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Article

Digital Economy and Green and Low-Carbon Transformation of Land Use: Spatial Effects and Moderating Mechanisms

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Abstract: The green and low-carbon transformation of land use (GLTLU) is a pressing global issue that requires urgent attention. The digital economy has emerged as a new driver for the GLTLU. However, current research mainly focuses on the measurement and environmental effects of the digital economy, with less exploration of how the digital economy influences the spatial effects and regulatory mechanisms of GLTLU, particularly regarding the differential impacts and specific mechanisms at the regional level. This study uses panel data from 283 cities in China from 2011 to 2019, employing the spatial Durbin model (SDM) and the panel threshold model to examine the spatial and regulatory mechanisms of the digital economy's impact on GLTLU. The findings reveal that digital economy promotes GLTLU not only within cities but also in surrounding regions. Robustness analyses support this conclusion. Notably, the digital economy's positive impact on GLTLU in surrounding areas is confined to the central region of China. In contrast, the Yangtze River Delta urban agglomeration experiences a significant negative impact on GLTLU in nearby regions due to the digital economy. The study also identifies that the positive spatial spillover effect of the digital economy on GLTLU reaches its peak at a distance of 450 km. Additionally, the digital economy's ability to promote GLTLU is contingent upon financial agglomeration levels exceeding 9.1728. Moreover, the local government's emphasis on the digital economy and intellectual property protection enhances the digital economy's impact on GLTLU. The promotion effect is maximized when these factors surpass the thresholds of 27.8054 and 3.5189, respectively. Overall, this study contributes to the understanding of how the digital economy influences sustainable land development, highlighting the critical role of regional factors and regulatory mechanisms in amplifying the digital economy's positive effects on GLTLU.

Keywords: digital economy; green and low-carbon transformation of land use; spatial spillover effect; financial agglomeration; intellectual property protection

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1. Introduction

Land is the fundamental space for various economic activities, including agriculture, industry, and infrastructure construction. Agricultural land ensures food security, serving as the foundation for human survival. Industrial land drives economic growth, providing significant employment opportunities and material wealth [1]. Additionally, land is crucial for human habitation and living. Residential land in urban and rural areas directly affects the quality of life and well-being of residents [2]. With the rapid advancement of global industrialization and urbanization, land resources are experiencing unprecedented pressure and challenges. Land use significantly contributes to environmental pollution and carbon emissions. In light of increasingly severe global climate change and environmental pollution, the green and low-carbon transformation of land use (GLTLU) has become particularly crucial. The GLTLU involves not only reducing greenhouse gas emissions but also improving energy and resource efficiency, reducing waste and pollution, protecting natural ecosystems, and enhancing residents' quality of life.

With the acceleration of China's industrialization and urbanization, land use issues have become increasingly prominent. First, China's land use structure is unreasonable. A large amount of high-quality farmland has been used for urban construction, reducing agricultural land and affecting food security [3]. Second, land development lacks systematic and long-term planning, leading to severe waste of land resources. Unreasonable land use methods have exacerbated environmental pollution. Traditional land use and development models are often accompanied by high carbon emissions. A large amount of land is used for high-energy consumption and high-emission industries, increasing greenhouse gas emissions and negatively impacting global climate change. The GLTLU is one of the urgent issues facing the world today. As the world's largest developing country, China faces severe challenges in land use but also has significant potential for transformation. Achieving GLTLU in China is crucial for its high-quality development and for promoting global climate governance goals.

Currently, an imminent revolution in information technology is approaching, where the digital economy (DE), powered by advanced technologies such as big data, cloud computing, artificial intelligence, and blockchain, is profoundly altering production and lifestyle patterns. This shift is becoming a pivotal force in reshaping global economic competition [4]. The DE improves the efficiency and transparency of urban land use by promoting the intelligence of public services and management. The government can use big data analysis and cloud computing technology to achieve real-time monitoring and precise management of land use. For example, using remote sensing technology and geographic information systems, it is possible to monitor land use changes in real time, detect illegal land occupation and land waste, and take timely measures. Policymakers can optimize land use planning and improve land use sustainability based on data-driven decisions.

However, the DE also faces some limitations and challenges in promoting GLTLU. First, the unbalanced development of the DE may exacerbate the gap in regional land use. Developed regions, due to better digital infrastructure and technical resources, can achieve land use transformation faster, while less developed regions may find it difficult to keep up with this transformation due to resource and technological constraints, leading to an imbalance in low-carbon land use development between regions. In addition, the development of the DE has brought about data privacy and security issues. As more and more land use data are collected and analyzed, ensuring the privacy and security of these data becomes an important challenge. If data are misused or leaked, it may lead to serious privacy violations and security risks. This requires governments and enterprises to jointly develop and implement strict data protection policies to ensure data security and user privacy protection. So, can China's DE influence GLTLU? What are the spatial effects and regulatory mechanisms, in particular? Is there heterogeneity? Exploring these issues can provide theoretical and empirical evidence for global developing countries to achieve sustainable land use from the perspective of the DE.

2. Literature Review

Currently, some of the literature focuses on evaluating GLTLU, using SBM (slack-based measure) or EBM (epsilon-based measure) models to assess green land use efficiency [5–9], low-carbon land use efficiency [10,11], and green low-carbon land use efficiency [12]. Another portion of the literature mainly focuses on individual key factors affecting GLTLU, such as the construction of free trade zones [13], low-carbon city pilot policies [14], innovation-driven development policies [15], urban form [16], industrial structure [17], regional integration [18], city administrative levels [19], land transfer marketization [20], industrial agglomeration [21], and urbanization [22,23]. Some of the literature has begun to examine the impact of the DE on the green and low-carbon transformation of manufacturing [24], urban carbon emission intensity [25], low-carbon inclusive growth at the provincial level [26], regional socioeconomic development [27], and enterprise low-carbon innovation [28]. Other studies have explored the impact of the DE on low-carbon transformation and the spatial spillover effects on urban low-carbon transformation, using the panel threshold model to examine the regulatory effects of public attention [29], examining the transmission paths of the DE on low-carbon development from the perspective of industrial structure [30,31], and evaluating the green and low-carbon development status of DE in the context of open innovation.

Recent studies have begun exploring the impact of the DE on land use transformation. Research based on data from Chinese cities indicates that the DE improves green land use efficiency through industrial optimization, green technological innovation, and digital talent attraction [32]. Some studies using provincial panel data from China found that the DE can reduce carbon emissions from farmland use through green technological transformation [33]. Research utilizing city-level data from China's Yellow River Basin reveals a dynamic, nonlinear relationship between the DE and land use ecological efficiency, with no mediating effect of industrial structure [34]. Other studies examine the impact of specific aspects of the DE, such as digital finance [35], the "Broadband China" pilot policy [36], and the smart city pilot policy [37], on land use transformation. While some of the literature explores the DE–land use transformation relationship, few studies address it from the perspectives of spatial and regulatory effects.

This study addresses the gap in understanding the spatial effects and regulatory mechanisms of the DE on GLTLU by analyzing panel data from 283 Chinese cities. The primary contributions of this research are as follows: First, compared to previous studies [32,34], this research expands the conclusions on the impact of the DE on GLTLU. This study finds that the DE not only promotes GLTLU in its own region but also promotes GLTLU in surrounding areas through a spatial spillover mechanism, verifying the spatial decay boundary between them. Second, this study focuses on the spatial effects of the DE on GLTLU across five major urban agglomerations in China, deepening the research on the differences in spatial effects between them. Third, unlike previous studies that examine the regulatory mechanisms between the DE and land use transformation from the perspectives of land finance dependence and the DE itself [32,34], this study examines the regulatory mechanisms of the DE's impact on GLTLU from the perspectives of financial agglomeration, local government focus on the digital economy, and intellectual property protection.

3. Theoretical Analysis and Research Hypotheses

The GLTLU involves the input and output elements of the land use system. Inputs include labor, capital, land, and energy utilization, while outputs encompass social and economic benefits, as well as carbon and pollution emissions.

In the perspective of input elements, digital technology and data elements, when combined with traditional production elements, form complementary, coordinated, and coupled development [38], enhancing the utilization efficiency of traditional production elements. First, in terms of labor utilization, the rapid development of the DE has changed labor production methods, enhancing total labor productivity. On the one hand, in the production process of enterprises, the development and application of digital technology have replaced some labor, especially low-efficiency labor, significantly improving labor utilization efficiency; on the other hand, the DE promotes information exchange and production collaboration, facilitating intelligent management, enhancing data integration and association efficiency in production and sales, thereby improving labor utilization efficiency. Additionally, the DE accelerates labor mobility, intensifies competition in the talent market, and workers continually strive to improve their skills to adapt to the DE developments, enhancing human capital and labor utilization efficiency. Improved labor utilization efficiency helps enterprises produce more products with less labor input, promoting GLTLU.

Second, in terms of capital utilization, the DE accelerates capital flow in exchange and consumption fields, breaking time and space constraints and enhancing capital utilization efficiency. On the one hand, with the rapid development of internet platforms, virtual platform business models [39] have emerged, accelerating the connection and efficiency between production, sales, and consumption [40], promoting capital utilization efficiency. On the other hand, digital payment is a key aspect of DE development. With the advancement of digital currency and virtual payment, payment methods have broken time and space limitations, leading to more convenient payment methods that accelerate monetary capital circulation, acting as accelerators of capital turnover, thereby enhancing capital utilization efficiency.

Third, in terms of land utilization, the development of the DE, especially the digitization of urban infrastructure, has led to data aggregation, enhancing land utilization efficiency. First, data elements, as new production elements, have characteristics such as fast dissemination and low marginal cost [41], which can revitalize land market resources and unleash the potential of land stock. Additionally, digital government construction helps monitor and manage land prices, policies, etc., improving land utilization efficiency. Second, the DE changes the demand structure for urban land. Data elements accelerate the construction of virtual spaces, breaking the constraints of traditional physical spaces, facilitating intensive and landless development [42]. By linking small land parcels through data, small land parcels can be fully and flexibly utilized, optimizing land use allocation and improving land utilization efficiency. Finally, the development of the digital economy helps form agglomeration effects [43], promotes the coordination of resources in urban clusters and the aggregation of urban development, and promotes GLTLU through the advantages of data elements such as virtuality, timeliness, and strong externality.

Fourth, in terms of energy utilization, compared to the traditional economy, the DE optimizes production and management processes, facilitating the optimization and integration of traditional economic resources, effectively enhancing energy utilization efficiency [44]. The DE, supported by digital infrastructure and technology, has led to innovations in energy production and consumption, such as solar, waste-to-energy, and energy storage technologies. This progression promotes new energy development and directs clean energy to more efficient production sectors [45], promoting the clean development and optimization of the energy industry chain. The vigorous development of the DE promotes the intelligent transformation of enterprises. The integration of digital technology optimizes production methods and processes, accelerating the elimination of outdated and inefficient production capacity, promoting clean production, and improving energy utilization efficiency [46].

In view of the output elements of the land use system, in terms of economic benefits, the positive impact of the DE on economic development has been confirmed by many scholars [47]. With the deepening integration of the DE with the traditional economy, the DE has become an important driving force for economic growth, contributing to the improvement of the utilization of traditional economic elements, industrial structure, and production modes, promoting the efficiency of traditional economic element utilization, the transformation and upgrading of the industrial structure, and significantly enhancing economic benefits. In terms of social benefits, the DE not only promotes economic benefits but also increases social benefits. On the one hand, with the continuous increase in the value of social data resources, the construction of digital government has entered a new stage, where digital governance can help standardize, unify, and make government management at all levels open and transparent, significantly increasing government work efficiency and gradually enhancing public satisfaction with government services, thus contributing to the advancement of modern government governance capabilities, which is an important manifestation of the social benefits brought by DE development. On the other hand, the DE accelerates industrial competition, especially competition among high-end industries, which will allow consumers to continually obtain high-end products and services with higher satisfaction, as differentiated high-end products are better able to meet user needs, meeting people's growing needs for a better life, and further compelling and stimulating enterprises to improve their products and services, thereby continuously enhancing social benefits in this virtuous cycle.

The DE impacts carbon emissions by reducing traditional economic activities through virtual networks and digital technologies, thus lowering resource and energy consumption.

E-commerce and remote work models have decreased carbon emissions by promoting online services. Moreover, advancements in digital technologies, such as artificial intelligence and the industrial internet, enhance the carbon trading market by addressing double counting and transparency issues. Technological progress, especially in green production, plays a vital role in reducing emissions and improving efficiency. At a macro-level, digital innovations like big data, blockchain, and AI accelerate clean production technologies, eliminating outdated capacities and promoting low-carbon industrial transformations. At a micro-level, digital technology compels enterprises to adopt clean production methods, altering consumption patterns and aiding in carbon reduction.

The DE mitigates pollution emissions by overcoming spatial limitations, enhancing market-based resource allocation, reducing information asymmetry, and integrating the industrial chain, thus lowering resource and energy consumption. The DE promotes green innovation through big data sharing and platform interconnection, enabling low input and high output, and transforming traditional high-pollution production models. Additionally, digitalization and greening are synergistic, with greening driving digitalization by creating new demands for digital technologies, further reducing emissions. The DE also guides green consumption and reduces emissions via digital platforms.

The DE can influence GLTLU through spatial spillover mechanisms, whereby the DE promotes GLTLU in its own region while also affecting neighboring regions. The main spatial spillover mechanisms include the network demonstration effect, the siphon effect, and the diffusion effect. From the network demonstration effect perspective, the DE plays a crucial role in bridging the digital divide. Through demonstration and imitation, the DE can drive the development of digital economies in adjacent regions, creating a spatial spillover effect on GLTLU. Regions with higher levels of DE development serve as positive examples for less developed areas, reducing the technological gap and fostering a regional integrated emission reduction system. In the internet era, digital technologies have strong dissemination capabilities. Advanced digital technologies can create powerful demonstration effects, forming network structures that encourage neighboring regions and enterprises to adopt similar practices, narrowing the technology gap and digital divide, and driving surrounding cities to collaborate on emission reductions. This process contributes to the integrated spatial development of the digital economy and further promotes GLTLU. Moreover, the demonstration effect of the DE enhances human capital levels in neighboring regions, accelerates enterprise innovation, and promotes GLTLU. The fundamental driving force behind technological innovation is talent. The level of human capital determines the future trajectory of low-carbon transformation for both governments and enterprises and is crucial for promoting GLTLU. The formation of human capital depends on the efficiency of information connections and the dissemination of knowledge and experience with the outside world [48]. As the DE develops, the ways of imparting knowledge and technology are also continually improving, thereby more effectively exerting the DE's demonstration effect, promoting the accumulation and enhancement of human capital in neighboring regions, thus contributing to GLTLU.

The siphon effect of the DE refers to its strong attraction to resources, talent, and capital, leading these elements to concentrate in the digital economy sectors or developed regions from traditional economic sectors or underdeveloped areas. This effect is significant to the research background as it reveals the trend of resource reallocation, helping to understand how the DE promotes economic growth and technological innovation. At the same time, the siphon effect brings challenges of regional economic disparities and industrial structure adjustment, emphasizing the necessity of formulating reasonable land use policies and regional coordinated development strategies to achieve sustainable and balanced development goals. From the perspective of the siphon effect, the DE attracts and aggregates elements such as technology, capital, and talent in regions with more advanced DE development due to their superior DE environments. This leads to the continuous accumulation of high-quality resources in these regions, while areas with a less developed DE experience a depletion of resources. The siphon effect of the DE is mainly evident in several key areas. Firstly, regarding research and development (R&D), technological innovation driven by the DE promotes the creation and expansion of innovation platforms. These platforms serve as crucial carriers of urban development, attracting talent and capital not only from within the region but also drawing high-quality human resources from neighboring areas [49], thus continuously improving the R&D level and competitive advantage of regions with higher levels of DE development, which will lead to a reduction in resources in surrounding areas and exacerbate regional disparities [50], thereby hindering GLTLU in neighboring regions. Second, regarding enterprise production, regions with higher levels of DE development typically exhibit higher economic development levels, abundant resources, and significant talent advantages. This environment creates a selection effect for businesses, attracting enterprises with advanced technological capabilities and high production efficiency to these regions. Conversely, enterprises with lower technological levels, lower production efficiency, and lower carbon emission efficiency are often pushed out to surrounding areas, which suppresses GLTLU in these neighboring regions. Third, in terms of infrastructure and public services, a crucial component of DE development is the enhancement of digital infrastructure. The improvement of digital infrastructure elevates residents' production and living standards, increasing their convenience and welfare, thus attracting high-quality talent and enterprise investment. This provides essential support for the low-carbon transformation and development of inflow regions. However, this process can deplete human and material capital in surrounding regions, thereby hindering GLTLU in those areas.

The diffusion effect of the DE refers to the process where regions with higher levels of DE development expand their production scale, causing the diffusion of data elements and digital technologies to neighboring regions. This diffusion promotes DE development in adjacent areas, reduces the gap in digital economic development levels between regions, and simultaneously advances GLTLU in surrounding areas. First, in terms of research and development (R&D), the DE development facilitates the innovation of green technologies and the creation of green products [51] and can diffuse to surrounding areas through the flow of production elements such as labor and capital. Furthermore, enterprises in neighboring areas can improve their digital economy levels and resource utilization efficiency through learning, imitation, and secondary innovation, addressing their shortcomings in green R&D and green innovation, which in turn promotes GLTLU in the process. Second, in terms of enterprise production, the DE plays an important role in driving new-type urbanization and Chinese-style modernization, facilitating the formation of an efficient and green industrial development pattern, promoting unified and coordinated regional development, and helping build symbiotic and complementary industrial clusters, promoting upstream and downstream industrial chain cooperation between different regions. In this process, it also drives the green transformation and upgrading of industrial structures in surrounding regions, thereby promoting GLTLU in these areas. Third, in terms of infrastructure and public services, as digital infrastructure continues to improve, industrial informatization becomes the main development trend, and efficient, convenient, and low-cost transaction and transportation methods play an important role in strengthening regional connections [52], making exchanges and cooperation between different regions more frequent and convenient, while also accelerating the sharing of knowledge, the flow of human capital, and changes in production methods, promoting the deep integration of the DE and the real economy in neighboring regions, which greatly promotes GLTLU in these areas. This study proposes the following hypothesis:

H1: *The DE can not only promote GLTLU in its own region but also have positive or negative effects on GLTLU in surrounding regions through spatial spillover mechanisms.*

Financial agglomeration can promote enterprise digital transformation by providing financial resources to enterprises, thereby promoting the DE. Numerous studies show that financial agglomeration enhances financial competition within the agglomeration area, creates financial tools, and helps provide more abundant financial resources to enterprises within the agglomeration area, improving financial efficiency. When enterprises seek financing, they have more choices and financing opportunities. Financial resources are the necessary funding guarantee for enterprises to undergo digital transformation. Typically, enterprises need substantial funds for digital technology R&D and the transformation of intelligent production facilities in the early stages of digital transformation. The difficulties and high costs of financing are significant obstacles to enterprises' digital transformation. Under these circumstances, a favorable regional financial environment plays a crucial role in alleviating enterprises' financing pressure and reducing financing costs, enabling enterprises to actively and proactively pursue digital transformation [53], thereby promoting GLTLU.

DE development depends on government guidance, and the level of local government attention on the DE directly affects the extent of the DE's impact on GLTLU. First, a high level of local government attention on the DE can result in the formulation of policies and measures to promote digital economy development, such as subsidies to encourage enterprises to undergo digital transformation, thereby promoting digital economy development [54]. Second, a high level of local government attention on the DE helps improve the comprehensive application capabilities of digital technology in the region [55], promoting the digital integration of the DE with the traditional economy. Third, a high level of local government attention given to the DE helps create a favorable digital economy development environment, increasing overall societal attention on the DE, providing policy guidance and support for enterprises to undergo digital transformation, thus enhancing the impact of the DE in promoting GLTLU.

As the DE continues to develop, the traditional intellectual property (IP) system faces significant impacts and challenges, highlighting the need for an IP system compatible with the DE. Specifically, a robust IP protection system can promote DE development in three key areas. Firstly, in the field of digital industrialization, a sound IP protection system safeguards new DE innovations, such as new digital technologies and digital derivatives. This protection strengthens the transformation of digital economic achievements, thereby sustaining the strong momentum of digital industrialization development. Secondly, in the field of industrial digitization, the digital transformation of enterprises is closely linked to IP protection. A robust IP protection system helps reduce security risks during the digital transformation process. Thirdly, in the field of data governance, data are crucial new production factors for improving production efficiency. A modern IP system helps protect the collection, storage, processing, and use of data elements, thereby promoting the realization of data element value. This study proposes the following hypothesis:

H2: *Financial agglomeration, local government attention on the digital economy, and intellectual property protection can enhance the effect of the DE in promoting GLTLU.*

4. Research Design

4.1. Model Specification

4.1.1. Spatial Durbin Model

Drawing on the existing literature [56], the SDM is used to examine the effects of the DE on GLTLU. The SDM is very effective in capturing spatial dependence, but it also has some limitations. First, the complexity of the model increases, making parameter estimation more difficult. Second, the data need to have a clear spatial structure, and the results are sensitive to the choice of the spatial weight matrix. Additionally, the SDM assumes uniform spatial effects and does not consider spatial heterogeneity. Boundary effects and the challenges of model validation may also affect the reliability of the results. Despite these limitations, the SDM remains a very valuable tool for dealing with spatially correlated data, revealing spatial dependence, and capturing complex spatial spillover effects. The model is constructed as follows:

$$GLTLU_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} GLTLU_{jt} + \beta DE_{it} + \varphi X + \delta \sum_{j=1}^{N} W_{ij} DE_{ijt} + \gamma \sum_{j=1}^{N} W_{ij} X_{ijt} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Among them, DE represents the digital economy, and X represents a series of control variables that affect GLTLU. α is the constant term, β and φ are the coefficients of the DE's impact on local and surrounding GLTLU, μ_i is the individual fixed effect, v_t is the time fixed effect, and ε_{it} represents the random disturbance term.

4.1.2. Moderation Effect Model and Threshold Model

Combining theoretical analysis, interaction terms of the moderating variable and DE are added to the bidirectionally fixed panel fixed effects model to accurately identify the moderating role of the variable in the impact of the DE on GLTLU, as shown in model (2):

$$GLTLU_{it} = \alpha_0 + \alpha_1 DE_{it} + \beta_1 TJ_{it} + \beta_2 DE_{it} \times TJ_{it} + \varphi X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{2}$$

Among them, TJ is the moderating variable, α_0 is the intercept term, α_1, β_1, and φ represent the effects of DE, the moderating variable, and X on GLTLU, respectively, and β_2 is the estimated coefficient of the moderating variable. The meanings of the other variables are consistent with those in model (1).

Additionally, to examine the possible threshold effect of the moderating variable, the panel threshold model is set according to the existing literature [57]. Based on the sample-estimated threshold value, the single-threshold model is set as follows:

$$GLTLU_{it} = \beta_0 + \beta_1 DE_{it}(q_{it} \le \gamma) + \beta_2 DE_{it}(q_{it} > \gamma) + \beta_3 X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{3}$$

Among them, q_{it} is the threshold variable, which includes financial agglomeration (FAGG), local government digital attention (GCON), and intellectual property protection (IPR). γ is the threshold value. For an example of a double-threshold model, the model is as follows:

$$\begin{gathered} GLTLU_{it} = \beta_0 + \beta_1 DE_{it}(q_{it} \le \gamma_1) + \beta_2 DE_{it}(\gamma_1 < q_{it} \le \gamma_2) + \beta_3 DE_{it}(q_{it} > \gamma_2) + \\ \beta_3 X_{it} + \mu_i + v_t + \varepsilon_{it} \end{gathered} \tag{4}$$

Among them, γ_1 is the first threshold and γ_2 is the second threshold value, and threshold models with three or more thresholds follow this pattern.

The existing literature generally uses geographic density, location quotient, or the E-G index to measure FAGG. Using financial geographic density can take into account the supply of financial resources and geographic factors, thereby clearly depicting the spatial distribution of financial resources with strong intuitiveness. Therefore, drawing on existing research [58], geographic density is used to measure FAGG. Combining government digital economy policy texts, text mining is used to construct word frequencies of digital technologies and applications to measure GCON. Drawing on existing research [59], the intellectual property demonstration city pilot policy is used as a proxy for IPR. The specific approach is as follows: if a city is designated as an IP demonstration city, the value is set to 1 for that year and subsequent years; otherwise, it is set to 0. Additionally, the number of full-time lawyers per 10,000 people is used to measure regional IPR. The more full-time lawyers there are in a region, the better the IPR effect in that region, and this variable is selected as the threshold variable for IPR.

4.2. Variable Definition

(1) Explained variable. Referring to the existing literature [60], the EBM model, which includes a hybrid model of radial and SBM distance functions, is used to measure GLTLU. Specifically, this study uses a non-oriented, variable returns to scale, super-efficiency EBM model to measure GLTLU. Referring to the existing literature [61,62], a land input indicator system and a land output indicator system are constructed.

The land input indicator system includes urban construction land area (km^2), total urban employment at the end of the year (ten thousand people), urban capital stock (CNY ten thousand), and total energy consumption of three types of energy such as natural gas (ten thousand tons of standard coal). The land output indicator system includes expected outputs such as urban GDP (CNY ten thousand), urban built-up area greening rate (%), and urban average wage of employees (CNY) as well as non-expected outputs such as total urban natural gas carbon emissions (ten thousand tons), total urban liquefied petroleum gas carbon emissions (ten thousand tons), total urban electricity carbon emissions (ten thousand tons), total urban thermal energy consumption carbon emissions (ten thousand tons), total urban industrial wastewater emissions (ten thousand tons), total urban industrial SO_2 emissions (ten thousand tons), and total urban industrial smoke (dust) emissions (ten thousand tons).

(2) Explanatory variables. This study constructs the DE indicator system using several metrics: the number of internet broadband access users per 100 people, the number of mobile phone users per 100 people at the end of the year, the proportion of employees in computer services and software (%), per capita telecommunications business income (CNY ten thousand), the breadth index of digital inclusive finance coverage, the depth index of digital inclusive finance usage, the digitalization index of digital inclusive finance, and the number of computers per 100 industrial enterprise employees. The entropy method is employed to measure the DE index. Due to the lack of data on digital agriculture at the urban level, the DE indicator system only includes indicators related to industry and services.

(3) Control variables. Referring to the existing literature [62,63], 10 control variables that affect ULCT are selected (see Table A1).

The theoretical mechanisms by which control variables affect ULCT are as follows: Temperature change (CIM) can prompt cities to increase green spaces, improve building energy efficiency, and formulate stricter environmental policies, thereby accelerating the low-carbon transition of land use. Transportation infrastructure (INFRA) can alleviate traffic congestion and reduce traffic carbon emissions per unit of land area. Environmental regulation (ER) effectively promotes ULCT by setting strict emission standards, promoting the use of renewable energy, and encouraging green buildings and low-carbon transportation methods. Openness (OPEN) contributes to ULCT by introducing advanced technologies, attracting green investments, and promoting international cooperation. Openness brings advanced environmental technologies and experiences, enhancing urban energy efficiency and environmental standards. Industrial agglomeration (AGG) significantly supports ULCT by improving resource utilization efficiency, promoting technological innovation, achieving economies of scale, optimizing logistics, and driving policy implementation. Industrial proportion (INDUSTR) significantly promotes ULCT by reducing the proportion of high-energy-consumption and high-emission industries while increasing the proportion of high-tech and low-carbon industries. Government intervention (GOV) can significantly influence ULCT through policy formulation, financial support, technology promotion, and regulatory oversight. Energy efficiency (ENER) has an important impact on ULCT. Improving ENER can significantly reduce energy consumption, thereby lowering carbon emissions per unit of land. For example, efficient building energy-saving technologies, advanced industrial production processes, and smart grid systems can all enhance energy utilization efficiency. Urbanization (URB) significantly affects ULCT through intensive management and efficient resource utilization. High-quality human capital (HUMAN) is conducive to promoting innovation and low-carbon technologies, improving energy utilization efficiency, and thereby benefiting ULCT.

4.3. Sample Selection and Data Sources

The original data for the variables primarily come from various annual editions of several statistical yearbooks: *China City Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Environment Yearbook*, *China Industrial Statistical Yearbook*, *China Science and Technology*

Statistical Yearbook, and *China Labor Statistical Yearbook*, as well as the EPS data platform. The digital inclusive finance data are sourced from the Digital Finance Research Center at Peking University. This study examines 283 prefecture-level-and-above cities from 2011 to 2019. Cities with severely missing data are excluded, and any missing values are supplemented and estimated using the linear interpolation method and Python data mining techniques.

5. Empirical Results

5.1. Overall Test of Spatial Effects

Before conducting the SDM regression, this study tested the SLM, SEM, and SDM. The test results indicated that the SDM could not be simplified into either a spatial error or spatial lag model. Additionally, the Hausman test rejected the null hypothesis of the random effects model at the 1% significance level. Therefore, a spatial and temporal bidirectionally fixed SDM is employed to examine the spatial spillover effects of the DE on GLTLU. Table 1 presents the regression results for the SDM, SLM, and SEM models, respectively. The results show that the spatial lag coefficients of GLTLU are significantly positive, indicating a substantial positive spatial correlation of GLTLU. This suggests that improvements in GLTLU in one region can promote GLTLU in neighboring regions. The regression results of the SDM indicate that DE not only enhances local GLTLU but also promotes GLTLU in surrounding areas, confirming Hypothesis 1.

Table 1. Empirical results of spatial spillover effects.

	SDM		**SLM**	**SEM**
	Main	**Wx**	**Main**	**Main**
DIG	0.4951 ***	2.6009 ***	0.5140 ***	0.5070 ***
	(7.151)	(4.234)	(7.411)	(7.269)
INFRA	0.0001	0.0167 *	0.0005	0.0005
	(0.112)	(1.891)	(0.591)	(0.527)
ER	0.0438 ***	−0.2214 *	0.0472 ***	0.0483 ***
	(2.808)	(−1.808)	(3.019)	(3.090)
OPEN	0.0033 **	0.0049	0.0030 **	0.0030 **
	(2.203)	(0.467)	(2.114)	(2.075)
AGG	−0.0963 ***	0.0904	−0.0943 ***	−0.0938 ***
	(−9.985)	(1.619)	(−9.861)	(−9.733)
INDUSTR	0.0038 ***	0.0012	0.0040 ***	0.0041 ***
	(9.496)	(0.574)	(10.308)	(10.337)
GOV	−0.1452 **	−0.0894	−0.2057 ***	−0.2100 ***
	(−1.982)	(−0.189)	(−2.879)	(−2.909)
ENER	0.0029 ***	0.0001	0.0029 ***	0.0029 ***
	(24.351)	(0.123)	(24.636)	(24.506)
URB	0.0011 ***	0.0003	0.0012 ***	0.0013 ***
	(4.184)	(0.226)	(4.908)	(5.065)
HUMAN	−0.0000	0.0003	−0.0000	−0.0000
	(−1.176)	(1.100)	(−1.254)	(−1.303)
CIM	0.0006	−0.0069	−0.0014	−0.0020
	(0.112)	(−0.312)	(−0.346)	(−0.467)

Table 1. *Cont.*

	SDM		SLM	SEM
	Main	**Wx**	**Main**	**Main**
ρ/γ	0.2451 ***		0.3140 ***	0.2751 ***
	(3.009)		(4.526)	(3.426)
sigma2_e	0.0040 ***		0.0041 ***	0.0041 ***
	(35.652)		(35.647)	(35.649)
N	2547		2547	2547
R^2	0.1797		0.1673	0.1596
Hausman	44.24		196.95	
	[0.0000]		[0.0000]	
Log-likelihood	3409.6992		3389.597	3385.427

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the z-statistics for the parameter estimates. Both spatial and temporal fixed effects are controlled.

After decomposing the SDM, the spatial effects of the DE on GLTLU can be further explored through the lenses of direct and indirect effects. As shown in Table 2, the DE not only promotes GLTLU in the local region but also in surrounding regions, indicating a significantly positive spatial spillover effect of the DE on GLTLU, consistent with the regression results in Table 1. This further validates Hypothesis 1, suggesting that the demonstration and diffusion effects of the DE outweigh the siphon effect, thereby contributing to GLTLU in neighboring areas.

Table 2. Decomposition results of the spatial spillover effect of the DE on GLTLU.

	LR_Direct	*LR_Indirect*	*LR_Total*
DE	0.5168 ***	3.6526 ***	4.1694 ***
	(7.247)	(3.953)	(4.468)
INFRA	0.0002	0.0212 *	0.0213 *
	(0.199)	(1.861)	(1.860)
ER	0.0440 ***	−0.2698	−0.2258
	(2.927)	(−1.604)	(−1.318)
OPEN	0.0033 **	0.0066	0.0099
	(2.296)	(0.496)	(0.750)
AGG	−0.0958 ***	0.0894	−0.0064
	(−10.198)	(1.176)	(−0.083)
INDUSTR	0.0039 ***	0.0032	0.0071 **
	(9.693)	(1.126)	(2.531)
GOV	−0.1468 *	−0.1703	−0.3171
	(−1.933)	(−0.262)	(−0.489)
ENER	0.0029 ***	0.0010 *	0.0039 ***
	(25.390)	(1.783)	(6.782)
URB	0.0011 ***	0.0007	0.0019
	(4.418)	(0.366)	(0.986)

Table 2. *Cont.*

	LR_Direct	*LR_Indirect*	*LR_Total*
HUMAN	−0.0000	0.0004	0.0004
	(−1.056)	(1.057)	(0.948)
CIM	0.0004	−0.0082	−0.0078
	(0.075)	(−0.310)	(−0.333)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the z-statistics for the parameter estimates. Both spatial and temporal fixed effects are controlled.

On one hand, the DE facilitates the development of green technologies and enables their diffusion to surrounding cities through the flow of capital, labor, and the widespread use of information technology, thereby enhancing GLTLU in these regions. On the other hand, the DE has a strong demonstration effect on neighboring cities, encouraging these regions to elevate their DE development through secondary learning and imitation, thus further empowering GLTLU.

The GLTLU is remeasured using the SBM model and re-estimated using the SDM, with regression results presented in Table A2. After updating the GLTLU measurement method, the estimated coefficient of the DE remains significantly positive at the 1% significance level. The DE continues to significantly promote GLTLU both locally and in surrounding regions.

Further robustness tests are conducted by changing the spatial weight matrix. Table A3 illustrates the spatial spillover effects of the DE on GLTLU under different spatial weight matrices: neighboring distance weight, economic spatial weight matrix, and distance spatial weight matrix. The regression results demonstrate that, regardless of the spatial weight matrix used, the SDM test results for the impact of the DE on GLTLU exhibit strong robustness.

5.2. Heterogeneity Analysis

5.2.1. Heterogeneity of Natural Geographical Location

The differences in the impact of the DE on GLTLU across China's three major regions are examined, with regression results shown in Table 3. The findings indicate that the promoting effect of the DE on GLTLU follows a pattern of "high in the east, lower in the central, and insignificant in the west".

Table 3. Regression results of heterogeneity in natural geographical location.

	Eastern			**Central**			**Western**		
	LR_Direct	*LR_Indirect*	*LR_Total*	*LR_Direct*	*LR_Indirect*	*LR_Total*	*LR_Direct*	*LR_Indirect*	*LR_Total*
DE	0.5895 ***	1.0036	1.5931	0.2474 *	2.1310 **	2.3785 **	0.0323	−1.1878	−1.1555
	(6.362)	(0.906)	(1.404)	(1.768)	(2.101)	(2.341)	(0.196)	(−0.940)	(−0.898)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the z-statistics for the parameter estimates. Control variables, spatial fixed effects, and temporal fixed effects are all controlled.

This variation can be attributed to several factors. The eastern region, compared to the central and western regions, has a stronger economic foundation, a higher concentration of talent, better production technology, and a more robust industrial base. These factors are conducive to DE development and enhance the DE's positive impact on GLTLU. Conversely, the DE in the eastern and western regions did not significantly impact the GLTLU of surrounding areas. In contrast, the DE in the central region significantly promoted the GLTLU of neighboring areas.

The economic development level in the western region is relatively low, and factors such as the "digital technology divide" hinder DE development. Additionally, geographical and physical space constraints prevent western cities from forming effective interactive effects. Although DE development in the eastern region is more advanced, issues of uncoordinated regional development hinder the formation of a robust interactive spatial pattern. In the central region, however, the spatial spillover effect of digital technology is more pronounced. The DE has created notable "demonstration effects" and "diffusion effects" in promoting GLTLU in this region.

5.2.2. Urban Agglomeration Heterogeneity

Table 4 shows the spatial spillover effects of the DE on GLTLU in the five major urban agglomerations. The results indicate that, except for the Yangtze River Delta and the Guangdong–Hong Kong–Macao regions, DE significantly promotes GLTLU in other urban agglomerations. The effects are observed in the following order: Central Yangtze River > Beijing–Tianjin–Hebei > Chengdu–Chongqing.

Table 4. Regression results of urban agglomeration heterogeneity.

	Beijing–Tianjin–Hebei Urban Agglomeration		
	LR_Direct	***LR_Indirect***	***LR_Total***
DE	0.8029 **	0.3277	1.1306
	(2.349)	(0.321)	(1.120)
	Yangtze River Delta Urban Agglomeration		
DE	−0.0193	−2.0230 *	−2.0423 *
	(−0.103)	(−1.799)	(−1.771)
	Central Yangtze River Urban Agglomeration		
DE	1.1192 ***	−0.3972	0.7220
	(4.047)	(−0.274)	(0.490)
	Chengdu–Chongqing Urban Agglomeration		
DE	0.4369 *	0.8528	1.2897 *
	(1.870)	(1.212)	(1.648)
	Guangdong–Hong Kong–Macao Urban Agglomeration		
DE	0.0798	0.6166	0.6964
	(0.239)	(0.687)	(0.779)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the z-statistics for the parameter estimates. Control variables, spatial fixed effects, and temporal fixed effects are all controlled.

Regarding the impact on surrounding areas, only the Yangtze River Delta's DE has a significant negative effect on the GLTLU of neighboring regions, while the DE of other urban agglomerations does not significantly affect the GLTLU of their surrounding areas.

Several factors explain these findings. In the Central Yangtze River, Beijing–Tianjin–Hebei, and Chengdu–Chongqing urban agglomerations, the DE aids GLTLU. These regions possess relatively concentrated knowledge resources, high levels of marketization, and advanced information technology. This environment allows for centralized administrative regulations and economic policies, effectively reducing transaction costs and improving production efficiency.

Conversely, in the Yangtze River Delta urban agglomeration, the DE has a significant inhibitory effect on the GLTLU of the surrounding areas. Although the economic foundation of the Yangtze River Delta is strong, regional disparities in development persist. The development speed of the DE is uneven, and policy inclinations vary, leading to significant differences between cities within the region. In areas where the DE is rapidly developing, the aggregation of capital, labor, and technology creates a severe "siphon effect" on the GLTLU of surrounding areas.

5.3. Spatial Effect Attenuation Test

After confirming the spatial effect of the DE on GLTLU, this study further examines the spatial attenuation boundary of the DE's impact on GLTLU. The threshold inverse distance spatial weight is used for identification, and its specific setting is as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, & d_{ij} \text{ beyond the distance threshold} \\ 0, & d_{ij} \text{ within the distance threshold} \end{cases} \quad (5)$$

In Equation (5), d_{ij} is the distance between region i and region j. When the distance between the two regions is beyond the threshold range, the spatial weight is the inverse of the square of the geographical distance between the two regions; otherwise, the weight is 0. The initial distance threshold is set at 100 KM and increased in 100 KM increments. Based on this, the SDM is used to sequentially derive the impact coefficients of the DE on GLTLU for different distance thresholds (see Figure A1). From the direct effects of the SDM, the DE shows a significantly positive promoting effect on GLTLU in its own region. From the indirect effects of the SDM, the promoting effect can be roughly divided into three intervals: First, within the distance threshold of 300 KM, the spatial spillover effect of the DE on GLTLU in neighboring regions is generally negative. The possible reason is that cities with relatively high levels of DE development often have a strong economic foundation and are usually central cities for economic development. While they radiate and drive surrounding areas, their superior development policies and complete infrastructure attract talent from surrounding regions, creating a "siphon effect" that may negatively impact the GLTLU of neighboring cities. Second, when the distance threshold is between 300 and 550 KM, the effect of the DE on the GLTLU of neighboring regions is significantly positive, peaking at 450 KM. Finally, beyond the range of 550 KM, this impact coefficient fluctuates around 0 and is not significant. Overall, the impact of the DE on the GLTLU of surrounding areas weakens as the geographical distance increases.

5.4. Test of Moderating Mechanisms

5.4.1. Test of FAGG Moderating Mechanism

Table 5 shows the estimated results of the moderating effect of FAGG on the impact of the DE on GLTLU. The results indicate that the estimated coefficient of the interaction term between the DE and FAGG is consistently significantly positive at the 1% level. Therefore, FAGG positively moderates the effect of the DE on GLTLU; the higher the level of FAGG, the greater the empowerment effect of the DE on GLTLU.

The reason is that FAGG can enhance the level of competition in financial development within the agglomeration area, improve financial efficiency, and provide more significant financing opportunities for enterprises to undergo digital transformation and promote digital development. FAGG also creates a favorable financing environment that leverages the innovation effects of the digital economy. Furthermore, FAGG attracts talent and knowledge agglomeration, generating economies of scale for enterprise development. Therefore, FAGG serves as an essential safeguarding mechanism for promoting the impact of the DE on GLTLU.

Table A4 shows the threshold test results for FAGG. The results indicate two thresholds for FAGG: 9.1728 and 27.3787. The LR plot of the FAGG thresholds is shown in Figure A2. The estimated results of the FAGG panel threshold model are presented in Table A5.

When the FAGG level is below 9.1728, the estimated coefficient of the DE is −0.0057 and not significant. When the FAGG level is between 9.1728 and 27.3787, the estimated coefficient of the DE is 0.3072 and significantly positive at the 1% level. When the FAGG level exceeds 27.3787, the estimated coefficient of the DE is 0.6410 and significantly positive at the 1% level.

These regression results indicate that the marginal impact of the DE on GLTLU is constrained by the level of financial agglomeration, demonstrating a significant double-threshold effect. Under the constraints of FAGG thresholds, the impact of the DE on urban carbon emission efficiency exhibits a "U-shaped" trend, initially negative and then positive. This suggests that FAGG not only plays a positive moderating role in the impact of the DE on GLTLU but also indicates that as the FAGG level continues to rise, the effect of the DE on GLTLU shifts from negative to positive. Moreover, when the FAGG level surpasses the second threshold, the promoting effect of the DE on GLTLU reaches its maximum.

Table 5. Test of FAGG interaction term.

	(1)	(2)	(3)	(4)
DE	0.6309 ***	0.5262 ***	0.1700 *	0.1471 *
	(10.041)	(6.758)	(1.808)	(1.767)
FAGG	0.0001	0.0001	−0.0000	0.000015
	(0.400)	(0.467)	(−0.159)	(0.080)
DE × *FAGG*	0.0139 ***	0.0127 ***	0.0125 ***	0.0111 ***
	(8.693)	(8.670)	(8.270)	(8.325)
City Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	NO	YES	YES
Constant	0.5717 ***	0.6777 ***	0.6321 ***	0.4870 ***
	(81.954)	(8.263)	(57.273)	(5.372)
N	2547	2547	2547	2547
R^2	0.7680	0.8182	0.8017	0.8535
$Adj\text{-}R^2$	0.7387	0.7944	0.7759	0.8337
F	263.0294	124.9405	72.1639	83.5068

Note: Values in parentheses are the *t*-statistics for the parameter estimates; ***, and * indicate significance at the 1%, and 10% levels. All control variables are controlled.

The double-threshold effect of FAGG levels on the impact of the DE on GLTLU can be explained by the cost pressures in the initial stage, adaptation and adjustment in the intermediate stage, synergies in the mature stage, and policy and regulatory support, as well as technology diffusion and innovation. At lower FAGG levels, inefficient resource allocation may lead to negative impacts; however, as FAGG levels increase, resource allocation efficiency and policy support gradually improve, and the impact of the DE on GLTLU turns positive, reaching its maximum at high FAGG levels.

5.4.2. Test of GCON Moderating Mechanism

Table 6 presents the estimated results of the moderating effect of GCON on the DE's impact on GLTLU. The interaction term between GCON and the DE is consistently significantly positive at the 1% level, indicating that GCON positively moderates the DE's impact on GLTLU. The greater the local government's focus on digital economic development, the more significant the empowerment effect of the DE on GLTLU.

The rationale is that local government attention on DE development is a crucial factor in ensuring the growth of the digital economy. When local governments prioritize DE development, they actively implement policy measures such as financial subsidies and tax incentives for digital enterprises to stimulate DE growth. Furthermore, higher government attention on the DE facilitates the integration of digital technology with the traditional real economy, creating a conducive environment for DE development. This increased public focus on digital economic development also encourages enterprises to pursue digital transformation.

Table 6. Test of GCON interaction term.

	(1)	(2)	(3)	(4)
DE	0.9444 ***	0.7249 ***	0.3754 ***	0.3089 ***
	(13.996)	(9.080)	(3.675)	(3.504)
GCON	−0.0016 ***	−0.0019 ***	−0.0011 ***	−0.0012 ***
	(−5.277)	(−6.558)	(−3.480)	(−4.081)
$DE \times GCON$	0.0112 ***	0.0129 ***	0.0087 ***	0.0086 ***
	(5.514)	(6.864)	(4.346)	(4.891)
Constant	0.5697 ***	0.6411 ***	0.6362 ***	0.5228 ***
	(78.668)	(7.402)	(49.801)	(5.543)
City Fixed Effects	NO	NO	YES	YES
Time Fixed Effects	YES	YES	YES	YES
N	2431	2431	2431	2431
R^2	0.7470	0.8054	0.7854	0.8447
$Adj\text{-}R^2$	0.7149	0.7796	0.7573	0.8235
F	182.3875	103.9512	23.8925	70.3547

Note: Values in parentheses are the *t*-statistics for the parameter estimates; *** indicates significance at the 1% level. Individual effects, time effects, and control variables are all controlled.

Table A6 shows the threshold test results for GCON, revealing two thresholds at 12.5809 and 27.8054. The LR plot of the GCON thresholds is depicted in Figure A3. Table A7 presents the regression results of the panel threshold model with GCON as the threshold variable. The results indicate that when GCON is below 12.5809, the estimated coefficient of the DE is 0.4071, significant at the 1% level. When GCON is between 12.5809 and 27.8054, the estimated coefficient of the DE is 0.5352, significant at the 1% level. When GCON exceeds 27.8054, the estimated coefficient of the DE is 0.6398, significant at the 1% level. These regression results demonstrate that the marginal impact of the DE on GLTLU is influenced by GCON, showing a significant threshold effect. As the local government's focus on the DE increases, the positive effect of the DE on GLTLU progressively strengthens. The specific reason is that as GCON increases, policy support and resource allocation also increase correspondingly. When GCON is low, policy and resources are limited, and the impact of the DE on GLTLU is minimal; at a medium level of GCON, policy incentives and resource support are strengthened, significantly increasing the positive effect of the DE on GLTLU; when GCON reaches a high level, policy support and resource allocation are maximized, promoting the deep integration of the DE with green low-carbon technologies, thereby maximizing the positive impact of the DE on GLTLU.

5.4.3. Test of IPR Moderating Mechanism

Table 7 shows the estimated results of the moderating effect of IPR on the DE's empowerment of GLTLU. The interaction term between the DE and IPR is consistently positive. After controlling for time effects and individual fixed effects, the interaction term coefficient is significantly positive at the 5% level.

These results indicate that IPR has a positive moderating effect on the DE's empowerment of GLTLU. The higher the level of IPR, the more significant the empowerment effect of the DE on GLTLU. The likely reason is that a robust intellectual property protection system not only facilitates the creation of new digital innovations but also reduces security risks such as data leaks and information breaches. This helps realize the value of data elements and provides a strong legal environment for DE development.

Table 7. Test of IPR interaction term.

	(1)	(2)	(3)	(4)
DE	1.0321 ***	0.7725 ***	0.4708 ***	0.4104 ***
	(18.991)	(10.807)	(5.102)	(5.015)
IPR	0.0318 *	0.0010	0.0372 **	0.0255 *
	(1.780)	(0.062)	(2.151)	(1.680)
$DE \times IPR$	0.0854	0.2030 **	0.1329	0.1492 **
	(1.012)	(2.573)	(1.636)	(2.072)
Constant	0.5541 ***	0.4768 ***	0.6186 ***	0.4962 ***
	(87.951)	(6.606)	(56.739)	(7.296)
City Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	NO	YES	YES
N	2547	2547	2547	2547
R^2	0.7507	0.8015	0.7917	0.8454
$Adj\text{-}R^2$	0.7192	0.7755	0.7646	0.8246
F	192.3944	108.1664	32.6032	75.9107

Note: Values in parentheses are the *t*-statistics for the parameter estimates; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All control variables are controlled.

Additionally, IPR can positively moderate the innovation and resource allocation effects induced by the DE. A stringent intellectual property protection system imposes severe penalties on intellectual property infringement, creating a favorable environment for innovation.

Table A8 shows the threshold test results for IPR, identifying a single threshold at 3.5189. The LR plot of the IPR threshold is depicted in Figure A4. Table A9 presents the regression results of the panel threshold model for IPR. The results indicate that when the estimated value of IPR is less than 3.5189, the estimated coefficient of the DE is 0.5048, significantly positive at the 1% level. When IPR exceeds 3.5189, the estimated coefficient of the DE is 0.6362, also significantly positive at the 1% level. These regression results demonstrate that the marginal effect of the DE on GLTLU is influenced by the level of IPR, showing a significant threshold effect. Under the constraint of the intellectual property protection system, the positive effect of the DE on GLTLU increases with the level of IPR. The specific reason is that the improvement of IPR enhances incentives for innovation and technology development, encouraging enterprises to conduct more R&D and investment in the DE field. When IPR is below 3.5189, although the DE already has a significant positive effect on GLTLU, the relatively weak intellectual property protection limits enterprises' enthusiasm for innovation investment. When IPR exceeds 3.5189, strong intellectual property protection motivates more enterprises to invest in innovation and low-carbon technology development, further enhancing the positive effect of the DE on GLTLU, showing a significant threshold effect. This indicates that the more robust the intellectual property protection system, the more significant the promotion effect of the DE on GLTLU.

6. Discussion

6.1. Result Presentation

This study reveals the spatial effects and regulatory mechanisms of DE in promoting China's GLTLU. Compared to the literature focusing on the environmental consequences of the DE [25,26,28,31], this study focuses more on how the DE achieves sustainable land use in China through spatial spillover mechanisms and regulatory mechanisms. The findings indicate that the DE not only benefits GLTLU in its own region but also significantly promotes GLTLU in surrounding regions.

Compared to the existing literature [32–34], this study enriches the land use effects of the DE from the perspective of spatial economics, emphasizing the importance of urban cooperation in the DE. Policymakers can leverage intercity connections to amplify the promotion effect of the DE on GLTLU. For example, in Beijing, China, the intelligent transportation system (ITS) optimizes traffic flow through real-time traffic monitoring and data analysis. The ITS reduces parking demand and optimizes land use in the city center, allowing more land to be used for green spaces and public facilities. After the successful implementation of the ITS in Beijing, surrounding cities (such as Tianjin and parts of Hebei) began to adopt and implement similar intelligent traffic management systems, leading to improved land use efficiency and environmental enhancement over a larger area. Additionally, adopting energy-saving technologies and running data centers with renewable energy can reduce their consumption of land resources and energy. Using big data and artificial intelligence for urban planning can optimize land use layouts, reduce traffic congestion, and minimize energy waste.

The spatial spillover effect of the DE varies by region. The DE in the central region can significantly promote GLTLU in surrounding areas, while the DE in the eastern and western regions does not show similar effects. This may be related to the economic development stage and industrial structure characteristics of the central region, which may be better able to utilize the technological and resource advantages brought by the DE to promote GLTLU in surrounding areas. In the analysis of urban agglomerations, the DE in the Yangtze River Delta region has had a negative impact on GLTLU in surrounding areas. This may be due to high-density development and resource competition in the Yangtze River Delta, causing the spillover effect of the DE in this area to become negative, reflecting issues of overdevelopment and environmental pressure.

Within a distance of 300 km, the spatial spillover effect of the DE is negative, possibly because resource competition and environmental pressure between cities are more pronounced at shorter distances. However, between 300 and 550 km, the positive spillover effect of the DE increases significantly, peaking at 450 km, indicating that cooperation and resource sharing between cities can more effectively promote GLTLU within this distance range. FAGG, GCON, and IPR have significant moderating effects on the role of the DE in promoting GLTLU. The double-threshold effects of FAGG and GCON indicate that these factors can significantly enhance the positive impact of DE only after reaching a certain level. The single-threshold effect of IPR suggests that improving intellectual property protection is key to enhancing the role of DE in promoting GLTLU.

This study not only has important implications for land use and DE policies in China but also provides valuable references for other countries, especially developing countries. Developing countries can learn from China's experience and explore the mechanisms by which DE affects green and low-carbon land use, formulating policies and measures suited to their own conditions. In addition, the methods and models provided in this study can be used for cross-national comparative research, helping different countries understand the role of the DE in various regions and environments. This study can encourage international data sharing and collaborative research, enhancing the overall level of global DE and land use research, and jointly addressing global environmental challenges.

6.2. Policy Recommendations

Based on the research conclusions, this study formulates a series of comprehensive and strategic policy measures. First, strengthening interregional cooperation and exchange in the digital economy is imperative. By establishing DE cooperation zones, we can break regional barriers, achieve resource sharing and complementary advantages, and thus enhance the DE development level of the entire region. This cooperation model will greatly promote intercity collaboration in data sharing, technological innovation, and market expansion, thereby maximizing the spatial spillover effects of the DE. Additionally, by regularly holding digital economy exchange forums and other activities, we can promote the sharing and dissemination of advanced experiences and successful cases, further accelerating the pace of digital economy development. We should also formulate specific urban DE industry layout guidelines to clarify the optimal locations for various digital economy enterprises.

Second, differentiated DE development strategies should fully consider the needs of GLTLU. Tailored DE development strategies for different regions are necessary to maximize GLTLU promotion.

For example, in the central region, the spatial spillover effects of the DE can be leveraged to promote green agriculture and eco-tourism in surrounding areas. In the eastern region, the DE can be used to promote industrial greening and the development of a circular economy. In the western region, the DE can facilitate the implementation of ecological protection and restoration projects.

In specific areas like the Yangtze River Delta, special attention should be paid to the environmental pressures that the DE may bring. Ensuring that DE development is coordinated with GLTLU requires reasonable resource allocation and the widespread application of green technologies. Digital economy enterprises can be encouraged and supported to innovate in energy saving, emission reduction, and resource recycling to reduce land resource consumption and environmental damage.

Additionally, optimizing the industrial layout of the urban digital economy is crucial for promoting GLTLU. By guiding digital economy enterprises toward green and low-carbon development, we can avoid resource waste and environmental pollution caused by excessive concentration and competition. Governments should establish special funds to support the research and promotion of green digital technologies, accelerating the process of GLTLU.

Finance, as the core of the modern economy, should also play an essential role in promoting GLTLU. Financial institutions can support digital economy enterprises by establishing green credit products and issuing green bonds, guiding investments in green and low-carbon projects. This financial support will help integrate the DE with GLTLU, achieving sustainable land use.

The government has a key role in promoting the integration of the DE and GLTLU. It should formulate relevant policies and standards, clarify the green direction of DE development, and strengthen supervision and evaluation to ensure effective policy implementation. Additionally, the government should enhance cooperation and communication with enterprises, research institutions, and society to jointly promote the process of GLTLU.

Intellectual property protection and application are critical for the innovative development of the DE. Strengthening and improving intellectual property laws and regulations, increasing the cost of infringement, and protecting the legitimate rights and interests of innovation achievements are essential. Establishing intellectual property trading platforms can promote the circulation and application of intellectual property, stimulate innovation, and support the continuous development of the digital economy.

Land use policies must be adjusted and innovated to support new economic models and technological developments, achieving sustainable development and environmental protection goals. First, supporting the construction of digital infrastructure is crucial. Policies should focus on promoting widespread broadband and 5G network coverage, especially in rural and remote areas. This not only lays the foundation for the development of the digital economy but also promotes balanced development between urban and rural areas. In addition, policies should encourage the optimization of data center locations, promote the construction of green data centers, prioritize the use of renewable energy, and reduce excessive consumption of land resources. Second, the promotion of smart cities and green buildings also requires policy support. By encouraging and supporting the use of big data and artificial intelligence for urban planning and management, urban land use efficiency can be improved, traffic congestion reduced, and carbon emissions lowered. Promoting green building standards and certifications, and encouraging the adoption of energy-saving technologies and sustainable materials, can significantly reduce carbon emissions in the construction process and improve the energy efficiency of buildings.

In the agricultural sector, precision agriculture and sustainable land management policies are particularly important. The government can provide financial support and technical training to encourage farmers to adopt precision agriculture techniques, thereby improving land use efficiency and reducing the use of fertilizers and pesticides. At the same time, policies should protect ecologically sensitive areas, encourage ecological restoration and reforestation, reduce land degradation and carbon emissions, and maintain ecological balance. The development of e-commerce and smart logistics also requires adjustments in land use policies. By adjusting commercial land use policies to support the development of e-commerce, reliance on traditional commercial real estate can be reduced, optimizing land use. Policies should also support the construction of smart logistics parks, using big data and artificial intelligence to optimize logistics routes and reduce carbon emissions during transportation. The rise of the sharing economy and emerging business models requires corresponding regulatory support. Policies should support models such as shared mobility and shared office spaces, optimizing urban space and land use, and reducing the occupation of private cars and traditional office buildings. Flexible land use policies can allow for the flexible change in land use, supporting emerging industries and innovation and entrepreneurship activities, thereby enhancing land use efficiency. Digital regulation and land management are important components of modern land use policies. Utilizing geographic information systems and remote sensing technology for the digital management of land use can enhance the transparency and efficiency of land use. Policies should also encourage the use of big data for land use planning and decision-making, enhancing the scientific and accuracy of policies. Finally, promoting the development of renewable energy also requires the support of land use policies. Policies should encourage the construction of renewable energy facilities such as wind and solar energy in suitable locations, reducing the waste of land resources. At the same time, they should support the installation of energy storage facilities and energy conversion equipment on existing buildings and land to improve energy utilization efficiency.

6.3. Limitations and Future Research

This study uses data from 283 cities in China to explore the spatial effects and moderating mechanisms of the DE on GLTLU, yielding a series of valuable conclusions. This study expands the understanding of the mechanisms by which the DE affects GLTLU, providing new perspectives and supplements to existing land use and environmental economic theories. However, there are also some limitations, as follows: (1) The data from 2011 to 2019 are relatively complete and reliable, providing a stable basis for analysis. The choice of this period ensures data continuity and the reliability of the research results and provides a pre-COVID-19 pandemic baseline, facilitating subsequent comparisons with post-pandemic data to analyze the impact of the DE on GLTLU after the pandemic. Subsequent research will continue to update the data for in-depth investigation. We are aware of the profound impact of the COVID-19 pandemic on digital payment methods and GLTLU. Future research will consider this factor and use updated data to further validate and extend our conclusions. (2) To address the limitations of the SDM in handling spatial heterogeneity, future research could consider using more complex spatial econometric models, such as the spatially varying coefficient model or geographically weighted regression, to better handle and interpret spatial heterogeneity issues. (3) As the data of listed companies in China are updated quickly, future research can use data from Chinese listed companies to examine the impact of the DE on green low-carbon land use at the enterprise level. (4) Future research can also continue to examine the impact of DE development on water resource demand.

7. Conclusions

This study examines the spatial effects and moderating mechanisms of the DE on GLTLU using data from 283 cities in China. The findings indicate that the DE not only benefits GLTLU in its own region but also significantly promotes GLTLU in surrounding regions. This conclusion remains robust after substituting the measurement method of the explained variable and modifying the spatial weights.

The regional analysis reveals that the DE in the eastern and western regions does not significantly affect the GLTLU of neighboring areas, whereas the DE in the central region significantly promotes GLTLU in surrounding areas. Within the context of urban agglomerations, only the DE in the Yangtze River Delta has a significant negative impact on the GLTLU of surrounding areas, while the DE in other urban agglomerations does not exhibit a significant impact on neighboring GLTLU.

The study further finds that the spatial spillover effect of the DE on GLTLU in neighboring regions is generally negative within a distance threshold of 300 km. When the distance threshold is between 300 km and 550 km, the effect of the DE on GLTLU in neighboring regions is significantly positive, peaking at 450 km.

Financial agglomeration shows a positive moderating effect on the DE's empowerment of GLTLU, characterized by a double-threshold effect. Similarly, local government attention on digital economic development positively moderates the DE's impact on GLTLU, also demonstrating a double-threshold effect. Intellectual property protection also has a positive moderating effect on the DE's empowerment of GLTLU, with a single-threshold effect. The higher the level of intellectual property protection, the stronger the empowerment effect of the DE on GLTLU.

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Abbreviations

DE	Digital economy
GLTLU	Green and low-carbon transformation of land use
SDM	Spatial Durbin model
SBM	Slack-based measure
EBM	Epsilon-based measure
FAGG	Financial agglomeration
GCON	Local government digital attention
IPR	Intellectual property protection

Appendix A

Table A1. Control variable indicator descriptions.

Indicator Name	Indicator Explanation
CIM	Annual Average Temperature (°C)
INFRA	Road Area per Capita (m^2/person)

Table A1. *Cont.*

Indicator Name	Indicator Explanation
ER	Composite Index Synthesized Using the Entropy Method for SO_2 Removal Rate, Industrial Smoke (Dust) Removal Rate, and Comprehensive Utilization Rate of Industrial Solid Waste (-)
OPEN	FDI as a Proportion of GDP (%)
AGG	Location Quotient of Manufacturing Employees (-)
INDUSTR	Proportion of Secondary Industry Added Value to GDP (%)
GOV	Proportion of Fiscal Expenditure (excluding Science and Education) to Total Fiscal Expenditure (%)
ENER	GDP per Unit of Energy Consumption (ten thousand CNY/ton)
URB	Proportion of Urban Population to Total Population at Year-End (%)
HUMAN	Number of College Students per 10,000 People (persons/10,000 people)

Table A2. SDM regression results with alternative GLTLU evaluation methods.

	LR_Direct	***LR_Indirect***	***LR_Total***
DE	0.2688 ***	7.8545 ***	8.1234 ***
	(3.794)	(3.184)	(3.277)

Note: *** indicates significance at the 1% level. Values in parentheses are the z-statistics for the parameter estimates. Control variables, spatial fixed effects, and temporal fixed effects are all controlled.

Table A3. SDM regression results with alternative spatial weights.

	LR_Direct	***LR_Indirect***	***LR_Total***
		Neighboring Spatial Weight	
DIG	0.4827 ***	0.3192 *	0.8019 ***
	(6.834)	(1.895)	(4.259)
		Economic Spatial Weight	
DIG	0.4376 ***	0.5280 **	0.9656 ***
	(6.078)	(2.225)	(3.920)
		Distance Spatial Weight	
DIG	0.4828 ***	4.0651 **	4.5479 **
	(6.770)	(2.003)	(2.228)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the z-statistics for the parameter estimates. Control variables, spatial fixed effects, and temporal fixed effects are all controlled.

Table A4. Threshold test results for FAGG.

Threshold Test	**Threshold Value**	**F-Value**	**Critical Value**		
			1%	**5%**	**10%**
Single Threshold	27.3787	154.34 **	21.6477	25.5977	37.1607
Double Threshold	9.1728	46.38 ***	19.0807	22.4287	30.5916
	27.3787				
Triple Threshold	9.1728	33.63	61.7985	73.8262	96.3345
	27.3787				
	48.0494				

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

Table A5. Regression results of FAGG threshold effects.

DE#Regime1	−0.0057 (*FAGG* < 9.1728)
	(−0.065)
DE#Regime2	0.3072 *** (9.1728 < *FAGG* < 27.3787)
	(4.119)
DE#Regime3	0.6410 *** (*FAGG* > 27.3787)
	(8.919)
Constant	0.5359 ***
	(6.086)
N	2547
R^2	0.5334
Adj-R^2	0.4704
F	122.1248

Note: Values in parentheses are the *t*-statistics for the parameter estimates; *** indicates significance at the 1% level. Individual effects, time effects, and control variables are all controlled.

Table A6. Threshold test results for GCON.

Threshold Test	**Threshold Value**	**F-Value**	**Critical Value**		
			1%	**5%**	**10%**
Single Threshold	27.5265	26.22 **	12.3393	14.6961	19.9872
Double Threshold	27.8054 12.5809	13.73 *	12.7827	16.1039	19.6489
Triple Threshold	27.8054 12.5809 5.5889	8.72	19.0253	22.3893	33.3512

Note: ** and * indicate significance at the 1% and 5% levels, respectively.

Table A7. Regression results of GCON threshold effects.

DE#Regime1	0.4071 *** (GCON < 12.5809)
	(4.892)
DE#Regime2	0.5352 *** (12.5809 < GCON < 27.8054)
	(6.818)
DE#Regime3	0.6398 *** (GCON > 27.8054)
	(8.192)
Constant	0.5226 ***
	(5.494)
N	2331
R^2	0.5090
Adj-R^2	0.4422
F	101.2326

Note: Values in parentheses are the t-statistics for the parameter estimates; *** indicates significance at the 1% level. Individual effects, time effects, and control variables are all controlled.

Table A8. Threshold test results for IPR.

Threshold Test	Threshold Value	F-Value	Critical Value		
			1%	5%	10%
Single Threshold	3.5189	27.18 **	18.8063	21.3231	27.8495
Double Threshold	3.5189	14.36	24.6664	29.7329	41.4372
	1.3511				

Note: ** indicates significance at the 1% level.

Table A9. Regression results of IPR threshold effects.

DE#Regime1	0.5048 *** (IPR < 3.5189)
	(6.792)
DE#Regime2	0.6362 ***(IPR > 3.5189)
	(8.008)
Constant	0.5420 ***
	(5.945)
N	2547
R^2	0.4991
$Adj\text{-}R^2$	0.4317
F	111.8138

Note: Values in parentheses are the t-statistics for the parameter estimates; *** indicates significance at the 1% level. Individual effects, time effects, and control variables are all controlled.

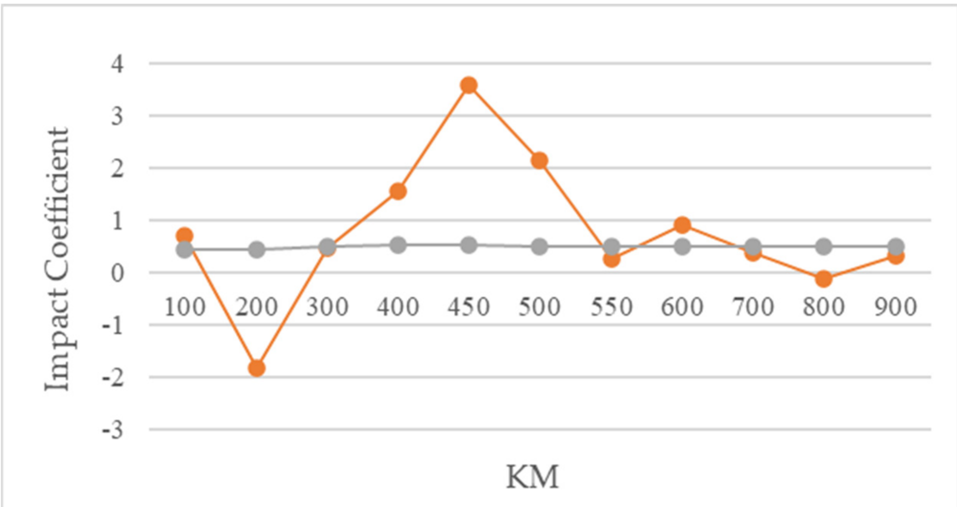

Figure A1. Attenuation of spatial spillover coefficients. Note: The orange line represents the indirect effect, and the gray line represents the direct effect.

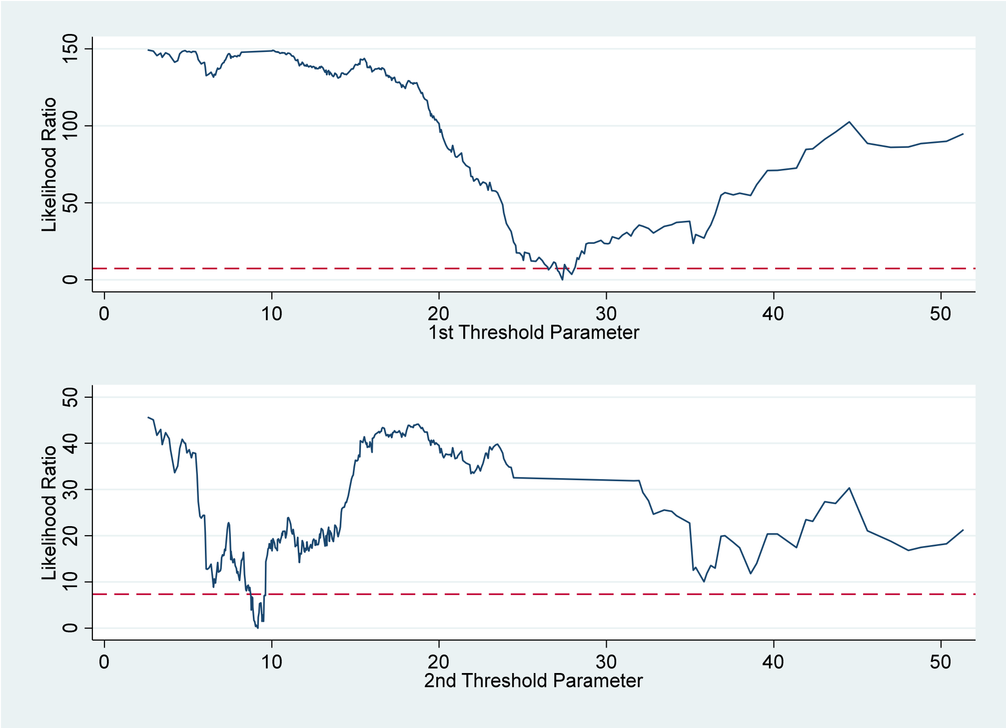

Figure A2. LR plot of FAGG threshold values.

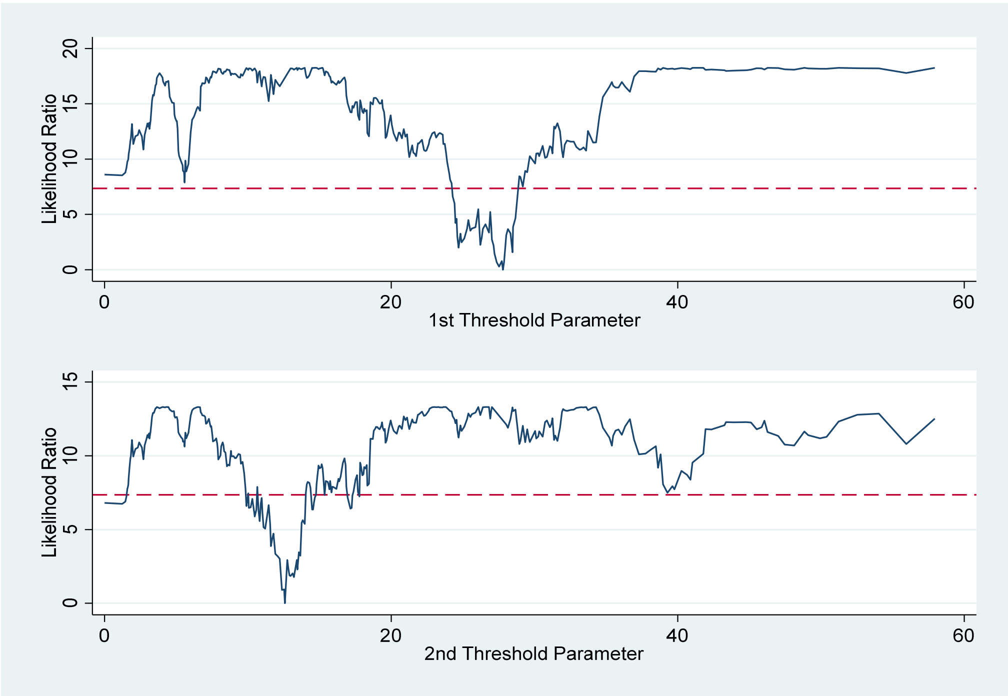

Figure A3. LR plot of GCON threshold values.

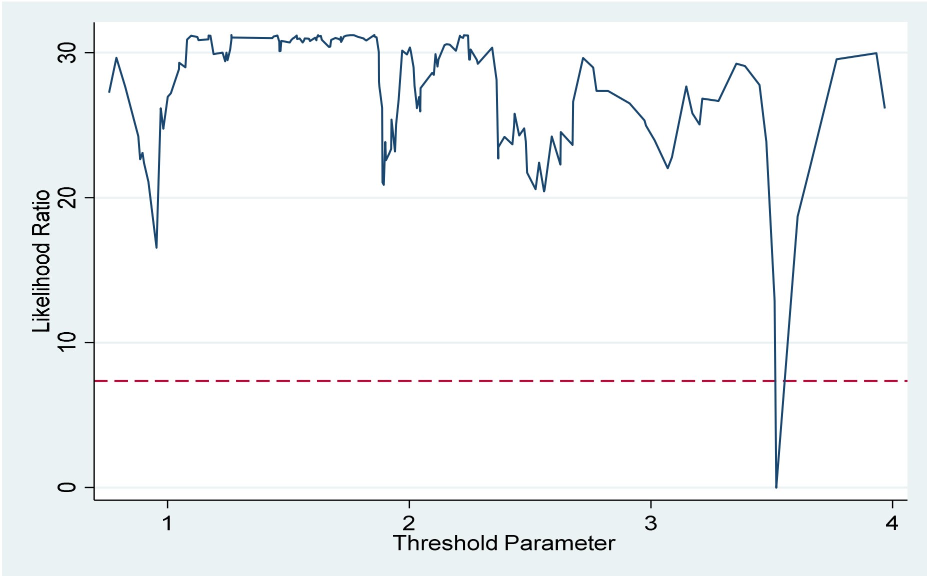

Figure A4. LR plot of IPR threshold values.

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