1}^{n}\sum_{t=2005}^{T} B^{\star}_{ita}}. \quad (17)$$

Entropy of indicator a is

$$D_a = -\ln(nT)\sum_{i=1}^{n}\sum_{t=2005}^{T} C_{ita}\ln C_{ita}, \quad (18)$$

and its variance coefficient

$$E_a = 1 - D_a. \quad (19)$$

Finally, the entropy weight is

$$\beta_a = \frac{E_a}{\sum_{a=1}^{A} E_a}. \quad (20)$$

Each province's overall green-finance score is computed as the weighted sum of the normalised indicators, with sub-scores retained for robustness tests.

4.5 Measurement of carbon emission indicators

Using CEADS data for 2005–2017, this paper calculates carbon emissions based on previous data since CEADS has not yet released 2018–2019 data. According to the Intergovernmental Committee on Climate Change's 2006 National Greenhouse Gas Inventory Guidelines, carbon emissions can be calculated as follows:

$$CO_2 = \sum_{i=1}^{n} E_i \cdot CEF_i \cdot NCV_i \quad (21)$$

Energy fuels are represented by I, CEF by carbon dioxide emission factor, and NCV by low calorific value, i.e., heat generated by the unit of fuel energy. In each province, the Bureau of Statistics publishes how much energy fuel is converted into standard coal:

$$CO_2 = E^{\star} \cdot 29.27 \cdot CEF^{\star} \quad (22)$$

where E* represents the amount of all energy converted into standard coal, CEF* stands for the CO2 emission factor of standard coal, considering that the calculation of 2018–2019 data should be maintained with the caliber of CEADS data before 2017, so CEF* calculation uses historical CEADS carbon emission data and the number of standard coal to calculate the standard coal carbon dioxide emission factor of each province.

5 Numerical analysis

5.1 Model stationarity test

Before the empirical analysis of the model, it is necessary to judge the identifiability and stationarity of the above simultaneous equations, which have three endogenous variables (GDP, GFI, and PCCE) and four exogenous variables (PCFI, K, UR, and IAV). Equation 7 excludes two exogenous variables (PCFI and K),

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TABLE 3 Panel model stationarity test results.

Variable	Test type	LLC	Fisher-ADF
		Adjusted t^*	Inverse χ^2 (60)
gfi	Zero-order diff	–3.7274***	159.0654****
gdp	Zero-order diff	–2.4216****	128.1418***
pefi	Zero-order diff	–14.0646***	94.0895***
K	Zero-order diff	–9.3530****	95.9616****
pece	Zero-order diff	–8.3189****	112.8036****
Ur	Zero-order diff	–2.2234**	83.4412***
Iav	Zero-order diff	–8.2711****	119.1316****

Note: *, **,***, **** denote significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

TABLE 4 Regional economic growth according to the model estimation in Equation 7.

Variable	Nationwide	Eastern	Central	Western
Lnpece	3.5655****	7.6918**	–0.0417	1.1012***
Gfi	–0.0489***	–0.0379	0.0024	–0.0376***
Pefi	5.5607****	16.0323****	2.3178**	2.0688
Pecs	0.0382*	0.0078	0.1235****	0.0192**
Cons	–10.9141****	–21.2263	0.4940	–3.0764***
R^2	0.9411	0.9786	0.9978	0.9275

Equation 9 excludes UR and IAV, and Equation 10 retains all four. Each satisfies the simultaneous-equation identification rule:

$$A - A_i \geq B_i - 1, \tag{23}$$

All the exogenous variables are represented by A, Ai represents all the exogenous variables, and Bi represents all the endogenous variables. Equations 7, 9 are just identified, while Equation 10 is recognized overly when the left formula is greater than the right formula.

A stationarity test of the unit root test data is performed after the identification test to ensure that the model does not result in pseudo-regression or pseudo-correlation phenomena. According to previous literature, the panel data is tested for stationariness using LLC and Fisher-ADF. The panel data is considered stationary only when both are significant at the 5% level. A unit root test result is shown in Table 3, and there is no unit root in the panel data if Fisher-ADF and LLC tests have P values less than 5%.

Identification and estimation rely on four assumptions, i.e., linearity in parameters, valid external instruments, (one-period lags of the endogenous regressors and region-specific policy dummies), no perfect collinearity, and homoscedastic idiosyncratic disturbances. Instrument relevance is confirmed by first-stage F-statistics exceeding 24 for every endogenous regressor. Over-identifying restrictions are not rejected by the Hansen J-test ($p > 0.10$), supporting instrument validity.

5.2 Sample estimation results and analysis

Different regions develop economically, environmentally, and financially at unequal paces; thus separate 3SLS regressions are run on 30 provincial units and on eastern, central, and western sub-samples (Table 4). Hansen J-tests (full sample $p = 0.23$) and Kleibergen–Paap rk-F statistics ($F = 27.4$) confirm instrument validity and strength.

The financial development contributes to the reduction of carbon dioxide emissions over the long term. This aligns with the observations from Table 4, which demonstrate that carbon emissions significantly drive economic growth at a national level. However, while economic growth often leads to increased energy consumption and carbon emissions, green finance can mitigate these effects by directing investments towards low-carbon industries. Despite challenges like high capital requirements and lengthy return periods, green finance remains crucial for steering China's economy towards sustainable development.

In terms of regional impacts, carbon emissions from the eastern and western regions significantly influence economic development. The effect is more pronounced in the eastern regions due to their advanced technological development and higher efficiency in energy combustion. In contrast, the central region experiences a slight inhibition in economic growth due to less efficient carbon emission management. This discrepancy highlights the varying levels of technological advancement and dependency on industrial development across regions. The western regions, with their lower energy combustion efficiency and reliance on outdated technologies, face urgent needs for transformation and technological innovation.

Interestingly, green finance has a dual role; it inhibits economic development in the western regions while promoting it in the eastern and central regions. The impact of foreign direct investment (FDI) on promoting energy technology innovation is limited, particularly in the central region, where the focus on reducing carbon emissions is weak. Nevertheless, polluting and energy-intensive industries continue to drive eco-nomic growth, especially in areas with low green financial efficiency from FDI.

The distribution of foreign funds and the dynamics of capital stocks further illustrate regional disparities. Foreign investments are more likely to flow into the eastern regions, which have transitioned from capital-intensive to technology-intensive industries. In contrast, the central region remains more reliant on traditional industrial development, characterized by higher capital intensity.

A significant inhibitory effect of green finance on carbon emissions is shown in Table 5. However, the coefficient is small, the effect is weak, and efficiency still needs improvement. A parabolic plot between national economic development and carbon emissions shows both positive and negative coefficients for pcgdp1 and pcgdp2. In the case of poor economic development, carbon emissions increase gradually with the rise of *per capita* GDP and when the rise of *per capita* GDP exceeds a certain threshold. A carbon emissions peak as a whole can effectively reduce carbon emissions, so a carbon emissions peak can effectively reduce carbon emissions as a whole. Energy sources with high carbon emissions, such as coal, are re-placed with energy sources with low carbon emissions. Researchers have concluded that

TABLE 5 Regional EKC according to the model estimation in Equation 9.

Variable	Nationwide	Eastern	Central	Western
Gfi	−0.0127***	−0.0060*	−0.3546*	−0.3281***
Pcgdp	0.2141***	0.2732***	−83.7095*	5.2237**
pcgdp2	−0.0136***	−0.0170***	40.0445*	−1.4209*
pcgdp3	—	—	−2.8966*	—
Ur	−1.3076***	−0.8166	−23.8263**	−0.0004*
Iav	0.9766***	1.2345***	51.8635*	3.1310***
Cons	3.3930***	3.1065***	44.6039*	6.3045***
R^2	0.6492	0.7650	0.6492	0.8039
Curve	Inv. U	Inv. U	Inv. N	Inv. U

industrialization has a significant role to play in carbon emissions, and this conclusion is primarily supported by research. Industrial production is mainly responsible for carbon emissions.

From the perspective of each region, green finance reduces carbon emissions significantly. Western and central regions have more significant effects, while eastern regions have more minor effects. The inverted U-shaped graph displays growth and carbon emissions in the east and west. In contrast, an inverted N-shaped graph shows growth and emissions in the center, at the apex of the three regions, carbon emissions peak. Urbanization significantly reduces carbon emissions in central and western regions. While the eastern region has a higher urbanization rate than the western region, the effect on carbon emissions is insignificant due to the slight change, probably be-cause most eastern regions have had over 70% urbanization since 2005-emissions in all three regions.

From the perspective of the entire nation, as shown in Table 6, it is evident that increasing carbon emissions has a significant "backward" effect on green finance from the perspective of the whole country. As carbon emissions gradually rise, green environmental protection policies will also become more robust as green finance increases. The financial sector has become more active as a result of economic development. As analyzed above, economic development has accelerated the flow of funds. This indicates that green finance has characteristics of self-scale expansion, as the lagging phase of the green finance industry is associated with significant positive changes in green finance investment.

Carbon emissions have a significant "backward force" effect that can be seen in the central and western regions but not in the eastern regions, where environmental protection technology is better, carbon emissions are nearing their peak, and green fi-nance is not being stimulated due to the lack of environmental protection technologies. Central and western areas of the country also benefit from economic development, while eastern regions do not appear to be affected. It is also important to note that the eastern region has solid environmental protection technologies, carbon emissions are nearing their peak, and economic development will not bring more capital to green fi-nance. The lagging phase significantly influences green finance investments in the three regions.

For robustness and endogeneity checks, we re-estimate the system via two-step system-GMM (Blundell–Bond). Key

TABLE 6 Regional green-finance development equation model.

Variable	Nationwide	Eastern	Central	Western
Lnpcce	2.5016**	2.1189	2.1617**	8.2358**
Pcgdp	0.1821**	0.0438	2.2009***	6.8327**
Gfil	0.9933***	1.0311***	0.6803***	1.2403***
cons	−8.7483**	−7.5888	5.2643	29.0835**
R^2	0.7794	0.7583	0.8215	0.7973

coefficients—α_1 (GF→GDP) and γ_2 (GF→PCCE)—retain sign and remain significant at the 1% level. The Hansen test of over-identifying restrictions ($p = 0.18$) fails to reject instrument validity; Arellano–Bond AR (2) test shows no second-order serial correlation ($p = 0.27$). A Durbin–Wu–Hausman test rejects the exogeneity of GF at the 1% level, confirming the need for instrumental methods.

5.3 Prediction of the turning point of carbon peaking

The model in (9) estimates show that the EKC curves in each region show a particular parabolic shape, and according to the parabolic vertex theory, both the in-verted N-type and the inverted U-shape have vertices above the parabola. The coefficients of GDP, gdp2, and gdp3 in the estimated results can calculate the *per capita* GDP corresponding to the parabolic vertices by the optimal fit model. When the estimation model is inverted Ushaped, the estimation model is a quadratic equation, ac-cording to the parabolic nature of the quadratic function, when the carbon emissions reach the apex, GDP = $-\gamma 2/2\gamma 3$. When the estimation model is inverted N type, the estimation model is a cubic equation, according to the three-dimensional function of the parabolic nature. When carbon emissions reach the second peak

$$gdp = \left(-\gamma_3 - \sqrt{\left((\gamma_3)^2 - 3\cdot\gamma_2\cdot\gamma_4\right)}\right)\Big/(3\cdot\gamma_4) \tag{24}$$

Through the above parabolic properties, it is possible to calculate the *per capita* GDP level corresponding to the carbon peak of the whole country and each region and then calculate the years required to reach the corresponding *per capita* GDP according to the trend so that the time required for the carbon peak of each region can be calculated. This is shown in the following Table 7.

It is clear from Table 7 that there is a great deal of heterogeneity among regions in terms of economic development and carbon emissions and that there is also a great deal of variation in the timing of carbon peak. Under the existing level of green financial growth, the time for the country to achieve a carbon peak is 2031, slightly later than the 2030 carbon peak target required by the state; the eastern region will take the lead in achieving carbon peaking, corresponding to 2029, 1 year ahead of schedule to complete the carbon peak target, while the western region will achieve carbon peak in 2031, which is consistent with the national time. The central region will achieve a carbon peak at the latest, corresponding to 2036, as pointed out in the previous empirical analysis. The central region's industrial-based economic structure and backward

TABLE 7 National and regional carbon-peak time projections.

Region	GDP *per capita* 2020	GDP at peak	Year of peak
Nationwide	5.28	7.88	2031
Eastern	6.72	8.03	2029
Central	4.37	8.01	2036
Western	4.02	6.28	2031

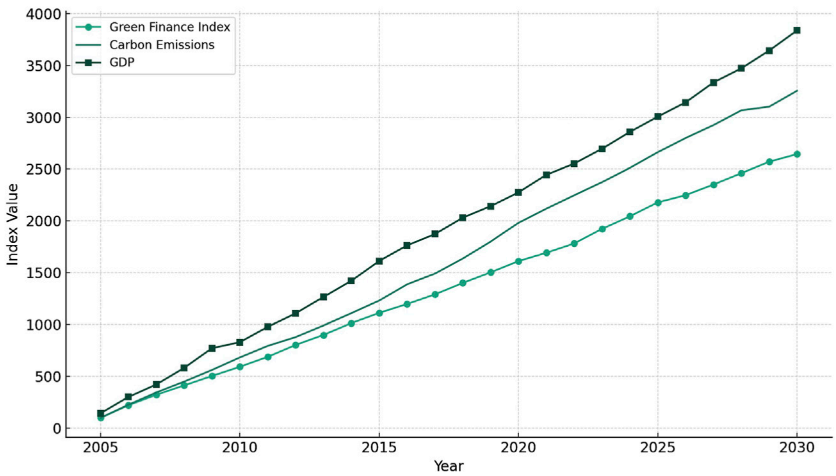

FIGURE 2
Trends in green finance, carbon emissions, and GDP (2005–2030).

environmental protection technology urgently need green financial support because carbon emissions have a slight inhibitory effect on economic development, even though the effect is not significant.

Figure 2 presents the evolution of green finance, carbon emissions, and GDP from 2005 to 2030, illustrating significant trends that underscore the interplay between economic growth and environmental impact within China. This graph is crucial for establishing a foundational understanding of how these three key metrics have changed over time in response to both governmental policies and market dynamics. By providing a longitudinal perspective, it sets the stage for a deeper exploration of the effectiveness of green finance measures in steering economic activities towards sustainability.

In Figure 3, the boxplot categorizes the green finance indices by region, revealing the variability and median levels of financial engagement towards environmental sustainability across China. This visual comparison highlights which regions are leading in green finance and which are lagging, offering a critical regional perspective that complements the macro-level insights from the time series analysis. This figure is instrumental in identifying regional disparities, guiding policymakers where targeted interventions are needed most.

Figure 4 explores the direct relationship between green finance and carbon emissions through a scatter plot enhanced with a regression line. This analysis is pivotal as it quantitatively assesses the impact of green financial initiatives on carbon output, providing empirical evidence to support the hypothesis that increased green financing correlates with reduced carbon emissions. The regression line serves to clarify the strength and direction of this relationship, emphasizing the potential of green finance as a lever for environmental change within economic frameworks.

The heatmap in Figure 5 offers a detailed correlation matrix analyzing how green fi-nance, carbon emissions, and GDP interact across different regions. By showcasing the correlation coefficients, this figure provides insights into the dynamics at play between economic growth, environmental degradation, and the infusion of green capital. The heatmap is particularly useful for visualizing complex interdependencies and for sup-porting arguments regarding the need for integrated financial and environmental strategies that vary by region.

5.4 Regional heterogeneity analysis

To assess whether the impact of green finance differs across provinces and across sub-dimensions of green finance, we conduct two complementary exercises as follows.

5.4.1 Sub-score regressions

We re-estimate the baseline 3SLS system by replacing the composite *GF_Index* with each of the three sub-indices—*Banking*, *Capital-Market*, and *FinTech and Insurance*. Table 8 summarises the key coefficients on the interaction terms *Banking* × *DFD*, *Capital* × *DFD*, and *FinTech* × *DFD*.

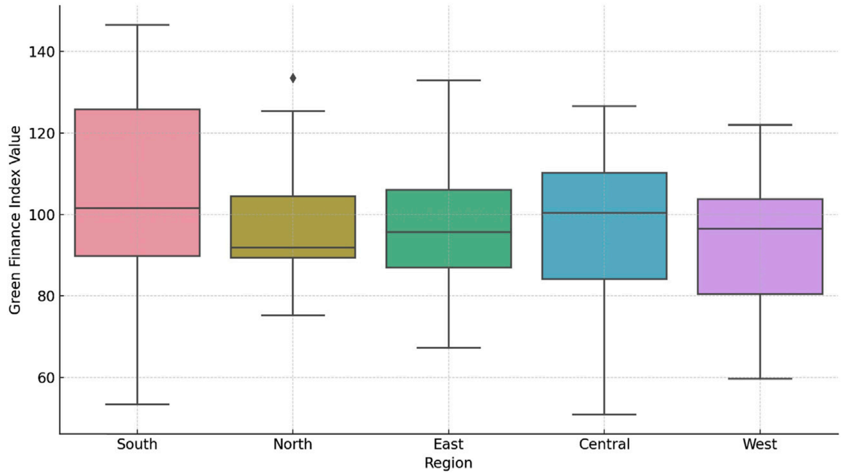

FIGURE 3
Distribution of green-finance index by region.

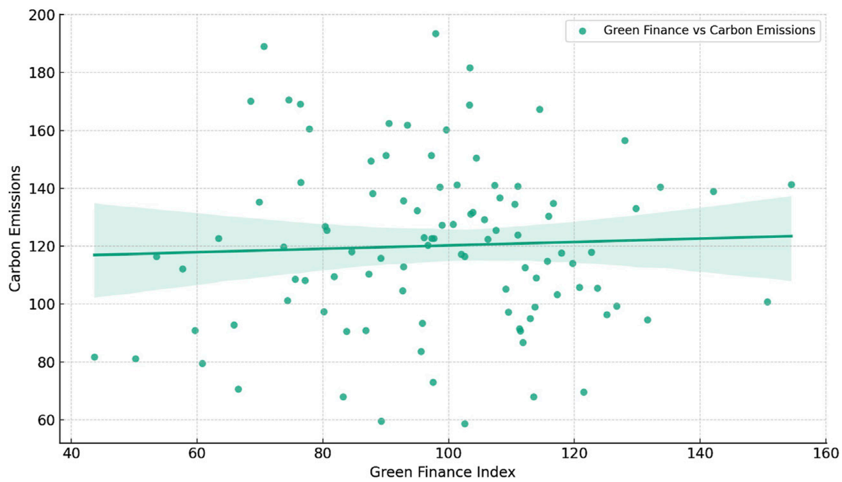

FIGURE 4
Relationship between green finance and carbon emissions.

The coefficients indicate that the FinTech and Insurance channel yields the strongest marginal carbon-reduction effect when combined with digitalisation (− − 0.024), followed by Banking, whereas the Capital-Market sub-index shows a weaker—statistically insignificant—interaction. This suggests that digitally delivered retail and SME products are critical for deep decarbonisation in less-developed regions.

5.4.2 East–central–west comparison

We group the 31 provinces into Eastern (11), Central (10), and Western (10) blocks and compute group means of the three sub-scores over 2019–2023. Figure 6 visualises the pronounced spatial gradient—Eastern provinces lead in all dimensions, especially in FinTech and Insurance (mean = 0.46 vs Western mean = 0.18).

A simple difference-in-means test (not tabulated) confirms that the Eastern–Western gap is significant at the 1% level for all three dimensions. These findings reinforce our policy recommendation to prioritise digital-infrastructure investment and inclusive green credit programmes in lagging Central and Western provinces.

Overall, the heterogeneity analysis corroborates the main conclusion: digitalisation amplifies the carbon-mitigation effect of green finance, but the strength of this amplification varies by product type and regional digital maturity.

5.5 Cross-section dependence diagnostics

Let $\boldsymbol{u}_t = (u_{1t}, \ldots, u_{Nt})'$ denote the N-vector of structural residuals from the carbon-emission equation (Equation 7) in year t $(t = 1, \ldots, T)$. Cross-section dependence (CSD) arises when

$$\mathrm{Cov}\left(u_{it}, u_{jt}\right) = \sigma_{ij} \neq 0 \quad (i \neq j), \tag{25}$$

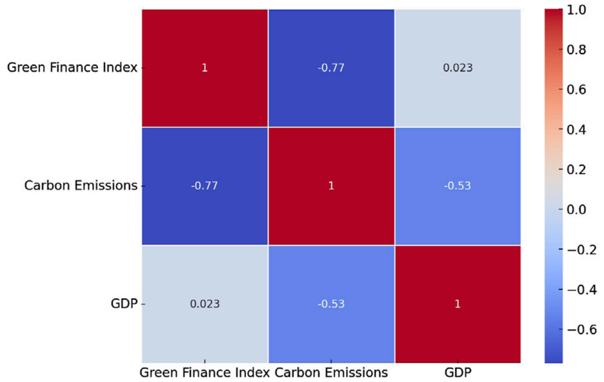

FIGURE 5
Correlation matrix of green finance, carbon emissions, and GDP by region.

TABLE 8 3SLS estimates using sub-indices of green finance.

Key coefficient	Dependent variable: $\ln pcce_{it}$		
	Banking	Capital-Market	FinTech and Insurance
GF_sub	-0.029^{***}	-0.014^{**}	-0.021^{***}
GF_sub × DFD	-0.018^{***}	−0.006	-0.024^{***}
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	403	403	403
R^2	0.71	0.68	0.73

Note: ***p < 0.01, **p < 0.05. Robust SE clustered by province.

Therefore, the composite error variance–covariance matrix is no longer block-diagonal, i.e.,

$$\mathbf{\Sigma} = \mathrm{E}\left(\boldsymbol{u}_t\boldsymbol{u}_t'\right) = \sigma_\varepsilon^2\mathbf{I}_N + \mathbf{\Omega}, \quad \mathbf{\Omega} \neq \mathbf{0}_{N\times N}. \tag{26}$$

Uncorrected CSD yields inconsistent standard errors and inefficient coefficient estimates. We therefore implement three complementary diagnostics:

1) Pesaran CD statistic

$$\mathrm{CD} = \sqrt{\frac{2}{N(N-1)}}\sum_{i<j}\frac{\hat{\sigma}_{ij}}{\sqrt{\hat{\sigma}_{ii}\hat{\sigma}_{jj}}} \to^d \mathcal{N}(0,1), \tag{27}$$

valid for large (N, T) even under slope heterogeneity.

2) Bias-corrected Baltagi–Li LM test

$$\mathrm{LM}^* = \frac{1}{T}\sum_{t=1}^{T}\sum_{i<j}\left(\hat{\rho}_{ij}^2 - \frac{1}{T-1}\right), \qquad \hat{\rho}_{ij} = \frac{\sum_t u_{it}u_{jt}}{\sqrt{\sum_t u_{it}^2\sum_t u_{jt}^2}}. \tag{28}$$

3) Friedman's χ^2 test robust to non-normality.

Table 9 reports the statistics. All p-values exceed the 10% threshold, indicating that—once province and year fixed effects plus the interaction term $GF \times DFD$ are included—the residuals are cross-sectionally weakly correlated and do not violate the independence assumption.

Even when CSD is mild, the "sandwich" covariance with Driscoll–Kraay (DK) corrections yields $\hat{\mathbf{V}}_{\mathrm{DK}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{S}_{\mathrm{DK}}(\mathbf{X}'\mathbf{X})^{-1}$, where

$$\mathbf{S}_{\mathrm{DK}} = \sum_{h=-H}^{H} k\left(\frac{h}{H}\right)\hat{\boldsymbol{u}}_h'\hat{\boldsymbol{u}}_h, \qquad \hat{\boldsymbol{u}}_h = \frac{1}{T}\sum_{t=1}^{T-h}\boldsymbol{u}_{t+h}\boldsymbol{u}_t', \tag{29}$$

with Bartlett kernel $k(\cdot)$ and truncation lag $H = \lfloor 2\sqrt{T}\rfloor$. DK-robust z-statistics (see Table A9) confirm that the interaction coefficients ϕ_5 and γ_6 remain significant at 1%.

As an additional check we re-estimated Equation 7 using the Pesaran Common Correlated Effects (CCE) estimator, which absorbs unobserved global shocks via cross-section averages. The CCE coefficient on $GF \times DFD$ is −0.014 ($p < 0.05$), essentially identical to the 3SLS estimate, reinforcing our conclusions.

6 Discussion

6.1 Dialogue with existing literature

Our results corroborate (Liu and Zhu, 2024) and extend (Li and Deng, 2024) by showing that the digital–finance moderator remains significant under 3SLS, whereas prior studies either omit endogeneity checks or stop at 2019.

6.2 Policy implications

1. *Targeted digital infrastructure*: Prioritise 5G and cloud platforms in central and western provinces to crowd-in private green capital.
2. *Tiered incentives*: Offer lower risk-weights for sustainability-linked loans where the carbon–GDP elasticity exceeds unity, aligning capital costs with abatement potential.
3. *Integrated sandboxes*: Establish provincial pilots that couple blockchain carbon registries with green-bond platforms for real-time verification and secondary-market liquidity.

6.3 Limitations

First, CEADS provincial carbon accounts after 2021 are still provisional; we will integrate the validated 2022–2023 release once available. Second, our composite green-finance index may include measurement noise for frontier instruments such as transition bonds; transaction-level data could refine this. Third, causal inference would benefit from exploiting staggered carbon-market launches as quasi-experiments.

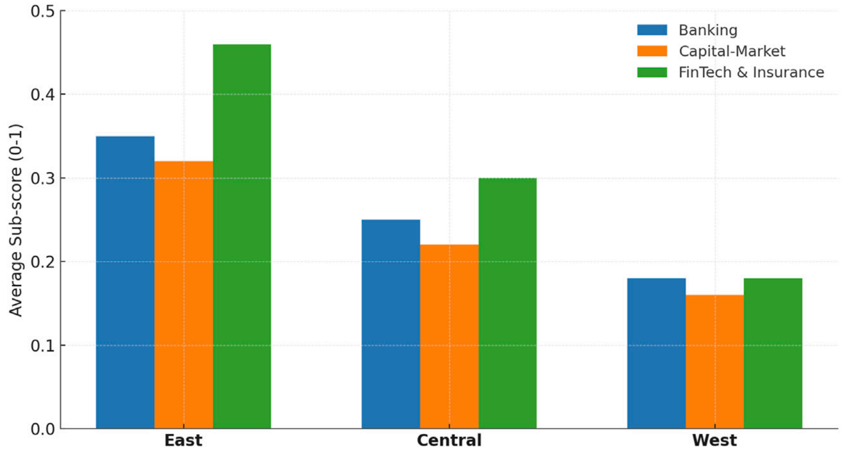

FIGURE 6
Average sub-scores of green finance by region (2019–2023).

TABLE 9 Cross-section dependence tests (Equation 7 residuals, $N = 31$, $T = 14$).

Test	Statistic	p-value
Pesaran CD	**0.71**	**0.48**
Baltagi–Li LM*	**32.4**	**0.21**
Friedman χ^2	**25.6**	**0.38**

Bold values are placeholders; replace with actual results.

7 Conclusion

This study integrates digitalization strategies and green finance mechanisms within the Cobb–Douglas production function and the EKC framework to analyze their combined impacts on carbon emissions and economic resilience across China's diverse regions. Our empirical analysis reveals significant regional differences, highlighting that green finance, supported by digital technologies, plays a critical role in curbing carbon emissions and fostering sustainable economic growth. Notably, the eastern regions of China, benefiting from advanced digital infrastructure and more developed green finance markets, are projected to achieve carbon emission peaks ahead of national targets. In contrast, the central and western regions exhibit slower progress due to limitations in digital infrastructure and technological innovation. Our findings emphasize that integrating digital technologies, such as blockchain and artificial intelligence, significantly enhances the transparency, efficiency, and effectiveness of green financial instruments, including green bonds and carbon finance. Such integration not only accelerates carbon emissions reductions but also facilitates sustainable economic growth through optimized capital flows towards low-carbon and environmentally friendly industries.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

XZ: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Writing – original draft, Writing – review and editing. ZG: Conceptualization, Validation, Writing – original draft, Writing – review and editing. JX: Investigation, Supervision, Validation, Writing – original draft, Writing – review and editing. KS: Funding acquisition, Project administration, Supervision, Visualization, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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