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Dynamic spatial spillover effects of digital finance on energy efficiency: The moderating role of traditional finance

Xiaorui Liu[a] and Wen Guo[b]*

[a]Business School, Suzhou University of Technology, Changshu 215500, China
[b]College of Accounting, Nanjing University of Finance and Economics, Nanjing 210023, China.

*Correspondence e-mail: xsyjst@126.com

Abstract

Building upon the moderating role of traditional finance (TF) and utilizing panel data from 30 Chinese provinces covering 2011-2023, this study employs a dynamic spatial Durbin model to examine the spatial spillover effects of digital finance (DF) on energy efficiency (EE) and their underlying mechanisms. The results show that DF directly enhances local EE and generates positive spatial spillovers in neighboring regions, exhibiting a time-lag effect that strengthens over time. Dimensional heterogeneity analysis reveals that DF usage depth contributes most substantially to EE improvement, followed by coverage breadth, while digitalization level has a weaker effect. TF exerts a significant positive moderating effect, with the strongest interaction on usage depth and the weakest on digitalization level. Mechanism tests confirm that DF improves EE in local and neighboring regions through four pathways: technological innovation, industrial upgrading, economic growth, and green finance development. However, only technological innovation transcends geographical constraints to generate multi-level spatial spillovers, whereas the other pathways demonstrate spatially localized containment effects.

Keywords: Energy efficiency, Digital finance, Traditional finance, Dynamic spatial spillover, Mechanism analysis.

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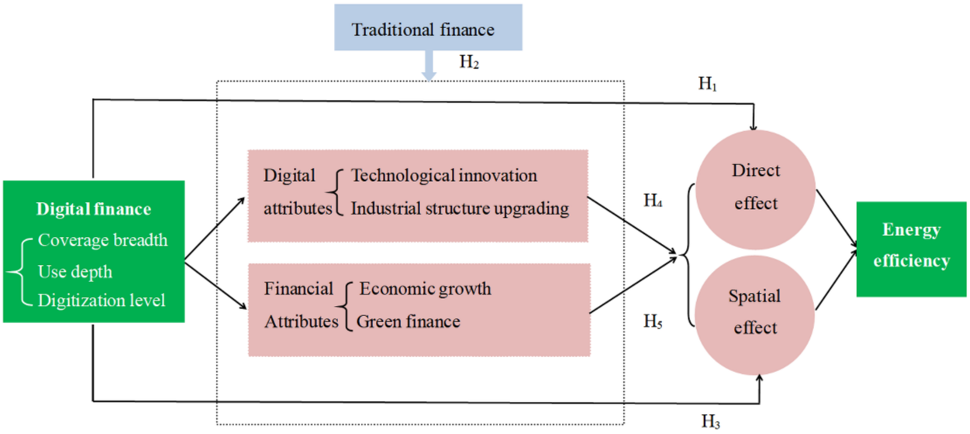
Graphical abstract



1. Introduction

Improving energy efficiency (EE) is a key goal for sustainable development. Many factors affect EE, and digital finance (DF) has recently drawn attention as a potential driver (Shi and Yang 2024). When we look at how DF influences EE, we cannot ignore spatial spillovers. These spillovers decide whether DF can reach across regions and how well interregional energy governance works. In practice, DF and related energy saving technologies do not stop at administrative borders. They spread relatively easily to neighboring regions. Moreover, nearby regions often have similar industrial structures and economic development levels, which creates a kind of spatial interdependence. What happens in one province can affect its neighbors through learning and imitation of better technologies or management practices. At the same time, energy consumption tends to follow past patterns. Current EE is inevitably shaped by previous levels, a feature known as path dependence or temporal inertia. This inertia likely interacts with spatial spillovers, producing complicated dynamic effects. Yet existing research has paid little attention to these dynamic spatial spillovers (Wu *et al.* 2024). A careful study of both direct and dynamic spatial effects is therefore needed to properly assess DF's role in raising EE and to set region-specific energy targets.

Another issue that is easy to miss is the potential moderating role of TF. How DF affects EE may depend heavily on how DF and TF interact. In the early stage of DF, its own capital and coverage are often limited. A sufficient supply of TF can fill this gap. The two can work together to broaden financing channels for high efficiency firms, which indirectly strengthens DF's positive effect on EE. But as DF grows and matures, too much TF may crowd out DF's market space. That crowding out could weaken DF's independent ability to improve EE. So when we study how DF directly influences EE and generates spatial spillovers, we also need to examine what role TF plays. Doing so helps us understand the limits of DF's effectiveness and how to adjust the financial system to better support EE improvement.

Given the above, current research still has clear gaps. Few studies have systematically examined the dynamic spatial spillover effects of DF on EE across different regions (Lin *et al.* 2024; Zou *et al.* 2025). More importantly, most existing work does not consider whether TF moderates the process through which DF affects EE, nor does it analyze TF's specific spatial mechanisms in this causal chain (Chen and Guang 2026). To address these shortcomings, we use panel data from 30 Chinese provinces from 2011 to 2023 and construct a DSDM. This model allows us to investigate the dynamic spatial spillover effects of DF on EE, the underlying mechanisms, and the moderating role of TF.

These limitations need attention. If DF creates spillovers that get stronger over time, looking at one province alone will not tell the whole story. Policies could end up missing where DF works best. The TF side matters too. Whether DF helps with EE may depend on how well it works with the banks and financial systems already in place. Ignoring that could lead to policies that do not fit well with the current system. Using provincial-level data is a natural choice to study these issues. China's DF market is the largest in the world, and the government aims to cut energy use under the dual carbon goals. DF has grown fast across Chinese provinces but not evenly. EE varies a lot from one province to another as well. That kind of variation makes it easier to see spillover effects. Many energy and financial policies are made at the provincial level, and neighboring provinces often share similar industries and environmental rules. So using provincial data makes sense.

This study makes three contributions. First, we build a DSDM, which extends the existing literature. Most existing papers look at static or single effects (Khan *et al.* 2026). Our DSDM puts time lag, spatial lag, and spatio-temporal lag together in one framework, helping us see how the impact of DF on EE changes over time and spreads across regions. Second, we improve the empirical setup by treating TF as a moderator and separating the digital and financial sides of DF. Earlier studies tend to leave out TF (Chen and Guang 2026) or see DF as one single thing (Li and Yang 2026). Our model includes both the moderating role of TF and the different functions of DF, namely coverage breadth, usage depth, and digitalization level. Third, our findings do not fully agree with what earlier work assumes. Some studies have suggested DF can spread through many channels to distant places (Hu *et al.* 2025). We find that only technological innovation creates multi-level spillovers, whereas the other pathways show spatially localized effects.

2. Literature review and research hypothesis

Some studies focus on what EE really means (Patterson 1996). Others develop ways to measure it (Maya *et al.* 2024). There is also work on what drives EE (Tang *et al.* 2025) and how policies can help improve it (Shahbaz *et al.* 2022). More recently, researchers have started to examine spatial spillover effects. For example, Tao *et al.* (2025) looked at how industrial structural upgrading in one region can affect EE in neighboring regions. But these studies mostly miss one important point. They tend to ignore the path dependence of EE, meaning past energy performance influences future outcomes.

Theoretically, DF may influence EE through multiple pathways. Regarding its coverage breadth (CB), DF enables broader access to financial markets for underserved populations, thereby promoting more efficient resource allocation and providing extensive financial support for developing green and low-carbon industries (Yang *et al.* 2024). In terms of its use depth (UD), DF alleviates financing constraints for numerous enterprises, encouraging them to increase investment in green technology research and development (Fang and Liu 2025). Concerning its digitalization level (DL), the operational model of DF, which facilitates online financing, payments, and investments, embodies a low-carbon and environmentally friendly approach by its very nature (He *et al.* 2025a). Furthermore, digital technologies underpinning DF, such as cloud computing, artificial intelligence, and big data analytics, may generate technological spillover effects to related industries, driving broader progress and enhancing sector-wide EE. However, the extensive availability of DF services may also stimulate firms to expand production and households to increase consumption, ultimately leading to elevated energy consumption (Horvey *et al.* 2024). Additionally, the manufacturing and operation of the requisite digital infrastructure contribute significantly to higher energy use, which could negatively affect EE. Thus, theoretical perspectives on the overall impact of DF on EE remain divergent, underscoring the critical need for further empirical investigation.

A large body of empirical research suggests that DF can directly enhance EE. DF services, such as online lending and digital payments, leverage sophisticated platforms and mobile terminals to facilitate transactions (Yadav *et al.* 2024). Furthermore, DF mitigates financial resource misallocation. It particularly optimizes capital allocation for industries with overcapacity and low EE, thereby accelerating the phase-out of obsolete production capacities and improving overall EE (Jin *et al.* 2023). The use of digital technologies to disclose the environmental credentials of projects and products helps curb corporate greenwashing. This enhanced transparency guides investors toward green investment opportunities and encourages sustainable consumption, ultimately promoting energy conservation (Yin and Yang 2024). Additionally, digital technologies like artificial intelligence and big data analytics permeate industries through digital industrialization and industrial digitalization. This penetration significantly improves the efficiency of production factor allocation across sectors, consequently leading to higher EE (Fan *et al.* 2025; Bergougui 2025).

Some studies suggest that the environmental benefits of DF do not come automatically. Shi and Yang (2024), for example, find that how well DF and green finance work together depends on the stage of development. Without the right policies, the expected energy savings may not materialize. He *et al.* (2025b) also point out that building and running digital infrastructure uses energy, which hints at a possible rebound effect. Still, most evidence from China shows that DF currently brings a net positive effect, as the gains in efficiency seem to outweigh any rebound effects (Shi and Yang 2024).

Hypothesis 1. DF has a direct positive effect on EE.

The relationship between DF and TF is not simply one of substitution or complementarity. Instead, it evolves in stages. In the early stages of DF, its resources and technological capabilities are relatively limited. TF, with its well-established channels and risk management experience, can effectively compensate for these shortcomings. The two form a complementary relationship, jointly expanding financing channels for corporate green transformation and thereby improving EE (Cheng *et al.* 2021; Ahmad *et al.* 2021). As DF matures, its low cost and high efficiency advantages become more pronounced, creating competitive pressure on TF. If TF expands too aggressively at this stage, it may crowd out the market space for DF and weaken its unique strength in resource allocation, which in turn reduces its positive impact on EE (Wang *et al.* 2024). Thus, the interaction between DF and TF follows a dynamic shift from complementarity to competition, and this shift determines the boundary conditions for their joint effect on EE.

In most Chinese provinces, DF is still expanding rapidly rather than reaching full maturity. At this point, TF tends to play a complementary role rather than a competing one. Although crowding-out effects may appear in the longer term, we expect a positive moderating role for TF within the sample period of this study.

Hypothesis 2. TF positively moderates the relationship between DF and EE.

With the continuous penetration of digital technologies and the expanding coverage of digital financial services, DF can generate significant spillover effects. Regarding its environmental benefits, DF mainly has spatial spillover effects on EE through a diffusion effect and pollution transfer effect (Sun *et al.* 2024). On one hand, DF facilitates the cross-regional flow of capital and technology, creating a diffusion effect that supports green initiatives in neighboring regions by enhancing their access to financing and advanced technologies, thereby improving their EE. On the other hand, while DF drives the digital transformation of traditional industries, certain high energy-consuming firms may relocate to adjacent regions due to transitional pressures and constraints, potentially undermining EE improvement in those regions (Liao *et al.* 2025). Although digital technology diminishes the constraints imposed by geographical distance, market fragmentation and administrative boundaries can hinder the free flow of capital, technology, and resources over increasing spillover distances. This results in declining efficiency in the transmission of financial information, suggesting that the spillover effects of DF may exhibit a decay trend with distance. Furthermore, the impact of DF on EE, whether locally or in neighboring regions, is not instantaneous but manifests with a time lag, indicating a dynamic temporal dimension.

Hypothesis 3. DF exerts dynamic spatial spillover effects on EE.

DF integrates both digital and financial attributes, with its digital nature being the primary feature that distinguishes it from TF. Technological innovation is a key manifestation of this digital attribute (Yang *et al.* 2025a). On one hand, empowered by digital technologies, financial institutions can more accurately assess the risks and returns of corporate technological innovation, thereby assisting enterprises in rationally planning innovation projects and mitigating associated risks. On the other hand, digital technologies embedded within the DF ecosystem can analyze user consumption data to identify trends and demands, providing direction and pathways for corporate innovation. This enhances the success rate of research and development and improves the commercialization of outcomes. From the perspective of ecological economics and China's national context, current corporate technological innovation exhibits a green orientation (Chen *et al.* 2024). Enterprises are focusing on developing technologies such as renewable energy utilization, resource recycling, and thermoelectric conversion. These efforts contribute to scaling up renewable energy adoption and improving energy conversion rates, thereby simultaneously boosting economic and environmental benefits and ultimately elevating EE. Furthermore, from a spatial spillover perspective, DF leverages information technologies such as the internet to improve the spatiotemporal allocation efficiency of capital, technology, and knowledge (Hui *et al.* 2023; Li *et al.* 2024). This initiative can foster positive interactions in technological innovation between the region and its neighbors, encouraging enterprises there to engage in innovation-related R&D and transformation, which ultimately enhances EE across these regions. More importantly, as shown in **Figure 1**, if DF can promote technological innovation in neighboring regions, it may further indirectly improve EE in those and even more distant regions through technological innovation in neighboring regions.

Industrial structure upgrading represents another crucial digital attribute of DF (Zhu *et al.* 2024). By leveraging the powerful information processing and risk-screening capabilities of digital technologies, DF effectively identifies and excludes zombie firms, promotes the rational allocation of production factors across industries, and facilitates the phasing out of backward production capacities. This process contributes to the restructuring and rationalization of the industrial landscape. Furthermore, DF accelerates the widespread adoption of digital technologies, providing critical support for the intelligentization of low-carbon processes in traditional industries and the digital transformation of entire industrial chains. These advancements promote the advancement and sophistication of industrial structures. Such upgrading drives the transition of traditional industries from high-carbon to low-carbon operations and from extensive to intensive modes of production, thereby improving EE (Xue *et al.* 2022). Additionally, DF transcends the temporal and spatial limitations of traditional financial services, offering cross-regional and flexible financial resource allocation, which supports industrial structure upgrading in neighboring regions. These spillover effects ultimately enhance EE in these regions (Xu and Hu 2025). Moreover, as shown in Figure 1, if industrial upgrading in the local region can enhance EE in neighboring regions, it is likely that DF further improves EE in those neighboring and even more distant regions by upgrading the industrial structure in neighboring regions.

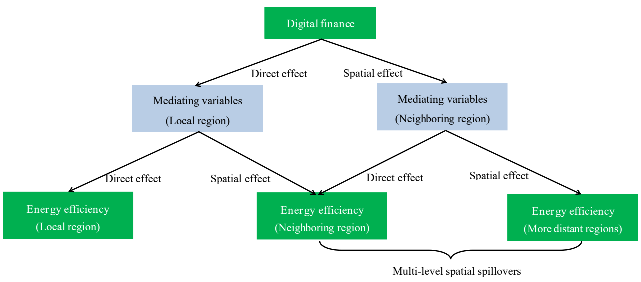


Figure 1. Spatial transmission mechanism diagram (conceptual illustration)

Hypothesis 4. DF enhances EE in local, neighboring, and more distant regions through its digital attributes, such as technological innovation and industrial structure upgrading.

Economic growth is a fundamental financial attribute of DF (Gong and Zhang 2025). On one hand, the inclusive nature of DF lowers barriers to financial services for underserved groups, alleviates financing constraints for private firms and SMEs, improves their operational performance, and consequently stimulates economic growth. On the other hand, it aggregates financial resources previously outside the formal financial system at a lower cost, transforming them into effective capital supply for businesses and enhancing the overall efficiency of financial resource allocation. An extensive body of research indicates an inverted U-shaped relationship between economic growth and EE (Adom *et al.* 2021). In the early stages of economic development, rapid growth often occurs at the expense of extensive energy consumption, leading to declining EE. However, when economic development reaches a certain stage, governments, firms, and households begin to place greater emphasis on environmental quality, enabling economic growth to drive improvements in EE. As China has now entered a phase of high-quality development, its economic growth is likely to contribute positively to EE. Furthermore, DF may significantly drive economic growth in neighboring regions by transcending geographical constraints, optimizing resource allocation, and thereby enhancing EE. These spillover effects ultimately enhance EE in these regions. More importantly, as shown in Figure 1, if local economic growth can enhance EE in neighboring regions, DF may further promote EE in both neighboring and more distant regions through facilitating economic growth in neighboring regions.

Promoting the development of green finance represents another essential financial attribute of DF (Hossain *et al.* 2024). By aggregating funds from a broad base of small and medium-sized investors, DF expands the capital base available for green finance initiatives. Moreover, the synergistic development of digital and green finance helps streamline approval processes for green financial services, reduces operational and transactional costs, and ultimately enhances the quality and effectiveness of green finance. Recent micro-level research further confirms that green finance plays an important mediating role (Hou *et al.* 2025). The collaboration between DF and green finance generates complementary advantages that comprehensively improve EE (Du and Zhang 2025). Additionally, DF addresses the geographical constraints and information asymmetry inherent in traditional green finance. By lowering the costs associated with green project identification and fostering cross-regional ecological collaboration, DF significantly promotes the development of green finance in neighboring regions, which in turn elevates their EE. Furthermore, as shown in Figure 1, if local green finance can enhance EE in neighboring regions, DF may further promote EE in both neighboring and more distant regions through facilitating the development of green finance in neighboring regions.

Hypothesis 5. DF can enhance EE in local, neighboring, and more distant regions through its financial attributes, such as economic growth and green finance.

The five hypotheses developed above indicate that the impact of DF on EE is characterized by three empirical complexities: temporal inertia, spatial dependence, and spatial transmission mechanisms. A conventional panel regression cannot adequately address these features. To simultaneously capture time lags, spatial spillovers, and spatio-temporal dynamics, this study employs a DSDM. The following section details the model specification, variable measurement, and data sources.

3. Methodology and data

3.1. *Model*

Before employing spatial econometric models, this paper uses the global Moran's I and local Moran's I indices to examine the spatial autocorrelation of interprovincial EE in China and to identify local spatial clustering patterns. The specific formulas are as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

$$I_i = \frac{n(y_i - \bar{y})\sum_{j=1}^{n} w_{ij}(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

In Equations (1) and (2), n, i, j, and wij represent the number of provinces, the i-th province, the j-th province, and the spatial weight matrix, respectively. y and $\bar{y}$ denote EE and their mean value, respectively. In this paper, the spatial weight matrix is set as the adjacent spatial weight matrix (W1), the geographical distance weight matrix (W2) and the economic distance weight (W3). Given that the DSDM provides the foundational basis for other dynamic spatial econometric models, this paper begins by specifying the following DSDM.

$$\ln EE_{it} = \alpha + \beta x_{it} + \tau \ln EE_{i,t-1} + \delta\sum_{j=1}^{n} w_{ij} \ln EE_{it} + \eta\sum_{j=1}^{n} w_{ij} \ln EE_{i,t-1} + \theta\sum_{j=1}^{n} w_{ij} x_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

In Equation (3), τ and η represent the coefficient of $\ln EE_{i,t-1}$ and the spatial effect term, respectively. **x** includes the core explanatory variables and control variables, with β denoting its associated coefficients. δ and θ capture the spatial spillover effects of lnEE and **x**, respectively. Furthermore, μ and λ represent the individual and time fixed effects, respectively, while α and ε are the constant term and the error term, respectively. We run a series of diagnostic checks to verify that our model is properly specified. These include the global Moran's I test to see if spatial dependence exists, the LM tests to help us decide between spatial and non-spatial models, and the Wald and LR tests to see if the DSDM can be reduced to a spatial lag or spatial error model.

Directly interpreting the results based on Equation (3) may be inaccurate; it is further necessary to decompose the total effects into long-term direct and spatial effects, as well as short-term direct and spatial effects (LeSage and Pace 2009). The direct effect measures the impact of a change in an explanatory variable in a given province on its own EE. The spatial spillover effect measures the impact on neighboring provinces. Short-term effects capture immediate impacts, while long-term effects incorporate dynamic feedback through the time lag of EE. The specific calculation formulas are presented in **Table 1**.

Table 1. Direct and spatial effects from a long-term and short-term perspective.

	Long-term effect	Short-term effect
Direct effect	$\{[(1-\tau)I-(\delta+\eta)w]^{-1}(\beta_k I_N+\theta_k w)\}^{\bar{d}}$	$[(1-\delta w)^{-1}(\beta_k I_N+\theta_k w)]^{\bar{d}}$
Spatial effect	$\{[(1-\tau)I-(\delta+\eta)w]^{-1}(\beta_k I_N+\theta_k w)\}^{\overline{rsum}}$	$[(1-\delta w)^{-1}(\beta_k I_N+\theta_k w)]^{\overline{rsum}}$

Table 2. Indicator system of EE.

Primary indicator	Secondary indicator	Measurement
Non-energy inputs	Labor	The number of urban employees at the end of the year
	Fixed capital stock	Capital stock was calculated using the perpetual inventory method (Depreciation rate: 10.96%; base year for price deflation: 2000)
Energy input	Energy consumption	The total energy consumption converted to standard coal
Desirable output	Gross domestic product	The gross domestic product of the region
Undesirable outputs	Carbon dioxide	Carbon dioxide emissions
	Sulfur dioxide	Sulfur dioxide emissions

In **Table 1**, I, $\bar{d}$, and $\overline{rsum}$ represent the identity matrix, the average of diagonal elements, and the average of off-diagonal row sums, respectively; k denotes the sequence number of the explanatory variables. To investigate the moderating effect of TF, this study employs a DSDM that incorporates a moderation mechanism, as specified below.

$$\ln EE_{it}=\alpha+\beta x_{it}+\tau\ln EE_{i,t-1}+\rho\ln DF\times\ln TF+\delta\sum_{j=1}^{n}w_{ij}\ln EE_{it}+\eta\sum_{j=1}^{n}w_{ij}\ln EE_{i,t-1}+\theta\sum_{j=1}^{n}w_{ij}x_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (4)$$

In Equation (4), ρ denotes the moderating effect. The existing literature has not adequately accounted for spatial transmission mechanism when examining the mediation effect of DF on EE. To examine whether DF effectively influences EE through spatial channels, using lnTI as an illustrative example of a mediating variable, this paper constructs the following DSPM.

$$\ln TI_{it}=\alpha_1+\beta_1 x'_{it}+\tau_1\ln TI_{i,t-1}+\delta_1\sum_{j=1}^{n}w_{ij}\ln TI_{it}+\eta_1\sum_{j=1}^{n}w_{ij}\ln TI_{i,t-1}+\theta_1\sum_{j=1}^{n}w_{ij}x'_{it}+\mu_{1i}+\lambda_{1t}+\varepsilon_{1it} \quad (5)$$

$$\ln EE_{it}=\alpha_2+\beta_2 x'_{it}+\kappa_2\ln TI_{it}+\tau_2\ln EE_{i,t-1}+\delta_2\sum_{j=1}^{n}w_{ij}\ln EE_{it}+\eta_2\sum_{j=1}^{n}w_{ij}\ln EE_{i,t-1}+\theta_2\sum_{j=1}^{n}w_{ij}x'_{it}+\varphi_2\sum_{j=1}^{n}w_{ij}TI_{it}+\mu_{2i}+\lambda_{2t}+\varepsilon_{2it} \quad (6)$$

In Equations (5) and (6), x' comprises the core explanatory variables, control variables, and the interaction term lnDF × lnTF, while **κ** and **ϕ** denote the coefficient of lnTI and its spatial effect, respectively.

3.2. *Variable*

The dependent variable in this study is EE. According to the number of input factors considered, the main methods for calculating EE in the academic circle include the single-factor method and the all-factor method. Compared to conventional single-factor method, the total-factor method incorporates inputs and outputs within an integrated analytical structure while accounting for undesirable outputs such as pollutant emissions. This method is generally regarded as a more effective way to gauge EE. Therefore, this paper draws on previous research experience and uses a super-efficiency SBM model that includes undesired outputs to measure total factor EE (Nyangchak 2024). Within this model, labor and fixed capital stock are treated as non-energy inputs, with energy consumption serving as the energy input. Gross domestic product (GDP) is included as the desirable output, while carbon dioxide and sulfur dioxide emissions are incorporated as undesirable outputs. The specific input and output variables used in our measurement of EE are comprehensively detailed in **Table 2**.

The core explanatory variable in this study is DF, measured using the digital financial inclusion index compiled by Peking University. This index integrates billions of anonymized transaction records from platforms such as Ant Group to construct a multidimensional dynamic evaluation framework covering provincial, prefectural, and county levels. It represents China's first systematic and authoritative indicator for assessing regional digital financial development. The index captures DF across three dimensions: CB, UD, and DL. It has been widely adopted in academic research (Yang *et al.* 2025b; Zhang *et al.* 2025).

As evidenced by the literature review and research hypotheses, this study identifies TF as the moderating variable, with technological innovation (TI), industrial structure upgrading (ISU), economic growth (EG), and green finance (GF) serving as mediating variables. TF is proxied by the ratio of total loan balances from regional financial institutions to GDP. TI and ISU are measured by the number of granted patent applications and the ratio of the GDP of the tertiary industry to that of the secondary industry, respectively. EG is represented by per capita GDP. The GF index is constructed using the entropy weight method based on six indicators. These indicators include green credit (credit allocated to environmental protection projects), green bonds (total issuance volume), green funds (total market value), green insurance (premium income from environmental pollution liability insurance), green investment (total investment in pollution control), and green equity (combined trading volume of carbon, energy, and emission permits).

The control variables in this study include population density (PD), human capital (HC), R&D investment (RDI), and foreign direct investment (FDI). Regions with higher PD tend to exhibit more equitable energy distribution and fuller utilization of energy resources, thereby contributing to higher EE (Morikawa 2012). HC enhances EE at both the corporate and industrial levels through knowledge application, technical progress, and management optimization (Samour *et al.* 2024). Increased RDI facilitates the development of energy-saving equipment, advances in renewable energy technologies, and optimization of industrial processes, thereby reducing reliance on traditional energy-intensive practices and transforming low-efficiency production modes (Le *et al.* 2025). FDI can improve national EE via technology spillovers, though it may also entail risks of technological lock-in (Ma *et al.* 2023; Soto *et al.* 2025). In this study, PD and HC are proxied by the number of inhabitants per unit region and average years of education, respectively. RDI and FDI are measured by the ratio of R&D expenditure to GDP and the ratio of actually utilized foreign capital to GDP, respectively.

3.3. *Data*

This study focuses on 30 provinces in mainland China, excluding Tibet, covering the period from 2011 to 2023, based on data availability. The raw data for measuring EE were primarily collected from the *China Statistical Yearbook*, *Provincial Statistical Yearbooks*, *China Energy Statistical Yearbook*, and *China Environment Statistical Yearbook*. Data for DF were sourced from the Peking University Digital Finance Research Center. Data for TF were obtained from the *China Financial Yearbook* and *China Statistical Yearbook*. Variables including TI, ISU, and EG were mainly drawn from the *China Statistical Yearbook*. Data for GF were primarily sourced from RESSET and CSMAR databases, supplemented by the *China Insurance Yearbook*, *China Statistical Yearbook on Science and Technology*, and provincial statistical yearbooks and environmental bulletins. Data for the control variables were gathered from the website of the Ministry of Civil Affairs of the People's Republic of China, *China Statistical Yearbook*, *China Science and Technology Statistical Yearbook*, *provincial statistical yearbooks*, and the Wind database. Descriptive statistics for all variables are presented in **Table 3**. To enhance the stability of the panel data, all variables were transformed using natural logarithms in the empirical analysis.

Table 3. Descriptive statistics.

Variable	Mean	SD	Min	Max	Q_1	Q_2	Q_3
EE	0.4339	0.2037	0.1703	1.2955	0.2791	0.3853	0.5257
DF	255.5444	111.3360	18.3300	473.8300	173.8200	267.9500	344.8600
CB	240.6228	115.9933	1.9600	466.5400	156.5600	248.3450	340.1000
UD	246.4487	109.5644	6.7600	510.6900	157.8800	258.3200	329.9300
DL	321.3559	118.2849	7.5800	476.9000	254.7500	371.9150	408.3800
TF	1.5359	0.4463	0.6700	2.7700	1.2100	1.4700	1.8200
TI	7.6241	11.9739	0.0502	87.2209	1.2763	3.4062	8.2318
ISU	1.3757	0.7613	0.5271	5.6898	0.9981	1.2155	1.4263
EG	6.0894	3.2228	1.5908	20.0186	3.8339	5.2125	7.2398
GF	0.3295	0.1266	0.0904	0.6542	0.2446	0.3612	0.4293
PD	0.0475	0.0706	0.0008	0.3926	0.0132	0.0295	0.0573
HC	9.3290	0.9132	7.4700	12.7800	8.7800	9.2400	9.6400
RDI	0.0183	0.0116	0.0042	0.0684	0.0102	0.0152	0.0231
FDI	0.0197	0.0201	0.0000	0.1210	0.0042	0.0167	0.0262

Table 3 reveals several notable patterns. EE varies substantially across provinces, indicating significant regional disparities. DF also shows wide variation, reflecting uneven development of digital finance across China. Among DF's sub-dimensions, DL has the highest mean, followed by UD and CB. TF exhibits moderate heterogeneity. These descriptive features justify the use of a spatial econometric approach that explicitly models regional heterogeneity and potential spillovers.

4. Results and Discussion

4.1. *Spatial Autocorrelation test of EE in China*

Prior to conducting spatial econometric analysis, it is essential to examine whether EE exhibits spatial autocorrelation (Abban *et al.* 2025). We used three spatial weight matrices (W_1, W_2, and W_3) to compute the global Moran's I for EE. **Table 4** reports the results. The choice of W_1 as the baseline matrix is based on the fact that neighboring provinces tend to be closely connected in terms of industrial activity and policy transmission. For this reason, geographical proximity provides a natural basis for spatial interactions in EE. We then calculated the global Moran's I to check for spatial dependence, and the results confirm that spatial autocorrelation is significant under this specification. This suggests that policymakers should consider setting up regional coordination mechanisms to support energy conservation and efficiency efforts.

To visually represent the spatial clustering characteristics of EE across Chinese provinces, this study constructed local Moran scatter plots of EE in 2011, 2015, 2020 and 2023, as illustrated in **Figure 2**. The results revealed that, throughout the study period, most provinces were located in the first quadrant (high-high clusters) and the third quadrant (low-low clusters), indicating significant spatial clusters of EE among **neighboring regions**. Provinces such as Shanghai, Jiangsu, and Zhejiang were consistently situated in the first quadrant, suggesting higher EE in both these provinces and their neighboring regions. In contrast, provinces including Hebei, Shanxi, and Inner Mongolia persistently fell within the third quadrant, reflecting lower EE in these provinces and their neighboring regions. A small number of provinces, such as Guangxi and Guizhou, were consistently observed in the second quadrant (low-high clusters), which denotes lower EE within the province itself alongside higher EE in **neighboring** regions. Similarly, provinces like Beijing and Sichuan were consistently found in the fourth quadrant (high-low clusters), implying higher EE within these provinces compared to their neighboring regions.

Table 4. The global Moran's index values of EE

Year	W_1			W_2			W_3		
	I	Z	P	I	Z	P	I	Z	P
2011	0.190	2.404	0.008	0.072	1.513	0.065	0.030	0.871	0.192
2012	0.253	3.023	0.001	0.147	2.530	0.006	0.030	0.849	0.198
2013	0.425	3.799	0.000	0.297	3.618	0.000	0.120	1.600	0.055
2014	0.177	2.070	0.019	0.160	2.521	0.006	0.077	1.376	0.084
2015	0.403	3.526	0.000	0.313	3.697	0.000	0.114	1.504	0.066
2016	0.418	3.632	0.000	0.298	3.525	0.000	0.129	1.653	0.049
2017	0.222	2.407	0.008	0.150	2.296	0.011	0.126	1.890	0.029
2018	0.403	3.663	0.000	0.305	3.765	0.000	0.105	1.467	0.071
2019	0.388	3.384	0.000	0.269	3.211	0.001	0.117	1.528	0.063
2020	0.498	4.322	0.000	0.338	3.990	0.000	0.081	1.175	0.120
2021	0.367	3.233	0.001	0.231	2.827	0.002	0.136	1.731	0.042
2022	0.340	3.035	0.001	0.263	3.186	0.001	0.099	1.360	0.087
2023	0.296	2.646	0.004	0.186	2.333	0.010	0.144	1.800	0.036

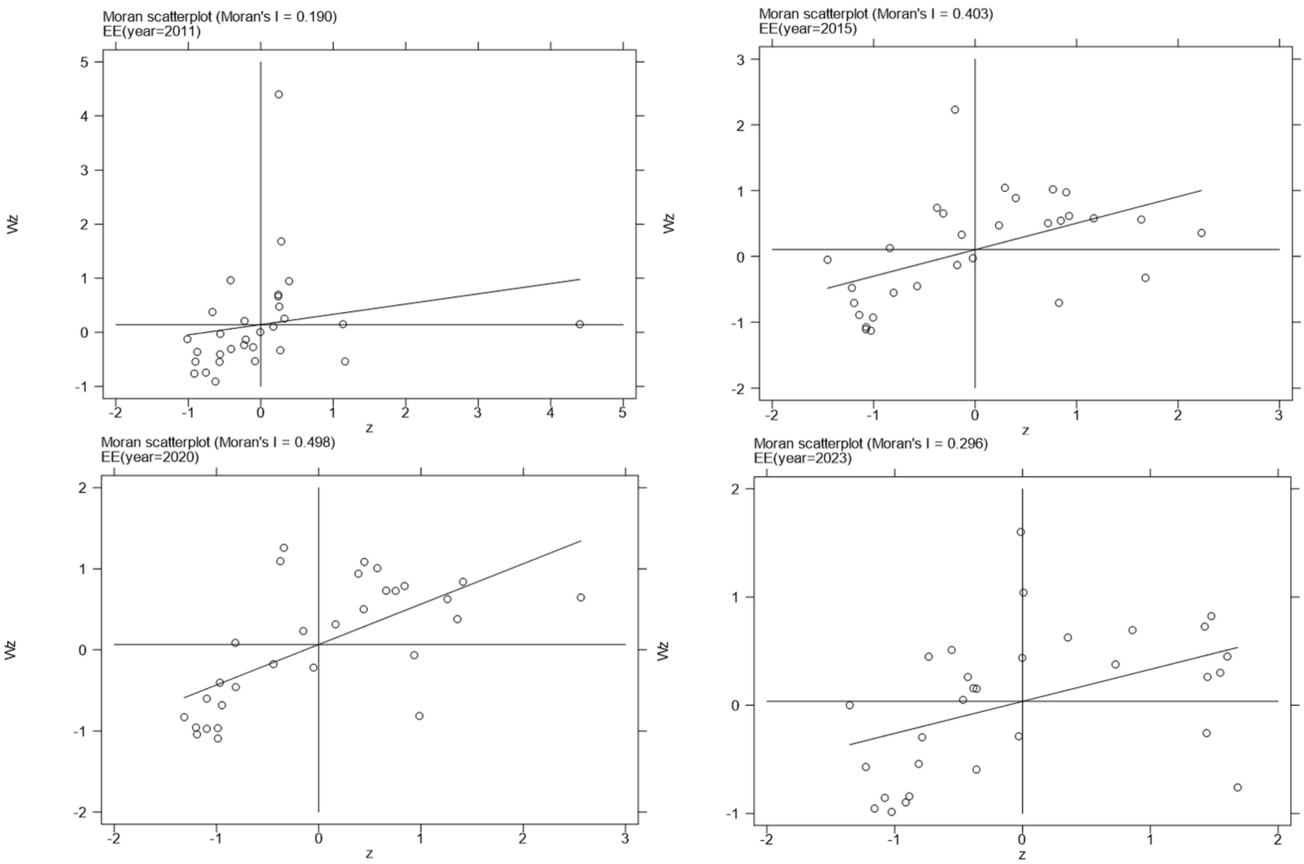


Figure 2. Local Moran scatter plot of EE in 2011,2015,2020 and 2023

We also presented the dynamic changes of provinces located in the first and third quadrants in **Table 5**. As shown in **Table 5**, high-high clusters were primarily concentrated in eastern China, whereas low-low clusters were mainly distributed across western China. This pattern could be largely attributed to the faster EG and more rapid accumulation of HC in the eastern region, which placed greater emphasis on high-quality development and pollution control. **Table 5** also revealed that Anhui exited the high-high clusters, mainly due to its role in undertaking the transfer of energy-intensive industries from Jiangsu, Zhejiang, and Shanghai. Conversely, Guizhou, Yunnan, and Shaanxi moved out of the low-low clusters, indicating that national strategies such as the Western Development Initiative and the West-East Electricity Transmission Project had begun to show positive effects in optimizing the energy structure. Chongqing entered the high-high clusters. This transition was mainly a result of improved EE, attributable to the rise of intelligent manufacturing and regional integration policies under the Chengdu-Chongqing economic initiative. Overall, the number of provinces within the high-high clusters increased, while those in the low-low clusters decreased, reflecting a gradual enhancement of EE across China.

Table 5. Dynamic Evolution of high-high and low-low clusters of EE.

Type	Year	Province
High-high clusters	2011	Shanghai Jiangsu Zhejiang Fujian Jiangxi Hubei Hunan Guangdong Anhui Hainan
	2015	Shanghai Jiangsu Zhejiang Fujian Jiangxi Hubei Hunan Guangdong Anhui Chongqing Shandong
	2020	Shanghai Jiangsu Zhejiang Fujian Jiangxi Hubei Hunan Guangdong Anhui Chongqing Guizhou Yunnan
	2023	Shanghai Jiangsu Zhejiang Fujian Jiangxi Hubei Hunan Guangdong Chongqing
Low-low clusters	2011	Hebei Shanxi Inner Mongolia Liaoning Jilin Heilongjiang Henan Gansu Qinghai Ningxia Xinjiang Guizhou Yunnan Shaanxi
	2015	Hebei Shanxi Inner Mongolia Liaoning Jilin Heilongjiang Henan Gansu Qinghai Ningxia Xinjiang Shaanxi
	2020	Hebei Shanxi Inner Mongolia Liaoning Jilin Heilongjiang Henan Gansu Qinghai Ningxia Xinjiang Shaanxi
	2023	Hebei Shanxi Inner Mongolia Liaoning Jilin Heilongjiang Henan Gansu Qinghai Ningxia Xinjiang

Table 6. Identification of spatial spillover pattern starting from the spatial Durbin model under W_1

	Without a moderating effect			With a moderating effect		
	Individual fixed	**Time fixed**	**Dual fixed**	**Individual fixed**	**Time fixed**	**Dual fixed**
LR spatial lag	49.90***	171.30***	46.06***	52.78***	138.65***	48.72***
LR spatial error	74.36***	177.35***	68.64***	77.66***	123.52***	71.69***
Wald spatial lag	51.40***	175.40***	47.44***	55.17**	139.29***	50.93***
Wald spatial error	70.26***	172.94***	64.86***	72.72***	126.45***	67.13***
Hausman	56.66***	303.19***	17.74**	57.86***	231.14***	16.32**
R^2	0.6897	0.1478	0.5885	0.7019	0.1100	0.5895

*Note: *, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The same below.*

Table 7. Estimation results of the DSDM with individual fixed effects under W_1

	Without a moderating effect			With a moderating effect		
	Time-lag	**Spatial-lag**	**Double-lag**	**Time-lag**	**Spatial-lag**	**Double-lag**
L.lnEE	0.4589*** (0.0499)	—	0.4531*** (0.0499)	0.4166*** (0.0501)	—	0.4125*** (0.0501)
W_1×L.lnEE	—	0.1505* (0.0810)	0.1060** (0.0467)	—	0.1192* (0.0693)	0.0861** (0.0378)
W_1×lnEE	0.0099*** (0.0021)	0.0311*** (0.0032)	0.0171*** (0.0036)	0.0134*** (0.0027)	0.0343*** (0.0067)	0.0150*** (0.0023)
lnDF	0.4152** (0.2038)	0.6166*** (0.2148)	0.4235** (0.2033)	0.2811** (0.1277)	0.3728* (0.2168)	0.2884** (0.1252)
W_1×lnDF	0.4525** (0.2045)	0.6532*** (0.2154)	0.4576** (0.2039)	0.4042* (0.2169)	0.5248** (0.2175)	0.4052** (0.2014)
lnTF×lnDF	No	No	No	Yes	Yes	Yes
CV	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.7301	0.7014	0.7314	0.7400	0.7181	0.7409
Log-L	245.0967	226.7525	246.1603	252.0654	237.3934	252.8152

Note: The standard error is in parentheses. The same below.

4.2. *Spatial spillover pattern and path dependence characteristics*

This study investigated the spatial spillover pattern of DF on EE through a series of tests, as presented in **Table 6**. Three spatial Durbin models without a moderating effect were constructed, namely the individual fixed effects, time fixed effects, and dual fixed effects models. The Wald and LR tests indicated that none of these three spatial Durbin models could be reduced to a spatial lag model or spatial error model. The Hausman test further confirmed that the fixed effects specification was more appropriate than the random effects specification for the spatial Durbin model. Based on the comparison of R^2 values, the individual fixed effects model was selected among the three fixed effects models. To examine the moderating role of TF, three additional spatial Durbin models incorporating a moderating effect and fixed effects were also developed. A similar series of tests demonstrated that the individual fixed effects model was also the preferred choice for the spatial Durbin model with a moderating effect.

Table 8. Moderating Role of TF under W_1

	Short-term			Long-term		
	SR_Direct	**SR_Indirect**	**SR_Total**	**LR_Direct**	**LR_Indirect**	**LR_Total**
Panel A: Using lnDF as the explanatory variable						
lnDF	0.3083*** (0.1022)	0.2335** (0.0989)	0.5418*** (0.1001)	0.5244** (0.2234)	0.3619*** (0.1149)	0.8863*** (0.2194)
lnDF×lnTF	0.0521*** (0.0151)	0.0283** (0.0128)	0.0804*** (0.0139)	0.0847*** (0.0248)	0.0380** (0.0158)	0.1227*** (0.0232)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Using lnCB as the explanatory variable						
lnCB	0.2532** (0.1265)	0.1895 (0.2624)	0.4427** (0.1816)	0.4296** (0.2041)	0.2934 (0.3036)	0.7230** (0.2986)
lnCB×lnTF	0.0516*** (0.0153)	0.0278 (0.0328)	0.0794*** (0.0203)	0.0667*** (0.0209)	0.0328 (0.0351)	0.0995*** (0.0301)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Using lnUD as the explanatory variable						
lnUD	0.4194*** (0.1437)	0.3193** (0.1576)	0.7387*** (0.1517)	0.4905*** (0.1758)	0.3203* (0.1793)	0.8108*** (0.1776)
lnUD×lnTF	0.0568*** (0.0211)	0.0367*** (0.0132)	0.0935*** (0.0206)	0.0746*** (0.0233)	0.0547** (0.0227)	0.1293*** (0.0222)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: Using lnDL as the explanatory variable						
lnDL	0.1731* (0.0959)	0.0531** (0.0245)	0.2262** (0.0938)	0.2281** (0.0956)	0.0733*** (0.0241)	0.3014*** (0.0925)
lnDL×lnTF	0.0260*** (0.0098)	0.0168** (0.0079)	0.0428*** (0.0094)	0.0277*** (0.0102)	0.0230** (0.0116)	0.0507*** (0.0100)
CV	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Results of robustness test.

	Short-term			Long-term		
	SR_Direct	**SR_Indirect**	**SR_Total**	**LR_Direct**	**LR_Indirect**	**LR_Total**
Panel A: Replacing the spatial weight matrix						
lnDF	0.2855** (0.1303)	0.2567** (0.1124)	0.5422** (0.2234)	0.4799** (0.2363)	0.3872*** (0.1332)	0.8671*** (0.2264)
lnDF×lnTF	0.0556*** (0.0157)	0.0554** (0.0281)	0.1110*** (0.0245)	0.0849*** (0.0275)	0.0843*** (0.0243)	0.1692*** (0.0263)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Adjusting the sample period						
lnDF	0.4187** (0.1762)	0.1763*** (0.0516)	0.5950*** (0.1748)	0.4600** (0.1983)	0.2423*** (0.0818)	0.7023*** (0.1926)
lnDF×lnTF	0.0558*** (0.0170)	0.0233** (0.0110)	0.0791*** (0.0204)	0.0818*** (0.0247)	0.0228* (0.0129)	0.1046*** (0.0243)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Performing a placebo test						
lnDF	0.1759 (0.1739)	0.7565 (0.9462)	0.9324 (0.8731)	0.2815 (0.2903)	1.2184 (1.4631)	1.4999 (1.3273)
lnDF×lnTF	0.1600 (0.1992)	0.0594 (0.0510)	0.2194 (0.1973)	0.2589 (0.2532)	0.0943 (0.0739)	0.3532 (0.2514)
CV	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: Replacing lnDF with L.lnDF						
L.lnDF	0.3203** (0.1531)	0.1475*** (0.0210)	0.4678** (0.1924)	0.5154** (0.2135)	0.2060** (0.0833)	0.7214** (0.2983)

L.lnDF×lnTF	0.0579***	0.0528**	0.1107***	0.0607***	0.0584**	0.1191***
	(0.0163)	(0.0246)	(0.0218)	(0.0231)	(0.0274)	(0.0256)
CV	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 presents the estimation results of the DSDM with individual fixed effects under W_1. The results indicated that, when the moderating effect was not considered, the double-lag model exhibited higher R^2 and Log-L values compared to both the time-lag and spatial-lag models. Furthermore, the sum of the coefficient estimates for L.lnEE, W_1×L.lnEE, and W_1×lnEE in the double-lag model was less than one, which suggests the stability of this model specification (Elhorst 2012). This conclusion was also found to hold for the individual fixed DSDM with a moderating effect. Therefore, the double-lag DSDM with individual fixed effects was ultimately selected for the empirical analysis in this study.

The coefficients in **Table 7** do not directly give us the precise direct and indirect effects, but they still tell us something about the path dependence of EE (LeSage and Pace 2009). First, looking at the time dimension, the coefficient of L.lnEE is positive and significant. This means EE in China has inertia. The reason is that updating energy technologies takes time and financial resources. China's industrial structure still relies heavily on energy intensive sectors, which cannot change overnight. Firms and households also have fixed energy consumption habits. Besides, energy policies take time to show results. Second, from a spatial point of view, the coefficient of W1×lnEE is also positive and significant. This suggests a regional contagion effect. Provinces with higher EE act as role models. Their neighbors learn from them and adopt better energy saving technologies and management practices. Third, considering both time and space together, the coefficient of W1×L.lnEE is positive and significant. That confirms a spatio-temporal lag effect. The spread of energy-saving technologies over time and space seems to follow a certain path.

4.3. *Direct and dynamic spatial spillover effects moderated by TF*

Table 8 presents the direct and spatial effects of DF on EE. Three findings stand out. First, DF significantly improves local EE. Among its three sub-dimensions, UD contributes the most, followed by CB, while DL has a smaller effect. Economically, a 1% increase in lnUD raises local lnEE by about 0.42% in the short term, more than twice the effect of lnDL. The practical functions of DF, such as green credit and digital payments, matter more than simply expanding user coverage or improving digital infrastructure. This finding differs from studies that treat DF as a single aggregate index, such as Shi and Yang (2024), who focus on the synergy between DF and green finance but do not compare across different dimensions of DF.

Second, DF generates positive spatial spillovers that grow over time. A 1% increase in lnDF in a given province raises lnEE in neighboring provinces by about 0.23% in the short term, and this effect rises to 0.36% in the long term. This time-lag pattern shows that DF's cross-regional benefits do not appear instantly. In the short run, spillovers mainly come from information diffusion and simple demonstration effects across neighboring regions, as noted by Shi *et al.* (2025). Over time, deeper channels such as investment and industrial coordination begin to work.

Third, TF positively moderates the DF-EE relationship, and the moderating effect is strongest on UD. A one standard deviation increase in lnTF amplifies the effect of lnDF on lnEE by about 0.05 in the short term. This confirms that TF and DF are complements rather than substitutes (Wang *et al.* 2024). Traditional banks help DF reach its full potential by providing physical branches, credit experience, and capital, especially for practical green financing activities. The moderating effect is weaker on CB and weakest on DL, suggesting that the synergy between TF and DF is most effective when DF is used for actual transactions and lending.

4.4. *Robustness tests*

This study conducted robustness tests on the results presented in **Table 8** by employing three main approaches: replacing the spatial weight matrix, adjusting the sample period, and performing a placebo test. First, given that EE also exhibits spatial autocorrelation related to geographical distance, W_1 was replaced with W_2. The results, shown in Panel A of **Table 9**, indicate that after changing the spatial weight matrix, the direct, indirect, and total effects of DF on EE remained significantly positive at the 5% level, with long-term effects being greater than short-term effects. Moreover, the coefficient of lnDF×lnTF was also significantly positive, suggesting that the moderating role of TF remains robust, confirming that the benchmark findings are insensitive to the choice of spatial weight matrix. Second, to eliminate potential distortions caused by the COVID-19 pandemic, the sample period was adjusted to 2011–2019. The results, presented in Panel B of **Table 9**, demonstrate strong consistency with those in **Table 8**, further affirming the stability of the conclusions.

Third, a placebo test was conducted to rule out the possibility that the results were driven by random chance. The specific procedure involved randomly shuffling the values of lnDF while keeping the order of all other variables unchanged, and then regenerating the interaction term. The modified dataset was re-estimated using the spatio-temporal double-lag DSDM with individual fixed effects. The results, presented in Panel C of **Table 9**, show that neither the coefficient of DF nor the moderating effect of TF was statistically significant in the placebo test. This outcome strongly confirms that the significant effects observed in the baseline model are not attributable to random data patterns or unobserved factors but genuinely reflect the spatial effects of DF and its synergistic interaction with TF on EE.

Finally, we addressed the concern about reverse causality by combining theoretical reasoning with empirical testing.

Theoretically, a potential concern is that regions with higher EE tend to have more active economies and stronger financial demand, which could in turn drive the development of DF. However, the DSDM we use already includes the time lag of EE, which helps mitigate concerns about reverse causality. Empirically, we replaced the contemporaneous lnDF with its one-year lag (L.lnDF) and re-estimated the model. If reverse causality were the main driver, past DF would not be expected to predict current EE significantly. As Panel D of **Table 9** shows, the direct and indirect effects of L.lnDF on lnEE remain significantly positive, and the interaction term L.lnDF×lnTF is also significant. This indicates that the positive effect of lnDF on lnEE is unlikely to be driven by reverse causality, and our baseline conclusions are robust. Therefore, based on these four robustness checks, the empirical findings reported in **Table 8** remain robust.

4.5. *Tests of Spatial Transmission Mechanisms*

According to the research hypotheses, DF influences EE through digital channels and financial channels. Most existing studies rely on conventional mediation tests and ignore spatial transmission. We use Equations 4 to 6 to examine how DF works through these channels across regions. **Tables 10** and **11** report the results.

Table 10 shows that TI plays the strongest mediating role. DF promotes TI, and TI then raises EE not only locally but also in neighboring and more distant regions. In economic terms, a 1% rise in lnDF increases lnTI by about 0.21% in the long run. That lnTI gain then raises lnEE by 0.08% locally and 0.05% in neighboring regions. This aligns with Hui *et al.* (2023), who show that DF helps share knowledge across regions. ISU also works as a mediator, but only for local and neighboring regions. Its effect does not reach farther away. Industrial upgrading depends more on local policies and physical infrastructure, unlike technical knowledge which can be shared online. **Table 11** shows that EG and GF both work as mediators. DF boosts EG and GF, which then improve local EE and create spillovers to neighbors. In the long run, a 1% rise in lnDF raises local lnEG by 0.05% and local lnGF by 0.07%. But like ISU, neither EG nor GF reaches farther regions. This matches Hossain *et al.* (2024) and Du and Zhang (2025), who find that DF helps GF grow, but our results further show that this effect does not spread far across space.

Taken together, DF helps EE in local and neighboring regions through all four channels, but only TI creates multi-level spillovers that reach farther away. As Nezhad *et al.* (2025) point out, digital platforms lower geographical barriers by design. Technological knowledge can be turned into digital code and sent across regions at a low marginal cost, allowing non-neighboring regions to skip intermediate steps and apply new technologies directly. The other three pathways rely more on local conditions and physical infrastructure, so they remain more confined to local and neighboring regions.

Table 10. Results of spatial transmission mechanisms under digital attributes

		Taking lnTI as the mediating variable		**Taking lnISU as the mediating variable**	
		lnTI	**lnEE**	**lnISU**	**lnEE**
LR_Direct	lnDF	0.2103*** (0.0653)	0.0431*** (0.0166)	0.2615** (0.1253)	0.0648** (0.0314)
	Mediating variable		0.0824*** (0.0311)		0.1013** (0.0421)
LR_Indirect	lnDF	0.1267*** (0.0334)	0.0365* (0.0189)	0.1323*** (0.0419)	0.0426*** (0.0163)
	Mediating variable		0.0533* (0.0298)		0.0599 (0.0722)
LR_Total	lnDF	0.3370*** (0.0624)	0.0796*** (0.0189)	0.3938*** (0.1237)	0.1074*** (0.0304)
	Mediating Variable		0.1357*** (0.0303)		0.1612** (0.0662)
	Moderating Effect	Yes	Yes	Yes	Yes
	CV	Yes	Yes	Yes	Yes
	R^2	0.7421	0.7426	0.7421	0.7433
	Log-L	253.4588	253.7881	253.4588	254.4111

Table 11. Results of spatial transmission mechanisms under financial attributes

		Taking lnEG as the mediating variable		**Taking lnGF as the mediating variable**	
		lnEG	**lnEE**	**lnGF**	**lnEE**
LR_Direct	lnDF	0.0526*** (0.0152)	0.1759*** (0.0413)	0.0652*** (0.0213)	0.0982*** (0.0345)
	Mediating variable		0.4537*** (0.1103)		(0.1580)
LR_Indirect	lnDF	0.0304*** (0.0114)	0.0945*** (0.0234)	0.0278** (0.0120)	0.0471*** (0.0162)
	Mediating variable		0.1867 (0.2638)		0.4451 (0.4327)
LR_Total	lnDF	0.0830*** (0.0221)	0.2704*** (0.0612)	0.0930*** (0.0211)	0.1453*** (0.0336)
	Mediating variable		0.6404*** (0.2186)		0.7397* (0.4082)
	Moderating Effect	Yes	Yes	Yes	Yes
	CV	Yes	Yes	Yes	Yes
	R^2	0.7421	0.7754	0.7421	0.7515
	Log-L	253.4588	281.6854	253.4588	260.8500

4.6. *Discussion*

The first three hypotheses hold. DF raises local EE, and UD matters more than CB or DL. This tells us that the real-world functions of DF, like green credit and digital payments, drive energy savings, while simply expanding coverage does not do nearly as much. TF also plays a positive moderating role. The interaction term shows that TF and DF work together, not against each other. Traditional banks bring capital, credit know-how, and physical branches, all of which help DF do its job. Spatial spillovers from DF get stronger over time. Benefits do not show up right away. In the short run, neighbors learn from each other. In the long run, capital flows, technology diffusion, and industrial restructuring take effect. Policy needs to allow time for these effects to play out.

The last two hypotheses only get partial support. TI raises EE not only locally but also in neighboring and more distant regions, whereas ISU works only for local and neighboring regions and does not reach farther away. The reason is that industrial upgrading depends heavily on local policies and physical infrastructure, while technical knowledge can be shared online at low cost. A similar pattern appears for EG and GF. Both help improve local EE and generate spillovers to neighboring regions, but neither produces significant effects on EE in more distant areas because they are tied to local investment, regulation, and market conditions. So if the goal is to spread DF's energy benefits to distant places, promoting TI is a more effective route than pushing ISU, EG, or GF.

All five hypotheses get some support, but only TI creates spillovers that reach far across regions. This finding shows that the digital and financial attributes of DF operate through different spatial mechanisms. Unlike TI, the other three channels are more constrained by local conditions. For policymakers, spreading TI is the most promising way to bring DF's energy benefits to distant regions.

5. Conclusions and policy implications

With panel data from 30 Chinese provinces and a DSDM, we find that DF improves EE. This is true for local provinces and their neighbors. This effect gets stronger over time. TF plays a positive moderating role, and the effect is strongest on UD. Among the four transmission channels, only TI creates multi-level spatial spillovers across regions. The other three channels mostly stay within local boundaries.

Three contributions are worth noting. First, earlier studies often look at static or single spatial effects. Our model puts together time lags, spatial lags, and spatio-temporal lags. This gives a better picture of how DF affects EE over time and space. Second, TF complements DF rather than replacing it. This clarifies how the two interact. Third, TI travels across regions more easily than other mechanisms. That is why it generates wider spillovers.

The results also line up with China's recent policies. UD matters most for EE. This fits with the current policy focus on practical uses of DF under the dual carbon goals. TI spills over across regions. This result aligns with the Western Development Initiative and the West-East Electricity Transmission Project. These projects spread green technologies from the east to central and western China. The moderating role of TF also suggests that policymakers should push traditional banks to go digital.

Two areas are worth looking into for future research. One is to extend the analysis to the prefecture-city level. Provincial data may hide important differences across cities within the same province. City-level data would give a finer picture. The other is to design region-specific policies. Eastern provinces, where DF is more mature, could focus on technology-driven spillovers. In western provinces, DF is still developing. Expanding CB and upgrading local industry may bring bigger gains. Different regions need different strategies. That way, each can hit its EE targets under the dual carbon goals.

Declaration of competing statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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