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Analyzing the Impact of Digital Economy Development on Carbon Finance Using Differences-in-Differences and Spatial Error Model

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Abstract: Traditional measurement methods often produce biased estimates when assessing the impact of digital economy development on carbon finance, as they neglect spatial dependencies between regions and the endogeneity of policy shocks. This failure to account for these factors hinders a comprehensive reflection of the multidimensional mechanisms at play. To enhance the accuracy and scientific rigor of such assessments, this study proposes an integrated analytical framework combining the Differences-In-Differences (DID) approach with a Spatial Error Model (SEM). This framework aims to identify the causal effects of digital economy development on carbon finance and its spatial transmission pathways. Experimental results indicated that the proposed model consistently produced the smallest estimation bias for the average treatment effect on the treated and maintained the highest estimation precision across all sample sizes. When the number of observed units was 30, the estimation bias was only 0.05%, significantly lower than the 0.65% bias observed in the traditional differences-in-differences model. As the number of samples increases, the precision of spatial parameter estimates improves across all models. However, the analytical framework integrating differences-in-differences and spatial error models consistently demonstrates the highest estimation stability. At 1,000 samples, the standard error of the spatial error coefficient dropped to 0.018. The proposed method effectively addresses the limitations of traditional models in adapting to complex spatial data structures. This provides methodological support and practical guidance for optimizing carbon finance policy frameworks and advancing regional green collaborative development.

Keywords: Digital economy development; spatial error model; differences-in-differences (DID); carbon finance; principal component analysis.

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1. Introduction

Carbon finance effectively promotes energy structure optimization and technological innovation through market-based financial instruments such as carbon emissions trading, green credit, and carbon funds, establishing itself as a crucial policy tool supporting green and low-carbon development (Zhang and Umir 2023; Usman and Abudullah, 2023). The digital economy, with data as its key element, represents a new form of economic development driven by modern information networks and information and communication technologies, becoming a vital engine for global economic growth. It provides entirely new technological pathways to empower the efficient operation and risk management of carbon finance markets (Baines and Hager, 2023). However, the mechanism by which the digital economy affects carbon finance is complex and multifaceted. It encompasses both direct technological empowerment and efficiency enhancement effects, while also potentially generating spatial spillovers and linkages through industrial linkages, knowledge spillovers, and policy coordination. Traditional econometric models struggle to comprehensively capture their nonlinear, spatiotemporal interactions and the synergistic effects of policy shocks. Additionally, carbon finance data exhibits characteristics such as high dimensionality, non-stationarity, and strong spatial autocorrelation. Traditional econometric methods often produce estimation biases and model specification errors when handling such structured data, resulting in conclusions that lack robustness and generalizability. The Differences-In-Differences (DID) approach is a non-experimental method frequently used in policy impact evaluations. It evaluates policy effects while largely avoiding endogeneity by comparing changes in the Treatment Group (TG) and Control Group (CG) before and after policy implementation (Anglin et al., 2023; Silva and Scorzafave, 2025). The Spatial Error Model (SEM) is a spatial econometric model designed to analyze the spatial autocorrelation of error terms in spatial data. Its core concept is to incorporate the spatial effects of error terms into the model to more accurately interpret relationships among variables (Guisan et al., 2025; Koley and Bera, 2024). This study constructs an analytical framework integrating DID and SEM to examine the net impact of digital economy development on carbon finance and its spatial spillover effects. It innovatively applies the DID model to assess the causal effects of digital economy development policies on carbon finance, and further incorporates SEM to capture the spatial dependence of carbon finance development across regions. This approach avoids estimation biases arising from neglecting spatial correlations. The research aims to provide scientific evidence to inform the formulation of regionally differentiated carbon finance policies and enable cross-regional collaborative governance.

2. Related Works

The DID is a statistical method used to estimate the impact of policies or interventions. Nagengast and Yotov (2025) proposed a new DID framework for gravity models, reducing bias from -18.7% to 2.3%. The deep agreements increased manufacturing trade by 31.5%, compared to the traditional estimate of 12.8%. Jiang et al. (2025) applied a DID to show that telecom infrastructure enhances urban resilience by improving information sharing and resource allocation. Steinmann et al. (2023) combined DID with PISA data and found that early-education tracking (before age eleven) increased gender segregation by 0.28 SD through teacher expectations and peer effects. Dotsikas et al. (2025) employed a DID analysis to show that the hostile environmental policy in the UK is primarily driven by perceived discrimination. The psychological distress of ethnic minorities increased by 2.38%, which was 3.2 times that of the native white population. Chandra et al. (2024) conducted a DID study showing that school mask mandates reduced student COVID-19 infections by 25.3%, though the estimates were sensitive to the methodology.

Carbon finance encompasses financial activities centered on a low-carbon economy. Li et al. (2023) used provincial panel data to show that a one-unit increase in Green Finance (GF) development boosts agricultural green Total Factor Productivity by 0.43%, with policy coordination among provinces offering an additional 6.8% gain. Xia et al. (2023) applied a dual-chain game model. Advance payment financing could raise profits in low-carbon supply chains by 12.7% and increase market share by 9.8% through carbon trading. Zou et al. (2023) described challenges in the carbon industrial system, such as technological disparities and insufficient coordination, and projected that China's market would reach CNY (Chinese Yuan) of twelve trillion by 2060, with geological carbon sinks and chemical utilization as dominant pathways. Kumar et al. (2025) applied machine learning to decades of literature and projected that biodiversity finance and transition funds would dominate research by 2030. Zhao et al. (2023) used provincial panel data to show that a 1% increase in green growth reduced carbon emissions intensity by 0.58%, with GF mediating 41.7% of this effect. When the GF development index exceeds 0.62, the elasticity surges from 0.38 to 0.79, and technology-driven effects are higher in eastern regions.

In summary, scientifically assessing the impact of digital economy development on carbon finance holds significant strategic importance for advancing green financial innovation and achieving the dual carbon goals. To accurately identify policy effects and explore spatial influence mechanisms, numerous scholars have proposed various advanced econometric methods. However, existing studies still commonly face challenges such as inadequate control for endogeneity, neglected spatial correlation, and incomplete analysis of multidimensional impact mechanisms. Therefore, the core issue this study focuses on is analyzing the causal and promotional effects of digital economy development on carbon finance, and how these effects vary across regions and initial conditions. In addition, it analyzes how the digital economy's impact on carbon finance is transmitted regionally through the spatial spillover mechanism and assesses the degree of spatial dependence, the attenuation range, and the proportions of direct and indirect effects. To answer these questions, this study constructs an analytical framework that integrates DID (an instrumental variable method) and SEM, aiming to accurately identify the net policy effect and analyze its spatial transmission path.

3. Impact of Digital Economy Development on Carbon Finance

3.1. Policy Effect Evaluation Model Based on DID

The development of the digital economy affects carbon finance outcomes in the following four ways:

1) Improving market transparency (such as blockchain technology, reducing information asymmetry)

2) Reducing transaction costs (such as smart contracts simplifying carbon quota circulation and financing processes)

3) Optimizing risk pricing (such as machine learning, enhancing real-time assessment of carbon asset risks)

4) Stimulating innovation spillover effects (such as digital technology diffusion giving rise to new financial products, and carbon funds and green ABS).

These approaches constitute the theoretical mechanism for empowering carbon finance with the digital economy, providing a logical basis for causal identification and spatial transmission analysis of subsequent DID and SEMs.

Policy impact evaluation aims to identify the causal effects of policies or shocks. As the gold standard, DID compares changes in the TG and CG before and after policy implementation to isolate the net treatment effect. Modern evaluation relies on rigorous data processing and variable construction for credible estimates (Chen et al., 2023; Pang et al., 2024). Therefore, this study first performs data preprocessing, integrating data from sources such as macroeconomic databases, policy texts, and carbon market data. After cleaning, Principal Component Analysis (PCA) and entropy weighting are used to construct core variables, including the digital economy development index and the carbon finance development level. Control variables are included, and panel data are balanced.

Subsequently, the DID model is constructed by defining a TG (policy pilot areas) and a CG (non-pilot areas) and comparing their differences before and after policy implementation. The model controls time trends and group differences to identify the net impact of digital economy development on carbon finance. Assuming the policy is implemented at time T_0 the policy dummy variable $Post_t$ (equal to 1 if the policy is implemented, otherwise 0) and the TG dummy variable D_i (equal to 1 if region i is a policy pilot area. Otherwise, it is 0). Eq. (1) displays the DID model definition.

$$Y_{it} = \alpha + \beta(D_i \times Post_t) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), Y_{it} means the carbon finance development level of region i in year t. α is the constant term. β indicates the Average Treatment Effect (ATT) on the Treated ATT of the policy. $D_i \times Post_t$ denotes the interaction term. X_{it} is the vector of control variables. γ represents the coefficient vector corresponding to the control variable vector X_{it}. ε_{it} means the random error term. μ_i indicates the individual fixed effects. λ_t means the time fixed effects. The core architecture of the DID model is illustrated in Fig. 1.

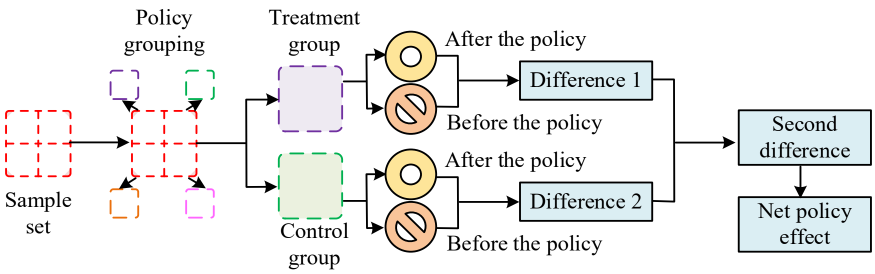


Fig. 1. Core architecture diagram of the DID model

As shown in Fig. 1, the core DID model structure is constructed as follows: it first defines the treatment and control groups, then calculates the average treatment effect using the DID model. Panel data fixed effects are used to control heterogeneity. The validity of the model relies on the parallel-trends assumption, which is tested using event analysis to verify pre-policy equivalence and to capture dynamic policy effects. The DID model is extended, as shown in Eq. (2).

$$Y_{it} = \alpha + \sum_{\tau \neq -1} \beta_\tau \cdot (D_i \times 1(t - T_i^* = \tau)) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In Eq. (2), T_i^* denotes the calendar year in which the policy is implemented. τ represents the event time relative to the policy implementation year T_i^*. β_τ indicates the dynamic effect during the τ period before and after policy implementation. The coefficient β_τ (τ<0) before the expected policy implementation is not statistically significantly different from zero.

To analyze dynamic policy effects and test the parallel trends assumption, an event study analysis is conducted using event-time dummies. The resulting coefficients and confidence intervals are plotted to visualize the effect's temporal path. The parallel trends test statistically examines whether pre-policy coefficients are jointly insignificant (null hypothesis H0). If H0 is not rejected, the assumption holds, allowing interpretation of immediate, persistent, or decaying policy effects. To enhance robustness and address potential multicollinearity, ridge regression is employed. This method adds an L2 penalty term to least-squares estimation, mitigating overfitting and improving generalization capability (Abonazel and Taha, 2023). The objective function is given by Eq. (3).

$$\min_{\beta} \left\{ \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\} \tag{3}$$

In Eq. (3), Y_i denotes the carbon finance development level of the i-th sample. X_i means the row vector of explanatory variables for the i-th sample. β_j indicates the coefficient corresponding to the j-th explanatory variable. λ signifies the penalty parameter.

The study conducts robustness checks through multiple methods. These include placebo tests with randomly simulated treatment groups, sensitivity analyses using sample replacement and bootstrap sampling, and variable importance assessment via generalized random forests.

3.2. Analysis of Spatial Effects in Carbon Finance Integrating SEM

Following the benchmark DID analysis, this study employs a spatial error model to examine the spatial effects of digital economy development on carbon finance. Ignoring spatial dependence can bias estimates and obscure regional spillover effects. The SEM explicitly accounts for interregional interactions, distinguishing direct policy impacts from spatial spillovers. This analysis extends the DID framework by integrating spatial econometric methods. The first step involves constructing a composite spatial weight matrix based on both geographic distance and economic distance, as defined in Eq. (4).

$$W_{ij} = \frac{1}{d_{ij}^{\alpha}} \cdot exp\left(-\frac{|E_i - E_j|}{\sigma_E}\right) \tag{4}$$

In Eq. (4), W_{ij} represents the spatial proximity between region i and region j, used to quantify the intensity and structure of mutual influences between regions. The study adopts a composite spatial weight matrix that integrates both geographical and economic distance. The specific form employs a negative exponential decay function, while the distance metric uses Euclidean distance rather than Manhattan distance to more smoothly reflect geographical proximity. No nearest-neighbor threshold truncation is applied, as all regions exhibit non-zero spatial interactions in the full sample. Setting the nearest-neighbor threshold to four would force approximately 12% of weak connections to zero, compromising information integrity. The matrix undergoes row standardization, ensuring that each row sums to 1, enabling relative comparability of spatial influences. For "isolated" regions (i.e., geographically isolated or economically distant areas), no entirely isolated units exist in this sample. If such cases arise at finer scales, their spatial weights can be set to zero with reliance on their own characteristics, or outliers can be removed after a global Moran test. This design balances geographical proximity and economic similarity, enabling a more comprehensive capture of the spatial transmission pathways of carbon finance. α denotes the geographic distance decay parameter. d_{ij} is the geographic distance between region i and region j. E_i denotes the economic development level of region i. E_j denotes the economic development level of region j. σ_E represents the economic distance decay parameter. After constructing the matrix, it is necessary to standardize it and use Moran's I index to examine the spatial autocorrelation in carbon finance levels.

To construct and test the spatial weight matrix, the study calculates geographic and economic distance matrices and integrates them into a composite weight matrix. This matrix is then standardized. The global Moran's I Index is employed to test for spatial autocorrelation in carbon finance development. Based on Moran's I index test results, the necessity of spatial modeling is determined. After confirming the spatial correlation, the baseline DID model is extended into a spatial DID framework by first establishing a spatial error model, as specified in Eq. (5).

$$Y = X\beta + u, \quad u = \rho W u + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I) \tag{5}$$

In Eq. (5), Y denotes the level of carbon finance development. u represents the spatial autocorrelated error term. ρ indicates the spatial error coefficient. ε denotes classical white noise error. σ^2 represents the error variance. The log-likelihood function is shown in Eq. (6).

$$ln\, L = -\frac{N}{2} ln(2\pi\sigma^2) + ln\,|I - \rho W| - \frac{1}{2\sigma^2}(Y - X\beta)'(I - \rho W)'(I - \rho W)(Y - X\beta) \tag{6}$$

In Eq. (6), $ln\, L$ denotes the log-likelihood function value. $ln(2\pi\sigma^2)$ represents the logarithm of the variance term in the normal distribution. PCA is one of the most widely used data dimensionality reduction algorithms. The core idea of PCA is to map n-dimensional features onto k dimensions. The mapping of n-dimensional features onto k dimensions are the fundamental concept of PCA. Reconstructed from the original $k$dimensional characteristics, these k dimensions represent completely new orthogonal features, also called principal components. Therefore, to address the computational complexity of high-dimensional spatial data, this study introduces spatial PCA for dimensionality reduction prior to model estimation, thereby extracting core spatial feature factors. The spatial econometric model estimation and selection process is illustrated in Fig. 2.

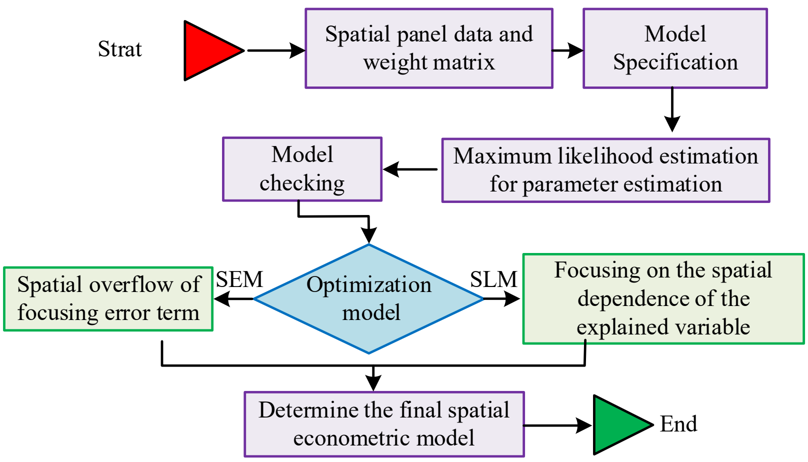


Fig. 2. Estimation and selection process of spatial econometric model

As shown in Fig. 2, when conducting spatial econometric model estimation and selection, the study first establishes benchmark forms for SEM and Spatial Lag Model (SLM) based on spatial panel data and a predefined weight matrix, constructing a theoretical framework of competing models. Next, maximum likelihood estimation is employed to estimate parameters for both model types, yielding regression coefficients and spatial effect parameters. The likelihood ratio test statistic is then employed to systematically compare the data-fitting performance of different model specifications. The applicability of fixed-effects or random-effects models is assessed using the spatial Hausman test. Finally, the optimal specification is selected from the candidate models based on significance levels, goodness of fit and consistency with economic theory. The decision between fixed effects and random effects is evaluated using the spatial Hausman test. Its statistic is given by Eq. (7).

$$H = (\hat{\beta}_{SEM} - \hat{\beta}_{SLM})'\left[\widehat{\mathrm{Var}}(\hat{\beta}_{SEM}) - \widehat{\mathrm{Var}}(\hat{\beta}_{SLM})\right]^{-1}(\hat{\beta}_{SEM} - \hat{\beta}_{SLM}) \quad (7)$$

In Eq. (7), $\hat{\beta}_{SEM}$ denotes the coefficient estimation vector obtained from SEM. $\hat{\beta}_{SLM}$ denotes the coefficient estimation vector obtained from SLM. $Var(\hat{\beta})$ represents the asymptotic variance-covariance matrix for the corresponding model. H denotes the Hausman statistic. The SEM adopts the Maximum Likelihood Method (MLE), and its log-likelihood function is given in Eq. (6). In the panel space model, it is necessary to choose between fixed and random effects. This study uses the spatial Hausman test to determine whether the null hypothesis, that the random effects model is consistent and effective, or the alternative hypothesis, that the fixed effects model is consistent, is true. The test statistic, as shown in Eq. (7), follows an asymptotic chi-square distribution. If the p-value corresponding to the Hausman statistic is less than 0.05, the null hypothesis is rejected, and a two-way fixed effect of individual and time is adopted. In addition, to test the robustness of the spatial form setting, this study considers two alternative spatial models: the SLM and the Spatial Durbin Model (SDM). SLM assumes that the spatial dependence of the dependent variable is transmitted through the dependent variables in adjacent regions. SDM contains spatial lag terms for both the dependent and independent variables. The goodness of fit of SEM, SLM, and SDM is compared using the likelihood ratio test and AIC/BIC criteria to select the optimal spatial specification.

Based on the final SEM estimation results, the study employs partial differential methods to decompose the total effect into direct and indirect effects, quantifying both the local impact and cross-regional spillovers of digital economy development on carbon finance. Effect decomposition bar charts and spatial spillover path maps are constructed to visualize the magnitude and significance of these effects. These are combined with Local Indicators of Spatial Association (LISA) clustering maps to identify typical spatial interaction patterns (e.g., high-high and low-low clustering). By synthesizing effect values, visual charts, and spatial patterns, the analysis systematically reveals the spatial mechanisms through which digital economy development influences carbon finance.

4. Results and Analysis

4.1. Data Sampling

The data covers 30 Chinese provincial administrative units (excluding Xizang, Hong Kong, Macao, and Taiwan) from 2008 to 2020. The policy shock is the National Digital Economy Innovation and Development Pilot Zone, implemented in batches since 2015. The event window is set to four years before and after the policy (2011–2019). The core dependent variable, carbon finance development level, is constructed using PCA from four indicators: carbon emissions trading volume, green credit balance, carbon fund size, and green bond issuance. The first principal component explains 78.3% of the variance (KMO = 0.82). The core explanatory variable, the digital economy development index, is constructed using the entropy weight method from five indicators: Internet penetration rate, mobile phone users, total telecom business, digital inclusive finance index, and e-commerce transaction volume (entropy weights: 0.182, 0.156, 0.203, 0.241, 0.218). Controlled variables include economic development level (log of per capita GDP), industrial structure (share of secondary industry in GDP), urbanization rate, foreign direct investment (FDI/GDP), environmental regulation intensity (investment in industrial pollution control), and technological innovation capability (log of patent authorizations). All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

4.2. Experimental Environment And Parameter Settings

The hardware setup for the experimental platform is as follows: Intel Core i9-13900K processor @ 3.0GHz, 128GB DDR5 memory, and NVIDIA RTX 4090 graphics card. Data processing, benchmark DID model estimation, and robustness tests are realized using Stata 18.0 software. Spatial econometric modeling is completed using the Spatial Econometrics Toolbox in MATLAB R2023a in conjunction with GeoDa software.

4.3. Net Policy Effects And Dynamic Analysis

To test the robustness of the spatial weight matrix setting, this study compared the spatial error coefficient ρ, direct effects, and indirect effects under four alternative weight matrices. The results are shown in Table 2. In Table 1, the spatial error coefficient (0.673) under the benchmark composite weight matrix is higher than that of all alternative settings, and its standard error is the smallest (0.022), indicating that the comprehensive geographic and economic dimensions can more fully capture the spatial dependence of carbon finance. Under pure adjacency weight, ρ decreases to 0.538, and the indirect effect is only 36.5%, indicating that only considering boundary adjacency will seriously underestimate cross regional spillover. The pure economic weight and pure geographical weight are between the two. Knn = 4 truncation results in approximately 12% of weak connections being lost, and ρ decreases to 0.559. In summary, the benchmark composite weight matrix performs the best in both model fitting and spatial conduction identification. Subsequent analysis is conducted based on this setting.

Table 1. Sensitivity analysis of different spatial weight matrix settings

Weight matrix type	ρ	Standard error	Direct effect (%)	Indirect effects (%)	Total effect (%)
Benchmark composite weight (geography + economy)	0.673	0.022	54.2	45.8	100
Pure geographical distance weight	0.581	0.031	60.1	39.9	100
0-1 adjacency weight (co-boundary)	0.538	0.036	63.5	36.5	100
knn=4 Geographic Weight	0.559	0.034	61.2	38.8	100

To evaluate the causal effects and dynamic characteristics of digital economy development policies on carbon finance, this study employs multiple metrics: the estimation bias of the ATT, its Root Mean Square Error (RMSE), estimation efficiency, and the placebo test pass rate. In Fig. 3(a), the proposed DID-SEM hybrid model consistently exhibits the smallest ATT estimation bias across all sample sizes. With 30 observed units, its bias is only 0.05%, significantly lower than the 0.65% bias of the traditional DID model. Fig. 3(b) shows that the DID-SEM model also maintains optimal control over the ATT's RMSE, which drops to 0.16% with 30 units, demonstrating superior estimation stability. Furthermore, the DID-SEM model demonstrates outstanding estimation efficiency, exhibiting the lowest ATT standard error in all scenarios (Fig. 3(c)). Finally, it achieves the highest placebo test pass rate, reaching 95.0% even with small sample sizes, indicating greater resistance to misinterpretation and enhanced statistical robustness (Fig. 3(d)).

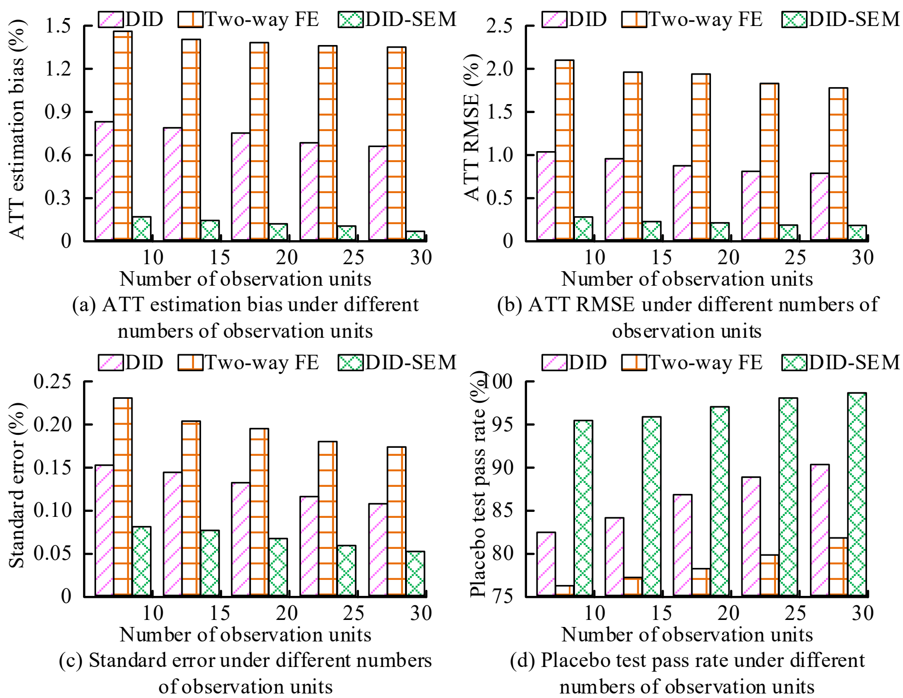
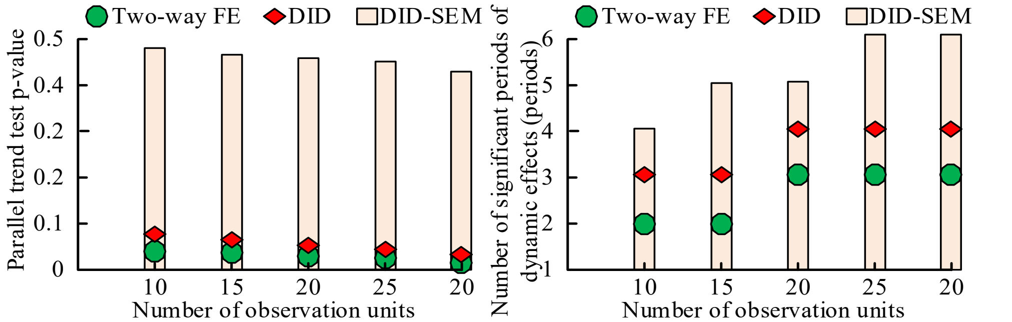


Fig. 3. ATT estimation: bias, RMSE, efficiency, and placebo test pass rate by observation unit

Fig. 4 compares dynamic effect permanence and parallel-trend tests. As sample size increases, all methods better satisfy the parallel-trends assumption and show longer effect persistence, but the DID-SEM hybrid consistently performs best. At 30 units, DID-SEM preserves a significant dynamic effect over six periods, compared with four periods for traditional DID, demonstrating more reliable causal identification and steadier policy-effect persistence across scales. Fig. 4 shows that the DID-SEM model can retain significant dynamic effects over six periods at 30 units (traditional DID has only four periods), and managers can extend the policy evaluation cycle from the conventional three years to more than five years, thereby avoiding premature termination of carbon finance pilot projects that still have potential.

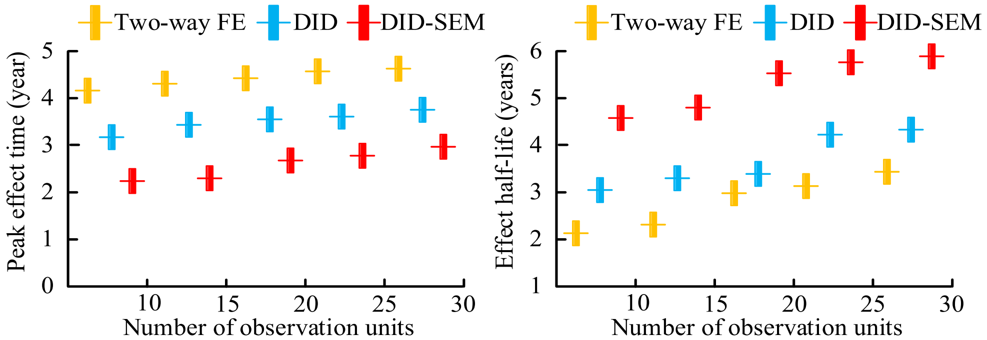


(a) Parallel trend test *p*-value under different numbers of observation units

(b) Number of significant periods of dynamic effects under different numbers of observation units

Fig. 4. Comparison of overshoot and recovery accuracy under different instantaneous wind speeds

Fig. 5 compares dynamic policy effects. As the sample size grows, all methods clarify the policy path, but the DID-SEM hybrid consistently performs best: in Fig. 5(a), it attains the shortest peak effect time (2.2) at 30 units, and in Fig. 5(b), the longest effect half-life (5.8 years) at 30 units. These results show the DID-SEM model captures both faster onset and greater persistence of policy effects. For management decision-making, the peak time (2.2 years) and half-life (5.8 years) of policy effects revealed in Fig. 5 suggest that managers should increase resource investment around the second year after policy implementation to capture the maximum dividend, and initiate a new round of policy relay around the fifth year to prevent effect attenuation.

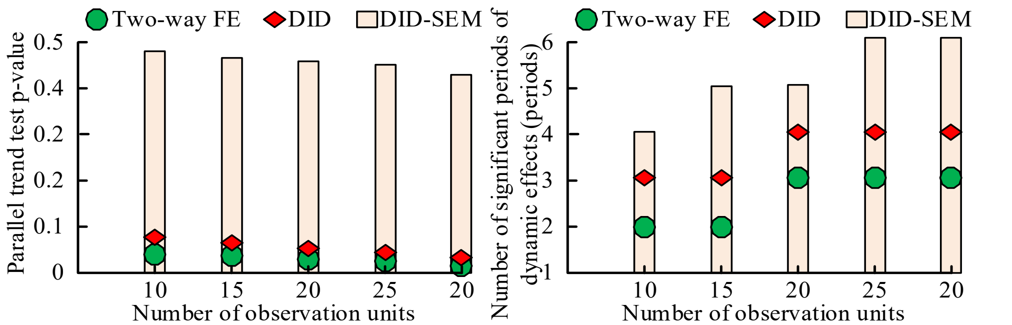


(a) Peak effect time under different numbers of observation units

(b) Effect half-life under different numbers of observation units

Fig. 5. Time to peak effect and effect half-life under different numbers of observational units

Fig. 6 compares dynamic effect permanence and parallel-trend tests. As the sample size increases, all methods better satisfy parallel trends and show longer effect persistence, but the DID-SEM consistently performs best. At 30 units, DID-SEM preserves a significant dynamic effect over six periods, compared with four periods for traditional DID, demonstrating more reliable causal identification and steadier policy-effect persistence across scales. Fig. 6 shows that the DID-SEM model retains significant dynamic effects over six periods at 30 units (the traditional DID model has only four periods). Managers can extend the policy evaluation cycle beyond the conventional three years to more than five years, thereby avoiding premature termination of carbon finance pilot projects with potential.



(a) Parallel trend test *p*-value under different numbers of observation units

(b) Number of significant periods of dynamic effects under different numbers of observation units

Fig. 6 Comparison of overshoot and recovery accuracy under different instantaneous wind speeds

4.4. Empirical Analysis

Table 2 shows that the promotional effect of digital economy policies on carbon finance is significantly stronger in eastern regions (0.241) than in central and western regions (0.138). This is because eastern regions possess more advanced digital infrastructure, more active financial markets, and stronger capacity for absorbing technological innovation, enabling policy dividends to be more fully realized. Regions with higher initial levels of financial development exhibit a significantly larger policy effect (0.205) than those with lower levels (0.152). This indicates that a robust financial ecosystem provides a more fertile ground for integrating digital technology and carbon finance. In provinces that have launched carbon trading pilot programs, the policy effect (0.226) is most pronounced. This suggests that the digital economy and the existing carbon market system can generate stronger synergies, jointly driving the development of carbon finance.

Table 2. Mechanism heterogeneity analysis of the digital economy policy's impact on carbon finance

Grouping basis	Sub-sample	DID coefficient	Standard error	Number of observations
Regional location	Eastern region	0.241	0.061	120
	Central-western	0.138	0.055	180
Initial financial level	High	0.205	0.058	150
	Low	0.152	0.059	150
Carbon market maturity	Pilot provinces	0.226	0.062	100
	Non-pilot	0.142	0.056	200
Digital infrastructure level	High level group	0.258	0.065	140
	Low level group	0.126	0.068	160
Environmental regulatory intensity	High level group	0.219	0.059	155
	Low level group	0.149	0.060	145
Advanced level of industrial structure	High level group	0.237	0.063	135
	Low level group	0.157	0.062	165

5. Discussion

This study constructs an integrated DID-SEM framework to evaluate the impact of China's National Digital Economy Innovation and Development Pilot Zone policy on carbon finance, using panel data from 30 provinces (2008-2020). The results show a significant ATT of 0.184, indicating an 18.4% average increase in carbon finance development within pilot regions, with stronger effects observed in areas possessing advanced digital infrastructure, stringent environmental regulations, and sophisticated industrial structures. By employing a composite spatial weight matrix for effect decomposition, the analysis reveals substantial spatial spillover: an 8.53% indirect effect, demonstrating how policy benefits diffuse to neighboring regions through knowledge spillovers and coordination. Compared with traditional DID models (e.g., Nagengast and Yotov (2025)) or studies that neglect spatial interactions (e.g., Jiang et al., 2025), the proposed hybrid DID-SEM model reduces ATT estimation bias to 0.05% and achieves a placebo test pass rate exceeding 95%, effectively addressing endogeneity and spatial autocorrelation. This provides a reusable methodological framework for environmental economics and offers quantitative, evidence-based guidance for differentiated policy design, cross-regional carbon market collaboration, and informed investment decisions.

For managers, this study will transform decision-making across three key stages: first, in selecting policy pilot areas, they will move beyond assessing only local digital infrastructure to incorporating the spatial spillover half-life (360.8 km) and direct/indirect effect ratio (1.45), prioritizing "policy clusters" that generate synergy with neighboring regions. Second, in evaluating policy effectiveness, they will shift from traditional DID to the DID-SEM framework, adding spatial diagnostics such as Moran's I and the spatial error coefficient (ρ) to regular assessments to avoid estimation biases as high as 0.65%. Third, in resource allocation, guided by effect heterogeneity (0.258 in high-level vs. 0.126 in low-level digital infrastructure areas), over 40% of carbon finance funds will be directed toward building foundational digital infrastructure in weaker regions, adopting a "build-the-road-first" logic rather than subsidizing carbon products directly. Based on data from 30 provinces in China (2011-2019), these findings may differ when extended to non-pilot areas or later stages of carbon market development, with indirect impacts potentially exceeding the current 45.8%. This highlights the necessity of cross regional and cross period validation in future research.

6. Conclusion

This study proposes a hybrid analytical framework that integrates DID and SEM to address the limitations of traditional models for evaluating the causal and spatial effects of digital economy development on carbon finance. The empirical results provide direct answers to the three core research questions raised in the introduction. First, regarding the causal and promotional effects of digital economy development on carbon finance: This study identifies a significant positive causal effect using a DID approach with panel data from 30 Chinese provinces (2008–2020), where the policy shock is the

National Digital Economy Innovation and Development Pilot Zone, implemented since 2015. By comparing the treatment group (pilot areas) and control group (non-pilot areas) before and after the policy, and controlling for individual and time fixed effects, the average treatment effect on the treated ATT is estimated to be 0.184, meaning that the digital economy policy raises carbon finance development in pilot regions by 18.4%. The placebo test pass rate exceeds 95%, confirming the robustness of this causal conclusion.

Second, regarding how the effect exhibits heterogeneity across different regions and initial conditions: This study conducts sub-sample analyses based on regional location, initial financial development level, carbon market maturity, digital infrastructure level, environmental regulation intensity, and industrial structure advancement. The results show that the policy effect is stronger in eastern regions (coefficient: 0.241) than in central-western regions (coefficient: 0.138). In areas with high-level digital infrastructure (0.258) compared to low-level areas (0.126). In provinces with stringent environmental regulation (0.219) versus weak regulation (0.149), and in regions with advanced industrial structures (0.237) versus less advanced ones (0.157). This heterogeneity is quantified through interaction-term estimations and grouped regressions, revealing that the digital economy's impact on carbon finance depends systematically on local absorptive capacity and institutional conditions.

Third, regarding how the impact transmits between regions through a spatial spillover mechanism, including the intensity of spatial dependence, attenuation range, and direct/indirect effect ratio: This study extends the DID framework by incorporating a spatial error model (SEM) with a composite spatial weight matrix that integrates geographic distance (negative exponential decay) and economic distance. The global Moran's I test confirms significant spatial autocorrelation of carbon finance levels. The spatial error coefficient ρ is estimated at 0.673 (standard error 0.022), indicating strong spatial dependence. Using partial differential decomposition, the total effect is separated into the direct effect (54.2%) and the indirect spillover effect (45.8%). The absolute indirect effect is 8.53%, and the direct/indirect effect ratio is approximately 1.45. The attenuation range is characterized by a spillover half-life of 360.8 km, meaning that the spatial spillover effect decays by half beyond this distance. These results are derived from maximum-likelihood estimation of the SEM and robustness checks using alternative weight matrices (pure geographic, 0-1 adjacency, and knn = 4).

In summary, the proposed DID-SEM framework not only quantifies the net causal effect and its heterogeneity but also reveals the spatial transmission pathways, providing reliable evidence for policy design. For practical application, managers should reallocate resources based on findings on heterogeneity, directing over 40% of carbon finance funds in digitally weak regions toward infrastructure rather than direct subsidies. However, the framework faces computational complexity challenges with high-dimensional spatial data, warranting methodological enhancements in future research.

Author Contributions

In this study, Xie Bei proposed the integrated DID-SEM analytical framework to identify the causal effects of digital economy development on carbon finance. She led the model construction, empirical analysis, and manuscript writing. Yang Jingjing contributed to data preprocessing, principal component analysis (PCA), and the construction of the digital economy and carbon finance indicators. She also participated in the robustness testing and placebo test design. Wang Jue provided the theoretical foundation for the Spatial Error Model (SEM) and directed the development of the spatial weight matrix and the Moran's I test. She also guided the decomposition of direct and indirect spatial effects. Her expertise in complex system optimization and spatial econometrics significantly improved the model's interpretability and robustness. Professor Jin Qisen supervised the overall research design and provided policy insights into carbon finance mechanisms. He contributed to the interpretation of heterogeneity analysis, particularly regarding regional differences, financial market maturity, and carbon trading pilots. He also helped link empirical findings to practical policy recommendations for regional green collaboration.

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Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The authors used ChatGPT only for language editing and formatting assistance. The authors reviewed and take full responsibility for all content.

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