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The impact of platform economy on urban–rural income gap: a mediation effect test based on land use efficiency

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This paper selects provincial panel data from China from 2015 to 2024. Based on measuring the development level of the platform economy, the Spatial Durbin Model is employed to empirically examine the intrinsic mechanism between the platform economy and the urban–rural income gap. At the same time, empirical tests have been conducted on the mediating effect of land use efficiency in the process of narrowing the urban–rural gap through the platform economy. The results indicate: (1) The impact of platform economy development on the urban–rural income gap exhibits a "U-shaped" trend of first narrowing and then expanding. Currently, most provinces in China remain on the left side of the "U-shaped" curve without crossing the inflection point, suggesting that platform economy development still contributes to narrowing the urban–rural income gap. (2) The impact of the platform economy on the urban–rural income gap demonstrates spatial spillover effects, where indirect effects outweigh direct effects, resulting in an overall negative total effect. (3) The platform economy can narrow the urban–rural income gap by improving land use efficiency. Currently, China's platform economy mainly reduces the urban–rural income gap through four aspects: revitalizing idle rural assets, optimizing agricultural land allocation, enhancing land output value, and comprehensively improving land capital knowledge density. (4) The impact of the platform economy on the urban–rural income gap is heterogeneous. Research has found that the promotion effect of the platform economy on the urban–rural income gap in the eastern region is greater than that in the central and western regions, while the promotion effect on the urban–rural income gap in the central region is smaller than that in the western region, indicating that the central region is an important area for the platform economy to narrow the urban–rural gap. Overall, this article studies how the platform economy can narrow the urban–rural income gap by improving land use efficiency from both theoretical and empirical perspectives, and proposes corresponding policy recommendations. This not only helps enrich the research on narrowing the urban–rural income gap, but also expands the research on land use efficiency from the perspective of the platform economy.

KEYWORDS

platform economy, urban–rural income gap, spatial Durbin model, land use efficiency, mediation effect

1 Introduction

In recent years, propelled by the continuous advancement and widespread adoption of digital technologies such as the internet, big data, and cloud computing, the platform economy has rapidly emerged as a significant new economic form. Built upon robust infrastructure including computing chips, network systems, and cloud services, this model aggregates fragmented resources through intelligent matching mechanisms, connects diverse user groups with complementary needs, and effectively facilitates economic interactions (Yin et al., 2025). This has injected fresh momentum into China's efforts to overcome economic challenges and achieve sustained and sound development. From the government's initial proposal in 2018 to "develop the platform economy" to the emphasis in the 2023 Government Work Report on "promoting the healthy and sustainable development of the platform economy," China's commitment to fostering this sector has been clear and consistent. The platform economy has expanded swiftly, extending its reach and influence on an unprecedented scale. The COVID-19 pandemic further accelerated this growth, spurring the integration of traditional industries with digital and smart technologies, creating substantial employment opportunities, and opening up new avenues for income growth, particularly among low-income groups. As a result, the platform economy is profoundly reshaping modes of production, lifestyles, and patterns of income distribution (Du et al., 2023).

China has achieved decisive success in poverty alleviation and is steadily progressing toward the second centenary goal of building a modern socialist country and realizing common prosperity. As emphasized in the 14th Five-Year Plan and the 20th National Congress of the Communist Party of China, "common prosperity for all people" is a core objective of Chinese modernization. However, structural imbalances rooted in urban–rural dualism continue to hinder progress toward common prosperity. Due to China's unique urban–rural dual economic structure, significant disparities in labor remuneration persist between urban and rural areas, leading to a pronounced income gap. According to the National Bureau of Statistics, in 2022, the per capita disposable income of urban residents was 2.47 times that of rural residents. Internationally, developed countries like Canada and the UK exhibit urban–rural income ratios close to 1.0, while developing countries like India report ratios around 1.9. China's urban–rural income gap remains notably high compared to global benchmarks. Traditional development models perpetuate these imbalances, obstructing coordinated urban–rural development and common prosperity. The rapid growth of the platform economy offers potential solutions to bridge this gap and advance shared prosperity.

During rapid industrialization and urbanization, land resources have grown increasingly scarce globally. Enhancing land use efficiency is not only a central aim of market-based factor allocation reform but also key to narrowing the urban–rural gap. By facilitating large-scale operations through land transfer, production costs can be lowered and output value raised. Developing high value-added industries and integrating primary, secondary, and tertiary sectors helps diversify farmers' income into a mix of "rent + dividends + wages," boosting rural economic vitality. Clear land policies attract urban capital and technology to the countryside, turning idle resources into productive assets. They also enable returning talents and migrant farmers to use land rights as entrepreneurial capital, creating a virtuous cycle of "factors flowing to the countryside, rights flowing to the city," and powering rural revitalization. Through scientific planning, clustered rural settlements make infrastructure and public services more economically viable. This significantly improves rural living quality, narrows the urban–rural gap in both hardware and software terms, and helps shape a new landscape of livable, business-friendly countryside (Lian et al., 2014).

Beyond directly narrowing the urban–rural income gap, the platform economy also indirectly contributes to this goal by enhancing land use efficiency. First, by digitizing idle rural resources such as homesteads and farmhouses, the platform economy meets urban demand by transforming them into operational assets—including homestays and wellness retreats. This conversion turns "dormant resources" into "active capital," directly generating property and business income for farmers, creating new avenues for revenue growth, and fundamentally strengthening the wealth-generating capacity of rural land. Second, the platform economy improves the matching of land supply and demand, facilitating the transfer of fragmented farmland to new agricultural entities and enabling scaled operations. At the same time, e-commerce channels allow agricultural products to reach the market directly, maximizing both land use efficiency and product value. This approach significantly boosts farmers' agricultural and operational incomes through cost reduction, efficiency gains, and increased output, thereby reinforcing agriculture's role as a stable income source. Finally, the platform economy guides capital and talent back to rural areas and promotes the deep integration of agriculture with sectors such as cultural tourism and e-commerce. As a result, the same parcel of land serves not only for production but also as a space for consumer experience, enabling composite spatial use and value multiplication. Farmers thus participate in high value-added service industries, forming a diversified income structure composed of "rent + wages + business income."

Therefore, an in-depth study of the impact of the platform economy on the urban–rural income gap from the perspective of land use efficiency holds significant theoretical and practical value. Such research is essential for advancing the narrowing of the urban–rural income distribution gap in China and achieving the goal of common prosperity. This will constitute the central focus of this article.

2 Literature review

The excessive income disparity between urban and rural residents in China is not only a significant impediment to further economic growth in the new normal but also the primary obstacle to achieving common prosperity. In recent years, the academic community has maintained a strong interest in the income gap between urban and rural areas in China. As the foundation of the digital economy, the impact of platform economy on the urban–rural income gap can be understood by referring to research on the impact of the digital economy on this gap. There is an abundance of studies on this topic. Against the backdrop of the rapid development of the digital economy, there is no consensus among scholars on whether it can reduce the income gap between urban and rural residents, with four main viewpoints emerging (Lv and Liu, 2023).

Firstly, some scholars believe that the digital economy can narrow the income distribution gap, promote urban–rural integration, and significantly advance the realization of common prosperity. For example, Song (2024) using 31 provincial panel data as samples for empirical testing, found that the development of digital inclusive finance can effectively reduce the income gap between urban and rural residents. Zhang et al. (2019) by combining the Chinese Digital Inclusive Finance Index with the China Family Tracking Survey data for empirical analysis, revealed that China's digital finance has developed more rapidly in less-developed areas and significantly increased household income, particularly for rural low-income groups. Han and Zhang (2017) utilizing panel data from 30 provinces, municipalities, and regions in China from 2003 to 2015 and applying the System GMM estimation method, found that internet penetration has a significantly positive impact on the income of both urban and rural residents. He et al. (2014) arrived at a similar conclusion, noting that the development of fresh agricultural e-commerce can shorten sales links, break through geographical restrictions, provide more marketing channels, and reduce the gap of business income between urban and rural residents.

Secondly, some scholars hold a pessimistic view of the digital economy's regulatory effect on urban–rural income distribution. They argue that the development of the digital economy has widened the urban–rural income gap and the "digital divide." Bai and Zhang (2021) found that the development of the digital economy has squeezed the relative income rights of medium-and low-skilled workers and weakened the rights and interests of low-skilled workers, thereby exacerbating income distribution inequality. Jiang and Fu (2020) discovered that between 2006 and 2013, the deposit-mobilization function of rural inclusive finance widened the urban–rural income gap, while its credit function was conducive to narrowing the gap. However, the former had a greater impact, resulting in an overall widening of the gap by rural inclusive finance. Liu (2020) based on Chinese provincial panel data and floating population monitoring data from 2001 to 2016, found from the perspective of labor employment behavior and income that industrial intelligence reduces the income and job stability of rural migrant workers, significantly widening the urban–rural income gap.

Thirdly, the impact of the digital economy on the urban–rural income gap is nonlinear, showing an inverted "U"-shaped or "U"-shaped relationship. Cheng and Zhang (2019) using provincial panel data from 2003 to 2016, found that internet penetration has an inverted "U"-shaped impact on the urban–rural income gap, having passed the inflection point around 2009. Now, its income-boosting effect on rural residents is greater than on urban ones, helping narrow the gap. Li and Li (2022) using provincial panel data, found that the digital economy's impact on the urban–rural income gap initially rises and then falls in an inverted "U"-shaped trend with a threshold effect. As per capita income and R&D intensity increase, the digital economy's role in reducing the gap becomes more evident. Chen and Wu (2021) also using provincial panel data, constructed digital economy indicators and found that the digital economy affects the urban–rural income gap via urbanization and entrepreneurship levels. A "U"-shaped relationship exists between digital economy development and the urban–rural income gap. In the early stage, the digital economy reduces the gap, but further development widens it, creating a digital divide.

The fourth view is that the platform economy narrows the urban–rural income gap by improving land use efficiency, with land use efficiency playing a mediating role. Zhang and Zhang (2024) used evidence from 255 cities in China to find that platform economy promotes contiguous land management, laying the foundation for modern agricultural technology applications such as large-scale agricultural machinery and intelligent irrigation, promoting the transformation of land from traditional farming to high value-added industries, comprehensively improving the capital and knowledge density of land, reducing unit production costs, and enhancing output efficiency. Zhang (2023) found through research that platform economy can introduce technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence into the process of improving land acquisition efficiency, achieving precise monitoring, scientific management, and efficient allocation of land resources, thereby greatly improving land output and utilization. Wu et al. (2023) believe that rural areas have created more diverse employment and entrepreneurial opportunities, increased the wage income and entrepreneurial income of rural labor, and curbed the widening income gap between urban and rural areas caused by talent outflow.

To sum up, existing literature mainly explores the relationship between the internet, digital inclusive finance, or the digital economy and the urban–rural income gap, with few studies from the platform economy perspective. Few adopt spatial effects analysis, ignoring the spatial spillover effects of the platform economy, which may bias the estimation of its impact on the urban–rural income gap. Moreover, most studies use overly single indicators to measure the platform economy, failing to comprehensively reflect its development level. To more accurately assess the platform economy's impact on the urban–rural income gap, this paper first constructs a platform economy evaluation index system from two dimensions, quantifies the development level of the platform economy in each Chinese province, and uses the global Moran's index and local Moran scatter plot to test the spatial autocorrelation of the platform economy level and the urban–rural income gap across provinces. Further assuming a spatial correlation between platform economy development and the urban–rural income gap, it then establishes a spatial Durbin model to explore the direct and spatial spillover effects of the platform economy on the urban–rural income gap, aiming to provide a reference for solving urban–rural income distribution issues and achieving common prosperity (Duan and Cai, 2023).

3 Theoretical mechanism and research hypothesis

3.1 The impact of platform economy development level on the urban–rural income gap shows a "U"-shaped pattern

At present, China is in a crucial stage of high-quality development. Narrowing the urban–rural income gap and promoting common prosperity have become the focus of policy-making. The development of the platform economy promotes economic growth mainly through platform information sharing, platform agglomeration effect, and empowering the real economy. This paper holds that the platform economy affects the urban–rural income gap through three channels: employment creation effect, human capital effect, and urbanization effect, which interact and promote each other.

The promoting effects of the platform economy on employment creation, human capital, and urbanization are reflected in the following aspects. First, the platform economy expands the market boundary and updates the market operation mode with Internet technology, providing new opportunities for rural residents to increase their income. The rapid development of the platform economy has given birth to a new type of market that transcends physical space, achieving information sharing and optimizing resource allocation. This helps less-developed areas and low-income groups establish connections with developed areas, thus obtaining more opportunities and information to achieve common prosperity (Hu and Lu, 2019). Second, the platform economy reshapes the role of workers and gives rise to new employment phenomena such as flexible employment and the gig economy. In other words, there are two types of jobs: online labor markets and app-based on-demand work. These jobs have relatively low entry requirements, can absorb a large number of low-skilled workers, and effectively match labor supply and demand. At the same time, they also alleviate the time and space constraints on the mobility of rural labor force, promote rural employment, solve the problem of rural surplus labor force, promote urbanization, and provide impetus for narrowing the urban–rural income gap. Third, the platform economy reconstructs the way of human capital accumulation and endows rural residents with new capabilities for income increase. Compared with urban areas, rural areas generally have weaker education levels, resulting in a lack of effective ways to improve human capital in rural areas. Individuals can improve their learning ability and technical level and enhance skill-based human capital through Internet information technology and various learning platforms, thereby achieving the effect of increasing entrepreneurship and income (Shen and Zhang, 2023). Farmers' access to effective information and advanced knowledge can drive their conceptual changes, stimulate their thinking, activate their initiative, and facilitate the updating of their knowledge system and transformation of thinking patterns. This is conducive to changing and optimizing farmers' traditional production and living patterns, achieving diversification of employment and production, and increasing agricultural income. This not only enhances the ability of rural residents to increase their income but also effectively narrows the urban–rural income gap. Overall, for the rural economy, the platform economy has the advantages of information sharing and agglomeration effect, can effectively integrate and allocate capital and labor elements, promote the transformation of the rural industrial structure (Zhao and Jiang, 2023), change the way of human capital accumulation, promote the transfer of surplus labor in rural areas, promote urbanization, and enhance the impact on narrowing the urban–rural income gap.

As the platform economy evolves, industrial upgrading occurs, with high-tech and knowledge-driven forces strengthening. Emergence of advanced technologies like blockchain and AI boosts demand for skilled labor in knowledge-and tech-intensive industries. Firms now favor highly-educated and skilled workers, reducing low-skill labor demand (Guo, 2005). Rural migrant workers, with generally lower education levels and less human capital (Oryoie and Vahidmanesh, 2022), find it hard to meet urban labor market demands. Urban areas have higher education returns than rural ones (Tobler, 1970), making it difficult for farmers to use smart products of the platform economy era. Though internet penetration enhances farmers' access to information, their ability to discern and utilize it is lacking. Additionally, unable to afford high digital training costs, low-skill rural workers face structural unemployment. Amid declining demographic dividends, the intelligent platform economy largely substitutes low-skill simple labor, reducing low-skill workers' welfare and income. Employment polarization worsens and the job environment deteriorates, thus worsening urban–rural income inequality among workers with different skills. Urbanization-wise, as "central" cities, oversaturated by platform economy growth, see economic benefits diminish and face issues like high land prices and traffic congestion, some economic sectors and resources shift to rural areas. Yet, cities keep extracting surplus value from rural regions, hindering rural self-development and widening the urban–rural income gap (Wei and Chen, 2020; Qange et al., 2025).

Initially, the platform economy can boost rural employment, reshape human capital accumulation, and advance urbanization, thus raising rural incomes and narrowing the urban–rural income gap. However, as it progresses, the urban–rural digital divide widens, leading to "counter-urbanization," resource migration from cities to rural areas, suppressed employment for low-skill rural workers, and deteriorating welfare and incomes, thereby expanding the urban–rural income gap. Overall, the relationship between platform economy development and the urban–rural income gap is not linear but "U"-shaped.

Based on the above theoretical analyses, the study proposes research hypothesis:

> *Hypothesis 1 (H1):* The impact of platform economy development on the urban-rural income gap follows a "U"-shaped pattern.

3.2 The impact of platform economy development on urban–rural income gap has spatial spillover effects

China is in a key stage of high-quality development. Narrowing the urban–rural income gap and promoting common prosperity are policy-making priorities. The platform economy can effectively reduce this gap and promote common prosperity. According to Tobler's First Law of Geography, everything is related to everything else, and nearby things are more related (Bathelt et al., 2002). Local digital economy development, driven by innovation, affects neighboring areas' urban–rural income gap through information/knowledge flow, learning/imitation, and cooperative R&D mechanisms, with positive/negative spatial spillover effects (Pan, 2012). As a new economic form in digital economy development, the platform economy has similar spatial spillover effects. Wei and Chen (2020) spatial econometric analysis of economic data from the Beijing-Tianjin-Hebei region and the Yangtze River Economic Belt shows local economic accumulation promotes surrounding areas' economic growth. Local digital economy development has a positive spillover effect on urban–rural integration in surrounding areas, with obvious regional differences. Zhao and Jiang (2023) used a spatial Durbin model to test the impact of digital economy on urban–rural income gap and its spatial spillover effect with China's provincial panel data from 2010 to 2016. Results show significant positive spatial autocorrelation of digital economy development, with "high-high clustering" and "low-low clustering" features. Yang and Li (2023) found that rural digital economy development first widens then narrows the urban–rural income gap, and this effect has significant spatial spillover. To explore the spatial correlation between platform economy development and urban–rural income gap, this study uses a spatial econometric model.

Based on the above theoretical analyses, the study proposes research hypothesis:

> *Hypothesis 2 (H2):* The impact of platform economy development on urban-rural income gap has spatial spillover effects, with other provinces' platform economy spillover effects widening the local urban-rural income gap.

3.3 The platform economy narrows the urban–rural income gap by improving land use efficiency

The platform economy accurately analyzes the supply–demand relationship between urban and rural areas through algorithms, and directs urban consumption power toward rural characteristic spaces. Idle farmhouses have been redefined as "shared courtyards," and cultivated land has been transformed into "traceable green factories" to achieve digital restructuring of production factors. This precise matching based on big data enables rural land to obtain market value beyond geographical limitations (Jiao and Sun, 2021). The IoT platform integrates scattered farmland into a "cloud farm" and achieves precise fertilization and irrigation through intelligent monitoring. The application of technologies such as unmanned aerial vehicle patrols and big data pest warning enables the production of higher quality agricultural products on the same land. Farmers have upgraded from traditional labor to agricultural data managers, achieving a career value leap while increasing land yield. The digital platform connects the direct channel from the fields to the dining table, and builds a quality trust system through blockchain traceability technology (Yu et al., 2019). Building a "one village, one product" digital brand based on geographical indication products, to achieve brand premium for specialty agricultural products. Consumers can understand the entire process of agricultural product growth by scanning the code, and this transparent supply chain significantly improves the economic benefits of land output. The platform will incorporate rural ecological resources into new markets such as carbon trading and ecological compensation (Ren et al., 2024). By monitoring forest growth through satellite remote sensing, ecological protection can be transformed into tradable carbon sink products; Showcasing rural ecological landscapes through live video broadcasts, transforming green mountains and rivers into "cloud healing" products. These innovative models make ecological protection itself a source of income, achieving a win-win situation between ecological and economic benefits (Magesa et al., 2023). To explore the mediating role of land use efficiency in narrowing the urban–rural income gap in the platform economy, this article adopts a mediation effect model to analyze it. The specific research hypotheses are as follows:

> *Hypothesis 3 (H3):* The platform economy indirectly narrows the urban-rural income gap by improving land use efficiency.

4 Research design

4.1 Model specification

4.1.1 Spatial weight matrix selection

This paper first constructs an inverse distance weight matrix (W1) by calculating the surface distance between provinces using longitude and latitude, and then constructs an inverse distance squared matrix (W2) using the square of the spatial unit distance.

The inverse distance weight matrix generates spatial effects regardless of whether regions are adjacent, with stronger effects at closer distances. As shown in Equation 1:

$$W_1 = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases} \tag{1}$$

The inverse distance squared matrix does not assume spatial effects only exist between contiguous areas, but deems that spatial effects emerge when the spatial unit $i \neq j$. As shown in Equation 2:

$$W_2 = \begin{cases} \dfrac{1}{d_{ij}^2} & i \neq j \\ 0 & i = j \end{cases} \tag{2}$$

4.1.2 Spatial autocorrelation test

Before applying spatial econometric models for regression estimates, it's essential to conduct a spatial autocorrelation test on the data to determine if there's spatial correlation. If so, spatial econometric models are appropriate. This study uses Moran's Index to assess the spatial correlation of variables, which can be global or local.

(1) Global Moran's Index I

The Global Moran's Index I reflects whether a variable has spatial autocorrelation across the entire study area, calculated as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

In Equation 3, x_i and x_j are variable values in regions i and j, $\bar{x}$ is the mean of variable x, n is the sample size, and w_{ij} is the element in row i, column j of the spatial weights matrix w.

The Global Moran's Index I ranges from −1 to 1. When $I \in (0, 1]$, it indicates that the variable has positive spatial autocorrelation, and the closer the value is to 1, the higher the degree of positive spatial autocorrelation. Regions with larger (smaller) variable values are more likely to cluster together. When $I \in [-1, 0)$, it indicates that the variable has negative spatial autocorrelation, and the closer the value is to −1, the higher the degree of negative spatial autocorrelation. Regions with larger differences in variable values are more likely to cluster together. When $I = 0$, it indicates that the variable does not have spatial autocorrelation.

(2) Local Moran's Index I_i

The Local Moran's Index I_i assesses spatial clustering around region i, calculated as:

$$I_i = \frac{n\left(x_j - \bar{x}\right)\sum_{i=1}^{n} w_{ij}\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_j - \bar{x}\right)^2} \tag{4}$$

In Equation 4, the Global Moran's Index I, the Local Moran's Index I_i is not restricted to [−1, 1], but its interpretation is similar. When $I_i > 0$, it indicates that the variable values in region *i* are similar in size to those in the surrounding region; When $I_i < 0$, it indicates that there is a significant difference in the variable values between region *i* and the surrounding region; When $I_i = 0$, it indicates that there is no spatial clustering phenomenon near region *i*.

4.1.3 Spatial Durbin model construction

Considering the potential nonlinear impact of platform economy development on the urban–rural income gap, this study constructs a baseline model. Equation 5 is a fixed-effects model with a quadratic term of the explained variable, and Equation 6 is a spatial Durbin model incorporating a spatial matrix:

$$\text{Theil}_{it} = \alpha_1 \text{pfed}_{i,t} + \alpha_2 \text{pfed}_{i,t}^2 + \alpha_c X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned}\text{Theil}_{i,t} = {} & \rho W \text{Theil}_{i,t} + \alpha_1 \text{pfed}_{i,t} + \alpha_2 \text{pfed}_{i,t}^2 + \gamma_1 W \text{pfed}_{i,t} \\ & + \gamma_2 W \text{pfed}_{i,t}^2 + \gamma_3 W X_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t}\end{aligned} \tag{6}$$

Here, Theil is the Theil index (explained variable), pfed is the platform economy development index, and X represents control variables (see Table 1). In Equation 5, ñ is the spatial autoregressive coefficient, W is the spatial weights matrix, and γ_1, γ_2, γ_3 are regression coefficients for the explained variable, its square, and control variables. μ_i is the regional fixed effect, θ_t is the time effect, and ε is the random disturbance term.

The relationship between platform economy development and the urban–rural income gap depends on the signs of coefficients α_1 and α_2. If $\alpha_2 < 0$, there's an inverted "U"-shaped relationship; if $\alpha_2 > 0$, there's a "U"-shaped relationship. If $\alpha_1 > 0$ and $\alpha_2 = 0$, the platform economy widens the income gap; if $\alpha_1 < 0$ and $\alpha_2 = 0$, it narrows the gap.

4.1.4 Construction of intermediary model

In order to test the mediating effect of land use efficiency, the article uses a mediating utility model to identify the causal relationship between explanatory variables and mediating variables in the selection and argumentation process. The selected mediating variable is land use efficiency, and the specific mediating effect model is constructed as follows:

$$\text{Lue}_i = \beta_0 + \beta_1 \text{Pred}_j + \beta_2 \text{Control} + \varepsilon \tag{7}$$

In Equations 2–7, Lue is the proxy variable for the mediating variable land use efficiency, and Pred is the explanatory variable platform economy; C is a series of control variables; â$_0$ is a constant term, â$_1$ and â$_2$ are estimated coefficients for the explanatory and control variables; å is a random interference term.

4.2 Variable selection

4.2.1 Spatial weight matrix selection

To measure urban–rural income gaps, scholars often use the ratio of urban to rural per capita disposable income, the Gini coefficient, or the Theil index. The income ratio is simple but ignores internal income and population distribution within urban and rural areas. The Gini coefficient, based on the Lorenz curve, is unevenly sensitive to income changes across

TABLE 1 Platform economy development level indicator system.

Primary indicator	Secondary indicator	Tertiary indicator	Attribute
Platform infrastructure	Platform Hardware Development	Optical Cable Route Length (km)	Positive
		Internet Broadband Access Ports (10,000)	Positive
		Internet Broadband Penetration Rate (%)	Positive
		Internet Domain Name Count (10,000)	Positive
	Platform Software Development	Software Business Revenue (10,000 Yuan)	Positive
	Telecommunications Equipment and Service Development	Telecommunications Business Volume (100 Million Yuan)	Positive
		Mobile Phone Penetration Rate (per 100 people)	Positive
		Information Technology Service Industry Output Value (100 Million Yuan)	Positive
	Platform Human Resource Input	Information Service Industry Employment (10,000 people)	Positive
Platform transaction level	E-commerce Development	Number of Enterprises with E-commerce Transactions	Positive
		E-commerce Sales Volume (100 Million Yuan)	Positive
		E-commerce Procurement Volume (100 Million Yuan)	Positive
		Express Business Revenue (10,000 Yuan)	Positive
		Express Total Volume (10,000 pieces)	Positive

different groups (Jin and Deng, 2022). In contrast, the Theil index, using information entropy theory, considers internal population and income distribution and is more sensitive to income changes in both high-and low-income groups, providing a more accurate and comprehensive reflection of income disparities. Thus, this study uses the Theil index, a positive indicator where a higher value signifies a larger urban–rural income gap. This model is shown in Equation 8:

$$\mathrm{Theil}_{i,t}=\sum_{i=1}^{2}\left(\frac{y_{i,t}}{y_t}\right)\times\ln\left[\frac{y_{i,t}}{y_t}\Big/\frac{x_{i,t}}{x_t}\right] \tag{8}$$

Where $i = 1$ and $i = 2$ represent urban and rural areas, t is the year, y is disposable income, and x is population. The Theil index is used in benchmark regressions, with the urban–rural per capita disposable income ratio used for robustness tests.

4.2.2 Core explanatory variable: platform economy development index (pfed)

Academia has no unified definition or measurement standard for the platform economy, and there are no official statistics. Scholars use various indicators, such as e-commerce transaction volumes and the "Internet +" index, to measure platform economy development. Some use a single indicator, while others employ multiple dimensions. For example, Huang et al. (2019) built an evaluation system from three aspects: platform infrastructure, input level, and output level. Yan and Liao (2023) Changchun et al. measured it from infrastructure and value interaction levels. He and Liu (2024) assessed it from infrastructure, transaction level, and development space dimensions. Additionally, some scholars use provincial e-commerce transaction volumes Zhang et al., 2019 and "Internet +" indices (Chen and Wu, 2021) as metrics. Therefore, drawing on existing literature, this study measures platform economy development from infrastructure and transaction levels (Table 1), using the entropy method to calculate weights of tertiary indicators, as follows:

Step 1: Range standardization of the 14 indicators (all positive indicators). As shown in Equation 9.

$$X_{ij}=\frac{x_{ij}-\min\left(x_{ij}\right)}{\max\left(x_{ij}\right)-\min\left(x_{ij}\right)} \tag{9}$$

where x_{ij} is the value of the jth indicator for province i (=1, …, 31, j = 1, …, 14).

Step 2: Calculate the proportion of the jth indicator for province. As shown in Equation 10.

$$P_{ij}=\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}} \tag{10}$$

Step 3: Calculate the entropy value of the jth indicator (n is the sample size). As shown in Equation 11.

$$e_j=-\frac{1}{\ln n}\sum_{i=1}^{n}P_{ij}\times\ln\left(P_{ij}\right) \tag{11}$$

Step 4: Calculate the redundancy of information entropy for each jth indicator. As shown in Equation 12:

$$d_j=1-e_j \tag{12}$$

Step 5: Calculate the weight of each jth indicator. As shown in Equation 13:

$$w_j=\frac{d_j}{\sum_{j=1}^{m}d_j} \tag{13}$$

Step 6: Calculate the platform economy development level for each of the 31 provinces. As shown in Equation 14:

$$\mathrm{pled}_{ij}=\sum_{j=1}^{m}w_jX_{ij} \tag{14}$$

4.2.3 Intermediary variable

This article uses the SBM model of unexpected output super efficiency to measure land use efficiency (Tone et al., 2020). Combined with relevant literature (Yang et al., 2022), the input indicators for measuring land use efficiency in this paper are selected from three levels: land input, capital input and labor input. The expected output indicators are, respectively, expressed by the area of urban construction land, the amount of urban fixed assets investment and the number of employees in the secondary and tertiary industries. The expected output indicators are selected from three levels: economic benefits, social benefits and environmental benefits. They are, respectively, expressed by the added value of the secondary and tertiary industries, the average wage of urban unit employees and the area of gardens and green spaces; the unexpected output indicators mainly consider the negative environmental benefits, expressed in terms of industrial sulfur dioxide emissions, industrial wastewater emissions, and industrial smoke emissions (Yang et al., 2022). As shown in Equation 15:

$$\beta_{SE}=\min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{X_{ik}}}{1-\frac{1}{s_1+s_2}\left(\sum_{i=1}^{s_1}\frac{y_r^d}{y_{rk}^d}+\sum_{i=1}^{s_1}\frac{y_r^d}{y_{rk}^d}\right)}$$

$$s.t\begin{cases}x_i^k\ge\sum_{j=1,j\ne k}^{n}x_{ij}\lambda_j-s_i^-\\ y_{rk}^d\le\sum_{j=1,j\ne k}^{n}y_{rj}^d\lambda_j-y_r^d\\ y_{tk}^{ud}\ge\sum_{j=1,j\ne k}^{n}y_{tj}^{ud}\lambda_j+y_r^{ud}\\ 1-\frac{1}{s_1+s_2}\left(\sum_{i=1}^{s_1}\frac{y_r^d}{y_{rk}^d}+\sum_{i=1}^{s_1}\frac{y_r^d}{y_{rk}^d}\right)>0\\ \lambda,s^-,s^+\ge0\\ i=1,2,\ldots,m;j=1,2,\ldots,n\left(n\ne k\right);r=1,2,\ldots,s_1;t=1,2,\ldots s_2\end{cases} \tag{15}$$

The SBM model provides a more accurate and comprehensive method for evaluating the efficiency of decision units, especially when unexpected outputs need to be considered. The application of this model can help enterprises and organizations improve resource utilization efficiency, reduce environmental impact, and achieve sustainable development.

4.2.4 Control variables

Referring to prior research, this paper controls for other factors affecting the urban–rural income gap in the regression equation.

(1) Economic Development Level (lnPgdp). Chen and Wu (2021) found an inverted "U"-shaped relationship between economic development and the urban–rural income gap. Following Jin and Deng (2022) per capita GDP is used as a measure. To mitigate heteroscedasticity, it is log-transformed in the model. (2) Urbanization (Urban). The urban–rural dual structure is a key factor in unbalanced development. As urbanization progresses, free factor mobility can develop rural areas and raise incomes, narrowing the income gap. However, talent flow to cities can have the opposite effect. Following Xu and Chen (2022) urbanization is measured by the share of secondary and tertiary industry employment. (3) Industrial Structure (Is). Industrial structure transformation can narrow the urban–rural income gap by increasing farmers' income and attracting rural-to-urban employment. Following Zhao (2020) it is measured by the tertiary industry's share of GDP. (4) Government Intervention (Gov). To reduce the urban–rural income gap, governments use redistribution via transfers and policies. Local government fiscal expenditure, especially on social security, can narrow the gap. Following Dong et al., it is measured by local fiscal expenditure's GDP share (Dong and Man, 2017).

4.3 Data sources and descriptive statistics

Pre-2015 Chinese Statistical Yearbooks lack data on e-commerce procurement and firms with e-commerce transactions. The National Bureau of Statistics also adjusted its data classification criteria, shifting from rural per capita net income to disposable income. Thus, this study uses 2015–2024 panel data from 31 Chinese provinces (excluding Hong Kong, Macao, and Taiwan), sourced from the China Statistical Yearbook, provincial yearbooks, and the NBS website. Descriptive statistics are in Table 2. The specific analysis is as follows: The mean and median of the dependent variable, the urban–rural income gap (Theil), are 0.0837 and 0.0823, respectively, which are very close, indicating that the data distribution may be relatively symmetrical and not significantly skewed. The standard deviation (0.3964) is much larger than its mean, indicating significant differences in the urban–rural income gap between different samples (which may represent different regions or years), providing sufficient variability for the study. The core explanatory and mediating variables—platform economy (pfed) and land use efficiency (Lue)—have a mean of 0.1898 for platform economy development (pfed), with a significant difference between the minimum and maximum values (0.0146–0.9311) and a standard deviation (0.2123) greater than the mean. This indicates that the development level of platform economy is extremely uneven among different samples, with some regions being very developed while others are just starting out. The land use efficiency (Lue) situation is similar to pfed, with a low mean (0.3212) but a wide distribution range (0.0145–0.8642) and a large standard deviation (0.4121), indicating significant differences in land use efficiency among different regions. The key test item is the square term ($Pfed^2$) of the platform economy, which is a key variable used to test whether there is a "U-shaped" or "inverted U-shaped" nonlinear relationship between the development of the platform economy and the urban–rural income gap. There is a huge difference between its mean (0.7889) and median (0.0132), and the standard deviation (0.1546) is relatively small. This strongly indicates that the data distribution of the variable is extremely right skewed. The $Pfed^2$ values of the vast majority of samples are very small (concentrated at low levels), but there are a few samples with extremely high levels of platform economy development. Squaring these samples produces huge values, thereby raising the average value. This point needs special attention in the subsequent model analysis. The logarithmic distribution of per capita GDP after controlling for the variable of economic development level (lnPgdp) is relatively concentrated (standard deviation 0.4352), indicating that the differences in economic development levels between samples are within a controllable range. The mean and standard deviation of urbanization rate (Urban) and industrial structure (Is) indicate that the data distribution is relatively normal and concentrated. Government intervention (Gov): The mean is 0.2923, but the maximum value (1.3823) is much higher than other values, and the standard deviation (0.2102) is also large, indicating that the scale of government fiscal expenditure varies greatly in different regions.

TABLE 2 Descriptive statistics of variables.

Variable	Number	Mean	Standard Deviation	Minimum	Maximum	Median
Theil	310	0.0837	0.3964	0.0181	0.2201	0.0823
pfed	310	0.1898	0.2123	0.0146	0.9311	0.1212
Lue	310	0.3212	0.4121	0.0145	0.8642	0.2521
$Pfed^2$	310	0.7889	0.1546	0.0003	0.8621	0.0132
lnPgdp	310	10.9786	0.4352	10.0512	12.1465	10.9011
Urban	310	0.5895	0.1231	0.2392	0.9141	0.5945
Is	310	0.4871	0.0934	0.3199	0.8442	0.4956
Gov	310	0.2923	0.2102	0.1071	1.3823	0.2364

5 Spatial geographical analysis of the level of platform economy and urban rural income gap

5.1 Spatial geographical analysis of platform economic level

The distribution of platform economy in China's 30 provinces shows distinct patterns, mainly characterized by regional imbalance. First, the development level of platform economy is higher in the eastern region than in the western region. Provinces such as Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong have a higher level of platform economy development. These regions have a strong economic foundation, abundant innovative resources, and a sound internet infrastructure. They are home to a large number of high-tech enterprises and innovative talents, which provide favorable conditions for the development of platform economy. The development level of platform economy in the central and western regions is relatively lower. However, it has been developing in recent years and the gap with the eastern region is gradually narrowing. Second, there is spatial agglomeration and positive correlation. Provinces with a high level of platform economy development tend to cluster with neighboring provinces of the same level, forming "high-high" agglomeration areas. For example, the eastern coastal regions, including Beijing, Shanghai, Jiangsu, Zhejiang, and Fujian, are such areas. Low development level provinces also show a certain degree of agglomeration, but this trend has weakened over time. The development level of platform economy in China shows spatial positive correlation, that is, the development level of platform economy in one region is related to that of its neighboring regions. Third, there is dynamic evolution. The development speed of platform economy in the eastern region is faster and the level is higher. Its average value increased from 0.313 in 2015 to 0.767 in 2024. Although the development level of platform economy in the central and western regions is lower than that in the eastern region, it is also rising. Some areas have explored new resource advantages and unleashed the potential of platform economy development. Fourth, there is a correlation with the level of economic development. The development of platform economy is highly correlated with regional economic development. The distribution pattern is basically consistent with the pattern of China's economic development level, which is higher in the east and lower in the west. Regions with a higher level of economic development also have a higher level of platform economy development and vice versa (He and Tiejun, 2025).

5.2 Spatial geographical analysis of urban rural income gap

The distribution of urban–rural income gap in China's 30 provinces shows the following patterns:

First, there are distinct regional differences. The urban–rural income gap is relatively small in the eastern region. In 2024, the urban–rural per capita income ratio in many eastern provinces has dropped to around 2, with Zhejiang's ratio falling to 1.94. The eastern region is more economically developed, with vast plains, abundant resources, convenient transportation, and a relatively low proportion of agricultural population. The development of cities has driven the development of rural areas, so the expansion of the urban–rural income gap is slow. The urban–rural income gap in the central region is higher than that in the eastern region, but it has been narrowing in recent years. The central region is mostly mountainous, with a relatively high proportion of agriculture in the local economy and less developed economy. However, with the implementation of digital economy and rural revitalization measures, the urban–rural income gap has gradually narrowed. The urban–rural income gap is the largest in the western region. The western region is vast, remote, and has a harsh environment and less developed economy. The implementation of the rural revitalization strategy is relatively difficult, so the expansion of the urban–rural income gap is relatively fast.

Second, the overall trend is that the urban–rural income ratio shows an inverse "U" shape, with 2009 as the turning point for decline. The absolute difference in urban–rural income continues to expand. However, the urban–rural income ratio in each region shows a downward trend as a whole.

Third, there are differences within each region. The eastern region has relatively small internal differences. However, the urban–rural income gap is relatively small in municipalities directly under the central government such as Beijing and Shanghai, as well as in coastal provinces such as Guangdong and Zhejiang. But the urban–rural income gap is relatively large in some provinces such as Liaoning. In the central region, the urban–rural income gap is relatively small in provinces such as Hunan and Hubei, while it is relatively large in provinces such as Shanxi and Jiangxi. In the western region, the urban–rural income gap is relatively large in provinces such as Guizhou and Yunnan, while it is relatively small in provinces such as Inner Mongolia and Shaanxi (Yu and Wu, 2020).

5.3 Spatial geographical analysis of narrowing the income gap between urban and rural areas by platform economy

The distribution pattern of the platform economy in reducing the urban–rural income gap in China's 30 provinces is as follows:

First, regional differences. The platform economy in the eastern region has a more significant role in reducing the urban–rural income gap, showing an inverse "U"-shaped characteristic. This is mainly because the eastern region has a strong economic foundation, sound digital infrastructure, and a high level of platform economy development. It can better play its role in promoting urban–rural integration, driving rural industrial development, and increasing rural residents' income, thus effectively narrowing the urban–rural income gap. The platform economy in the central region has a positive "U"-shaped impact on the urban–rural income gap. Its role in reducing the urban–rural income gap is relatively weaker than that of the eastern region. However, in recent years, with the implementation of the digital economy and rural revitalization measures, the urban–rural income gap has also been narrowing continuously. The impact of the platform economy on the urban–rural income gap in the western region is not significant. The western region has relatively backward economic development and digital infrastructure construction, and a low level of platform economy development. Its role in reducing the urban–rural income gap has not been fully exerted. However, with the advancement of relevant policies, it is expected to gradually improve in the future.

Second, the overall trend. From the national perspective, the development of the platform economy generally has a positive effect on reducing the urban–rural income gap. As the platform economy continues to develop, its role in promoting the balanced allocation of urban–rural resources, driving the digital transformation of rural industries, and improving rural residents' digital literacy and skills is gradually revealed. This, in turn, promotes the income growth of rural residents and narrows the urban–rural income gap.

Third, the mechanism of action. The platform economy promotes rural industrial development by integrating rural resources and driving the development of rural e-commerce, rural tourism, and other industries. It creates more employment opportunities and sources of income for rural residents, which helps to increase their income levels. The development of the platform economy promotes the popularization and application of digital technology in rural areas, improves rural residents' digital literacy and skills, and enables them to better use digital platforms to obtain information and carry out production and business activities, thereby enhancing their income levels. The platform economy breaks down the information barriers between urban and rural areas, promotes the rational flow and balanced allocation of urban–rural resources, and enables rural areas to better the transfer of urban industries and investment of resources. This drives rural economic development and narrows the urban–rural income gap (Figures 1–4).

6 Empirical analysis

6.1 Spatial autocorrelation test

6.1.1 Global Moran's index

Based on the global Moran's index formula, the Stata software was used to calculate the global Moran's index of the explained variable from 2015 to 2024 on the basis of the standardized inverse distance squared matrix (W2), and the results are shown in Table 3.

As can be seen from Table 3, the Moran's index of the Theil index from 2015 to 2024 has almost passed the significance test at the 1% level, and the coefficients are all positive. This indicates that there is a positive spatial correlation of the explained variable, and it is reasonable to include the spatial effect in the regression model for the urban–rural income gap in the subsequent analysis. Meanwhile, it also shows that the spatial distribution of the urban–rural income gap in each province of China is not random, but shows a clustering pattern, that is, provinces with similar urban–rural income gaps tend to cluster in space. In addition, looking at the dynamic changes in the Moran's index, the spatial correlation of the Theil index does not show a relatively stable trend, but an overall significant downward trend, indicating a continuous weakening of the spatial clustering of China's urban–rural income gap and a trend toward more balanced urban–rural development.

6.1.2 Local Moran scatter plot

The global Moran's index reflects the overall trend of spatial correlation, but cannot describe the differences between local regions. In order to test the spatial differences between each region and its surrounding regions, this paper draws local Moran scatter plots of the Theil index and platform economy development level for 2015 and 2024, based on the standardized inverse distance squared matrix (W2), as shown in Figures 5, 6.

As can be seen from Figures 5, 6, most provinces are concentrated in the first and third quadrants, which are "high-high" and "low-low" clusters, respectively. This shows that China's provincial urban–rural income gaps and platform economy development levels commonly have spatial clustering. First, taking 2024 as an example, in Figure 5, the local Moran's index of the Theil index of each province mainly falls in the first quadrant for Yunnan, Guizhou, Gansu, Tibet and 11 other provinces. This indicates a high-value clustering of the urban–rural income gap. These provinces have similar economic development levels, but a significant, even large, urban–rural income gap. The third quadrant mainly includes 12 provinces such as Shanghai, Beijing, and Tianjin, which have similar economic development levels and small urban–rural income gaps. It can be seen that high-urban-rural-income-gap provinces are clustered in the central and western regions, indicating that urban–rural coordinated development has not been achieved in China. Second, taking 2024 as an example, in Figure 6, the local Moran's index of the platform economy development level of each province mainly falls in the first quadrant for five provinces: Shanghai, Jiangsu, Zhejiang, Shandong, and Fujian. The third quadrant mainly includes about 12 provinces, including Qinghai, Gansu, and Tibet, which have low levels of platform economy development. The weak areas of platform economy development are concentrated in the central and western regions with relatively backward economic development, indicating that the platform economy development of most provinces in the central and western regions is relatively backward. Third, some provinces are distributed in

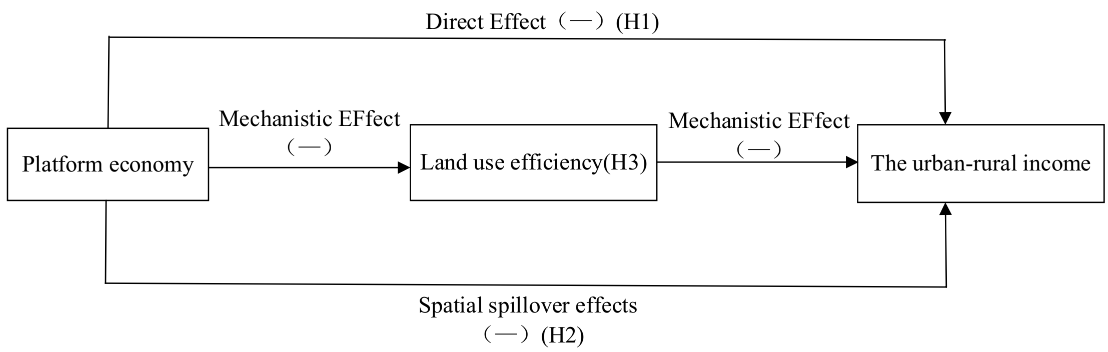

FIGURE 1
Theoretical mechanism of platform economy narrowing urban–rural income gap by improving land use efficiency.

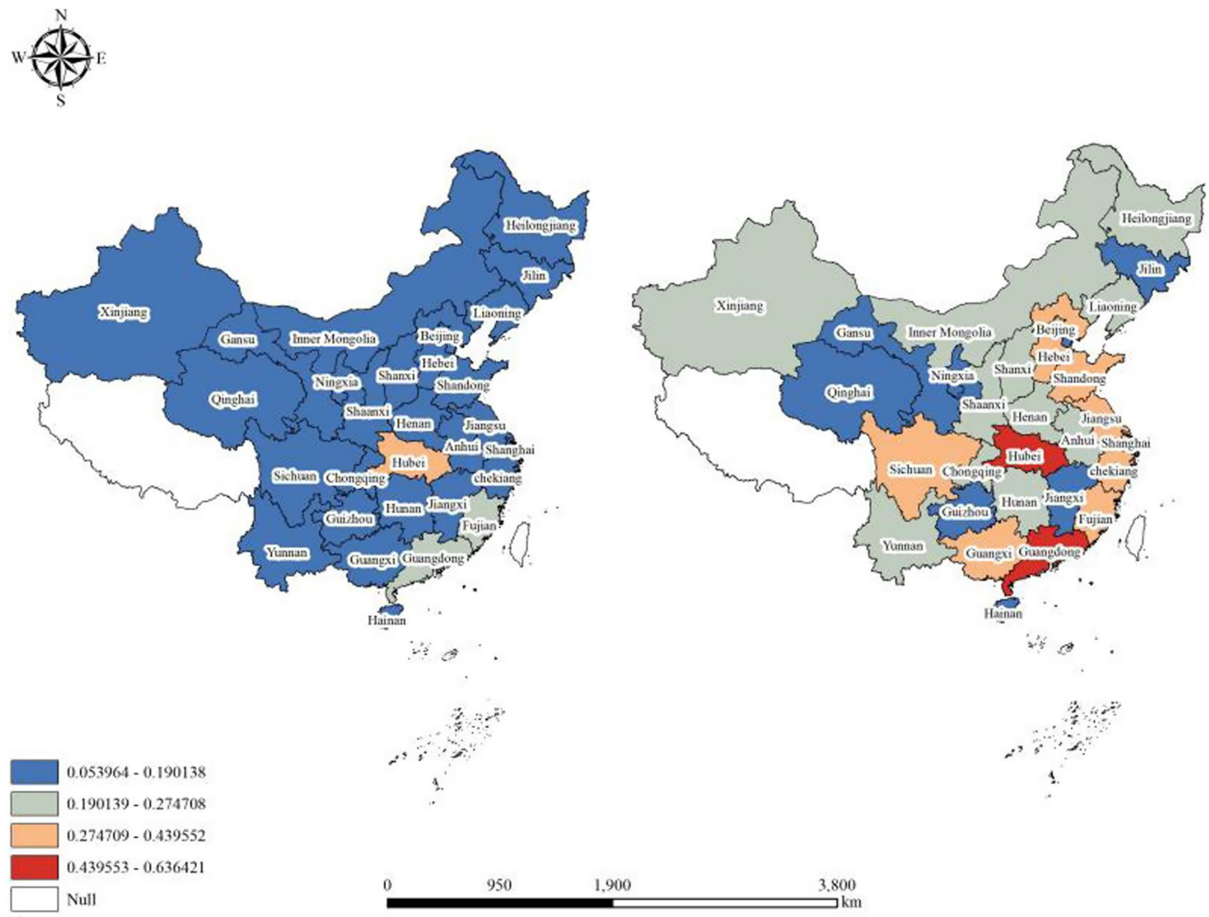

FIGURE 2
Comparative analysis of spatial characteristics of digital economy level between 2015 and 2024.

the second and fourth quadrants. For example, Guangdong has a high level of platform economy development and a small urban–rural income gap, but the surrounding provinces have a low level of platform economy development and a large urban–rural income gap, indicating that the radiation and driving effect of Guangdong on the surrounding provinces has not yet been exerted.

From the above analysis, the Theil index of each province is spatially correlated, and the platform economy development index is also spatially correlated, manifested as "high-high" and "low-low" clustering. Then, whether there is a spatial correlation between the platform economy development level and the urban–rural income gap needs further analysis. Based on this, this paper assumes that there is a spatial correlation between the two, and adds a spatial effect to the regression model of platform economy affecting urban–rural income gap for regression estimation and testing.

6.2 Spatial econometric model test

As shown above, there is spatial correlation between the urban–rural income gaps of each province, so a spatial weight matrix is introduced into the model. Spatial econometric models need to be selected for estimation to make the estimation results more accurate. Table 4 presents a series of test results for spatial econometric models. The results show that the p-values of the LM test and the robust LM test all pass the 1% significance level, indicating the presence of spatial error effects and spatial lag effects, and the spatial Durbin model is initially selected. The test statistics of the LR test and the Wald test both pass the 1% significance level, indicating that the initially selected spatial Durbin model will not degenerate into a spatial lag model and a spatial error model. Therefore, this paper selects the spatial Durbin model for subsequent empirical analysis. In addition, the result of the Hausman test is negative. Referring to the simulation analysis results of existing studies, it is known that the main reason is that the asymptotic assumptions of the basic assumptions of the random effects model cannot be satisfied. Therefore, when the test value is negative, a fixed-effects model should be chosen. By comparing the adjusted R^2 of the fixed-effects model, it is found that the adjusted R^2 of the time-fixed-effects model is larger. Therefore, the time-fixed-effects SDM is finally chosen for empirical analysis (Ling et al., 2014).

6.3 Analysis of spatial econometric regression results

6.3.1 Benchmark regression model estimation

Table 5 presents the benchmark regression results for platform economy development and urban–rural income gap.

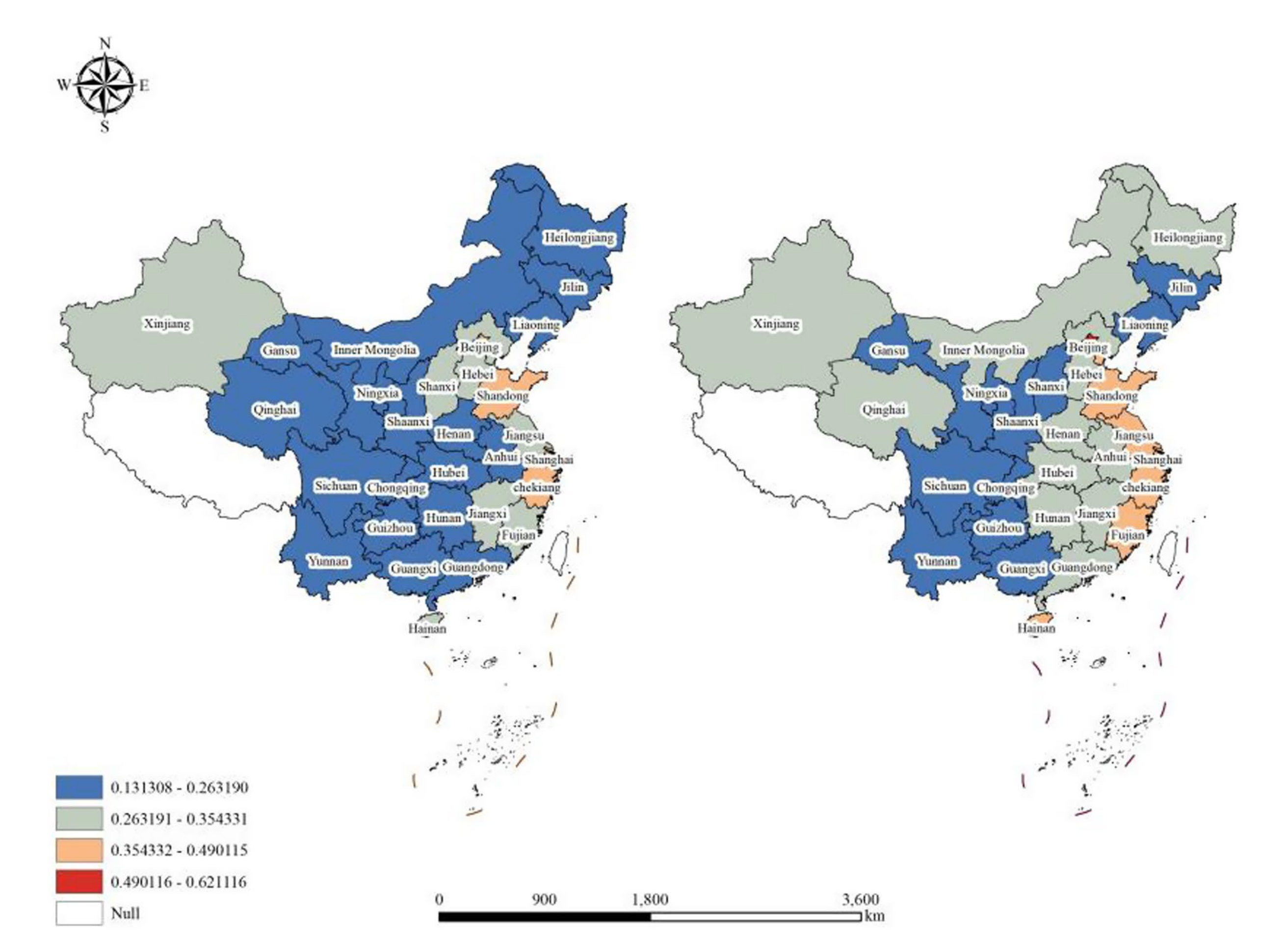

FIGURE 3
Comparative analysis of spatial characteristics of urban–rural income gap between 2015 and 2024.

Column (1) includes the core explanatory variables' linear and quadratic terms. Column (2) adds control variables. In Column (1), pfed is negative and significant at 1%, while pfed2 is positive and significant at 1%, indicating a "U"-shaped relationship. Column (2) confirms this with significant coefficients. Platform economy initially narrows the income gap but widens it later. This is because digital economy boosts rural economic development and income, but as platform economy evolves, employment polarization worsens, and the income gap increases. The inflection point of the "U"-shaped curve is estimated at a platform economy development level of 0.4637. Descriptive statistics show the average and median platform economy development levels of Chinese provinces are 0.1908 and 0.1213, below the inflection point. Most provinces are to the left of the inflection point and need to boost platform economy development to reduce income gaps. This verifies Hypothesis 1.

6.3.2 Spatial Durbin model estimation

For comparative analysis, this paper uses the inverse distance squared matrix to establish a spatial econometric model, and the regression results are shown in Table 6.

By introducing the spatial matrix for spatial econometric analysis, the results in columns (1)–(3) of Table 6 show that the spatial autoregressive model ρ of the fixed-effects model is significantly positive at the 1% level, indicating the rationality of incorporating spatial factors into the model. The spatial spillover coefficients of the time-fixed-effects, province-fixed-effects, and double-fixed-effects models mostly pass the 5% significance level. In the fixed-effects model, pfed, the core explanatory variable, has a negative coefficient that passes the 1% significance test, indicating reliable model specification and that platform economy development narrows the urban–rural income gap. Its spatial spillover coefficient is significantly positive at the 5% level, showing a positive spatial spillover effect. That is, a higher level of platform economy development in one province tends to widen the urban–rural income gap in neighboring provinces. This may be due to the province's vigorous development of the platform economy attracting the inflow of production factors such as talent, capital, and technology from adjacent provinces, creating a suction effect, and thus exacerbating the urban–rural income gap in neighboring provinces. The spatial spillover coefficient of pfed2 is about −0.286, indicating that the platform economy development level in other provinces affects the local urban–rural income gap by approximately −28.6%. In summary, both the ordinary panel regression and spatial econometric regression results confirm Hypothesis 1.

Looking at the control variables, in the fixed-effects model, increases in per capita GDP and the proportion of the tertiary industry tend to widen the urban–rural income gap. This may be because the

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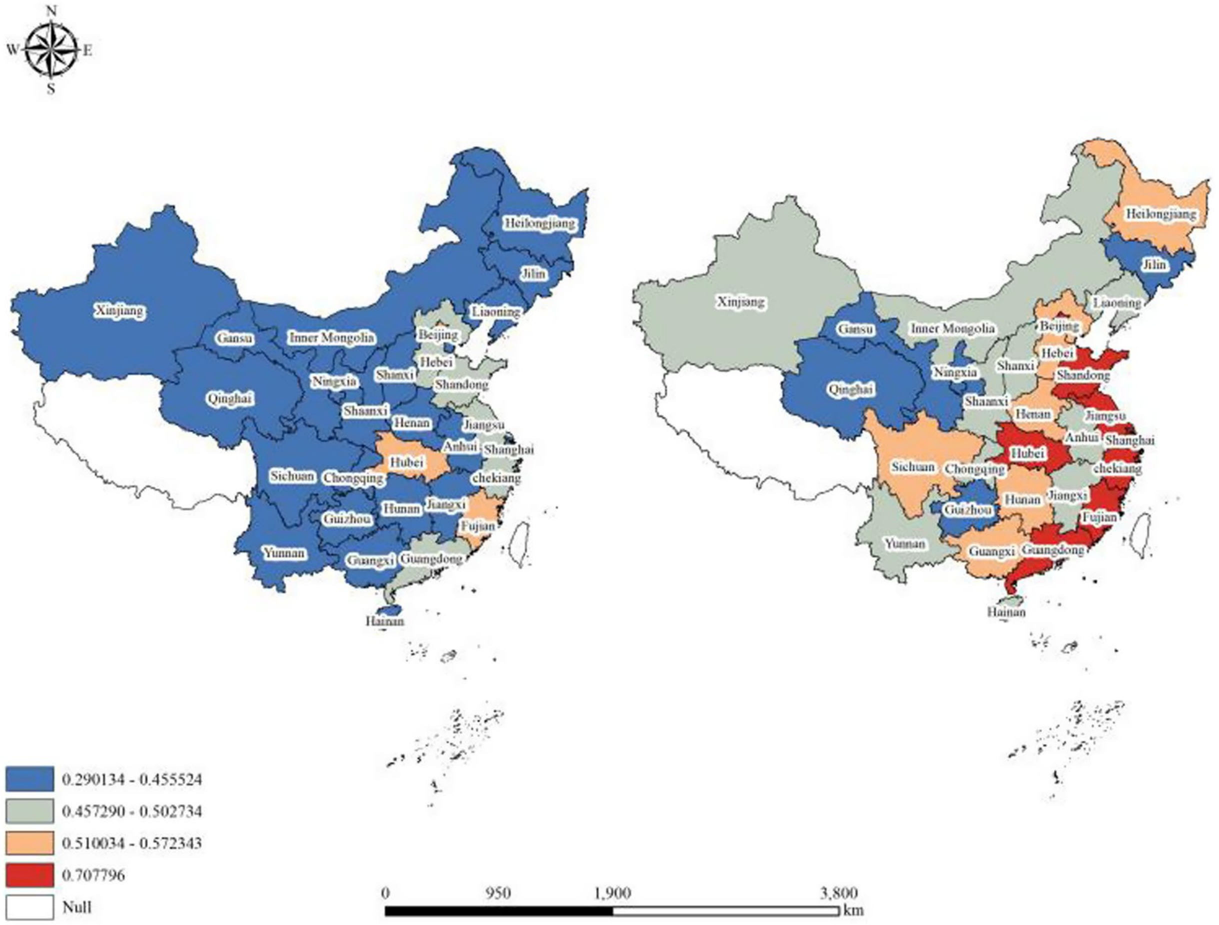

FIGURE 4
Comparative analysis of the spatial characteristics of the level of narrowing the income gap between urban and rural areas of the platform economy in 2015 and 2024.

TABLE 3 Global Moran's index values of variables from 2015 to 2024.

Year	2015	2016	2017	2018	2019
Theil	0.457***	0.468***	0.472***	0.459***	0.226***
Year	**2020**	**2021**	**2022**	**2023**	**2024**
Theil	0.432***	0.446***	0.423***	0.411***	0.387***

*** indicates significance at the 1% level.

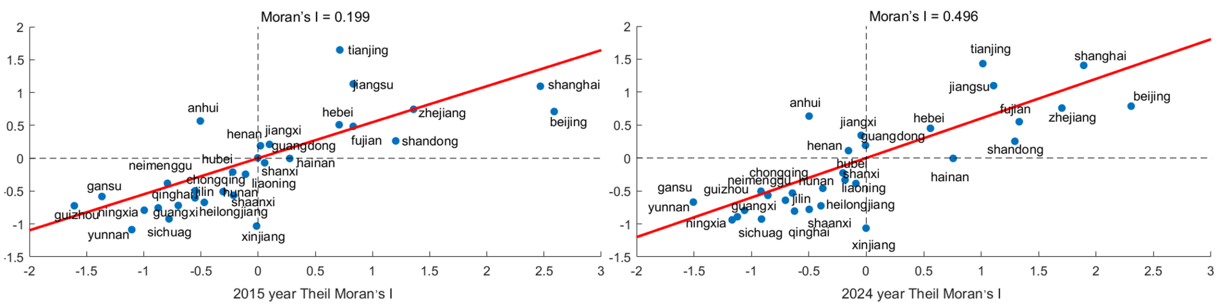

FIGURE 5
Morland scatter plot of Theil index.

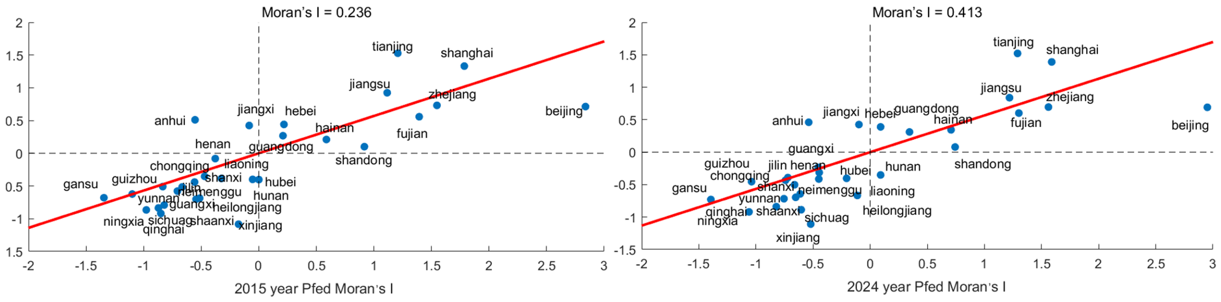

FIGURE 6
Moran scatter plot of platform economy development level.

TABLE 4 Results of spatial econometric model verification.

Test method	Test statistic	W_2 statistic
LM Test	LM Spatial Error Test	181.797***
	Robust LM Space Error Test	59.173***
	LM Space Lag Test	126.307***
	Robust LM Space Lag Test	10.324***
LR Test	Robust LM Space Lag Test	89.46***
	LR Space Lag Test	66.57***
Wald Test	Wald Spatial Error Test	22.98***
	Wald Space Lag Test	22.03***
Fixed Effects Test	Fixed Time R^2	0.7324
	Individual Fixed R^2	0.7125
	Time and Space Fixed R^2	0.6021

*** indicates significance at the 1% level.

TABLE 5 Benchmark regression results.

Explained variable	(1)	(2)
	Thile	*Thile*
pfed	−0.2879***	−0.146***
	(−11.07)	(−4.68)
pfed2	0.2387***	0.154***
	(7.72)	−5.13
lnpgdp		0.006
		−0.58
Urban		−0.291***
		(−9.68)
Is		0.075***
		−3.74
Gov		−0.019**
		(−2.24)
Constant term	0.158***	0.202***
	(23.43)	−2.86
ind	Control	Control
time	Control	Control
R^2	0.5123	0.7648
Sample size	310	310

*** indicates significance at the 1% level.

TABLE 6 Spatial econometric regression results.

Explained variable	(1) *time*		(2) *ind*		(3) *both*	
	Explanatory variable	Spatial variable	Explanatory variable	Spatial variable	Explanatory variable	Spatial variable
pfed	−0.082***	0.186**	−0.065	−0.479***	−0.098	−0.744***
	(−2.864)	(2.264)	(−0.691)	(−2.698)	(−1.231)	(−2.965)
pfed2	0.071**	−0.286***	0.046	0.436*	0.095	0.657**
	(2.654)	(−3.031)	(0.32)	(1.943)	(1.015)	(2.275)
lnpgdp	0.018**	0.028*	0.02	−0.03	0.034**	0.076**
	(2.123)	(1.832)	(1.106)	(−0.812)	(2.475)	(2.149)
Urban	−0.315***	−0.276***	−0.219***	−0.211**	−0.346***	−0.436***
	(−12.014)	(−3.573)	(−4.379)	(−2.13)	(−4.598)	(−3.765)
Is	0.123***	0.112**	−0.008	0.167***	0.021	0.367***
	(6.843)	(1.876)	(−0.154)	(3.402)	(1.431)	(5.126)
Gov	−0.042***	0.231***	0.006	−0.142*	0.008	0.038
	(−4.721)	(6.876)	(0.041)	(−1.971)	(0.247)	(0.229)
ρ		0.029***		0.189***		−0.037
		(3.1)		(2.699)		(−0.299)
ind	No control		Control		Control	
time	Control		No control		Control	
R^2	0.811		0.764		0.631	
Sample size	310		310		310	

*, **, *** indicates significance at the 10%, 5%, 1% level.

TABLE 7 Results of spatial spillover effect.

Explained variable	Direct effect	Indirect effect	Total effect
pfed	−0.083***	0.187**	0.117
	(−2.924)	(2.546)	(1.289)
pfed^2	0.078**	−0.314***	−0.278**
	(2.456)	(−2.876)	(−2.145)
lnpgdp	0.018**	0.043*	0.052**
	(2.26)	(1.932)	(2.61)
Urban	−0.345***	−0.278***	−0.678***
	(−11.976)	(−4.543)	(−8.997)
Is	0.121***	0.109**	0.207***
	(5.789)	(2.131)	(3.921)
Gov	−0.042***	0.224***	0.187***
	(−4.413)	(6.978)	(5.651)

, * indicates significance at the 5%, 1% level.

tertiary industry consumes too many production factors, and the government may increase investment in the tertiary industry for economic development while neglecting agriculture, indicating the need for industrial structure optimization. An increase in the urbanization rate narrows the urban–rural income gap, as does an increase in the proportion of local government expenditure. From the spatial variables' results, per capita GDP, the proportion of the tertiary industry, and the proportion of local government expenditure tend to worsen the urban–rural income gap in neighboring provinces, while the urbanization rate has an improving effect, and these impacts are significant.

6.3.3 Decomposition of spatial Dubin model effects

As shown in Table 7, the direct effect of platform economy development level on urban–rural income gap is negative, and the indirect effect is positive, both passing the 5% significance test. This means that as the platform economy development level increases in a province, the urban–rural development gap within that province decreases. At the same time, a higher level of platform economy development in neighboring provinces leads to a larger urban–rural income gap in the local province. The direct effect coefficient of the platform economy is −0.083, indicating a

1% increase in local platform economy development reduces the urban–rural income gap by 8.3%. The platform economy, as a key part of the digital economy, can break down information barriers and use digital resources to create scale economies, boosting employment in rural and poor areas, increasing low-income groups' wages, and narrowing the urban–rural income gap to promote common prosperity. The indirect effect coefficient is 0.187, showing a 1% increase in neighboring provinces' platform economy development widens the local urban–rural income gap by 18.7%, with the indirect effect exceeding the direct effect. Overall, the platform economy development level has a positive but insignificant effect on the urban–rural income gap. These findings confirm the spatial spillover effects of the platform economy on the urban–rural income gap, consistent with the previous spatial Durbin model estimation results, thus supporting Hypothesis 2.

For other variables, the local government fiscal expenditure ratio shows a pattern similar to the core explanatory variable. The urbanization rate has the same sign for direct and indirect effects, which are significantly negative, indicating that spatially proximate provinces influence each other's urbanization development, narrowing the urban–rural income gap. The per capita GDP and the tertiary industry's output value ratio have the same sign for direct and indirect effects, both significantly positive. A higher per capita GDP and tertiary industry output value ratio in the local province increase the urban–rural development gap within the province. Similarly, higher levels in neighboring provinces also enlarge the local urban–rural income gap, underscoring the importance of advancing urbanization.

6.4 "U" relationship test

Scholars typically incorporate a nonlinear (usually quadratic) term into a standard linear regression model. If this term is significant and the estimated extremum lies within the data range, a "U"-shaped relationship is considered to exist. However, Lind and Mehlum (2010) deem this criterion too weak. Haans et al. (2016) also point out that a significant quadratic term alone does not fully confirm an (inverted) U-shaped relationship. Thus, it's necessary to test for inverted U-shaped relationships. This paper tests the relationship between platform economy development and the urban–rural income gap, with results shown in Table 8.

The platform economy development level ranges from 0.0142 to 0.9326, with an inflection point at 0.4637. The slope for the left interval is −0.1317, significant at the 1% level, while the slope for the right interval is 0.1401, also significant at the 1% level. This indicates a "U"-shaped relationship between platform economy development and the urban–rural income gap (see Figure 7), further supporting Hypothesis 1.

6.5 Robustness test

Based on the characteristics of spatial econometric analysis, this paper first chooses to replace the spatial weight matrix for robustness testing, with results shown in Table 9. Columns (1)–(3) present regression results using a contiguity matrix as the replacement, where the time-fixed-effects model fits well, yielding significant

TABLE 8 Results of U-shaped relationship test.

Variable	*Lower bound*	*Upper bound*
Interval	0.0142	0.9326
Slope	−0.1317	0.1401
t-value	−4.721	4.468
$p > \|t\|$	0.000	0.000

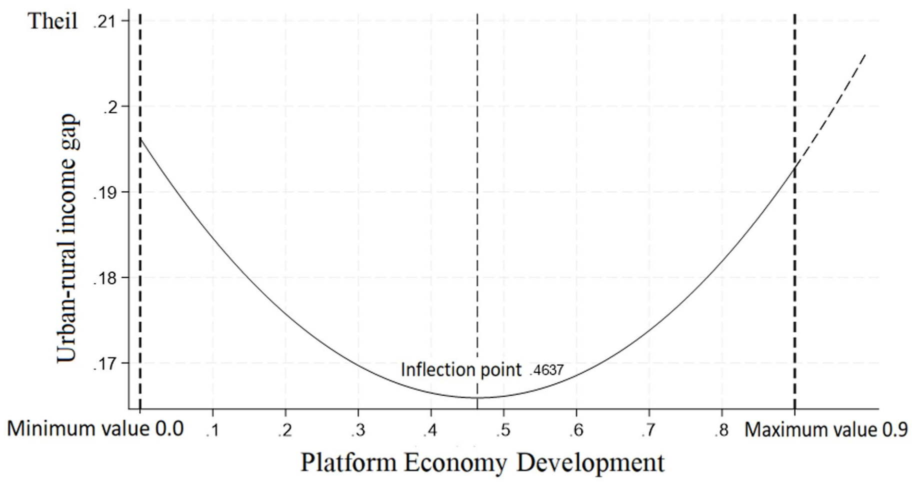

FIGURE 7
U-shaped relationship between pfed and urban-rural income gap.

TABLE 9 Results of robustness test.

	(1) *time*		(2) *ind*		(3) *both*		(4) *Pcid*	
	Explanatory Variable	Spatial Variable	Explanatory Variable	Spatial Variable	Explanatory Variable	Spatial Variable	Explanatory Variable	Spatial Variable
pfed	−0.166*** (−5.128)	0.162*** (3.172)	−0.019 (0.91)	−0.491*** (0.02)	−0.077 (0.55)	−0.721*** (0.00)	−0.571 (−1.298)	1.245 (1.123)
pfed^2	0.162*** (5.142)	−0.173*** (−3.432)	0.067 (0.52)	0.362*** (0.00)	0.125 (0.26)	0.478*** (0.00)	0.579 (1.467)	−2.458* (−1.871)
lnpgdp	0.009 (0.924)	−0.042** (−1.151)	0.009 (0.577)	−0.008 (0.714)	0.019* (0.092)	0.028** (0.062)	0.156 (1.421)	0.993*** (3.698)
Urban	−0.312*** (−9.221)	−0.178* (−1.799)	−0.231*** (0.008)	−0.134* (0.065)	−0.241*** (0.005)	−0.324*** (0.0162)	−1.617*** (−4.278)	−3.689*** (−4.416)
Is	0.134*** (5.712)	0.021 (0.298)	−0.061 (0.123)	0.178*** (0.004)	0.006 (0.976)	0.299*** (0.006)	1.567*** (1.413)	−0.157 (−0.179)
Gov	−0.042*** (−3.567)	−0.015 (−0.592)	−0.021 (0.34)	−0.067 (0.21)	0.004 (0.79)	0.041 (0.63)	−0.297** (−2.145)	2.926*** (5.997)
ρ		0.077*** (4.67)		0.341*** (0.026)		0.031*** (0.812)		0.189*** (2.251)
ind	No control		No control		No control		No control	
time	Control		Control		Control		Control	
R^2	0.914		0.633		0.511		0.367	
Sample size	310		310		310		310	

*, **, *** indicates significance at the 10%, 5%, 1% level.

TABLE 10 Analysis of intermediary effects based on land use efficiency.

Variable	(1) Land Use Efficiency	(2) Land Use Efficiency	(3) Land Use Efficiency	(4) Land Use Efficiency
Platform economy	0.455*** (0.004)	0.368*** (0.041)	0.283*** (0.011)	0.366*** (0.021)
Intercept	1.432*** (1.442)	0.576*** (0.467)	0.576*** (0.467)	0.576*** (0.467)
Time fixed effect	YES	YES	YES	YES
R^2	0.972	0.976	0.916	0.837
N	310	310	310	310

*** indicates significance at the 1% level.

results with coefficients and spatial spillover effects of pfed and pfed2 matching those in Column (2) of Table 6. Next, the dependent variable is replaced with the urban–rural disposable income ratio (Pcid), calculated as the ratio of urban to rural disposable income. Regression results in Column (4) of Table 9 show the spatial spillover effect coefficient of pfed2 remains significant with the same sign, confirming the robustness of the original regression results (Fei et al., 2022).

Based on spatial econometrics, this paper first substitutes the spatial weight matrix for robustness testing, as shown in Table 9. Columns (1)–(3) present regression results using a contiguity matrix, where the time-fixed-effects model fits well, yielding significant results with coefficients and spatial spillover effects of pfed and pfed2 matching those in Column (2) of Table 6. Next, the dependent variable is replaced with the urban–rural disposable income ratio (Pcid), calculated as the ratio of urban to rural disposable income. Regression results in Column (4) of Table 9 show the spatial spillover effect coefficient of pfed2 remains significant with the same sign, confirming the robustness of the original regression results.

7 Empirical analysis

7.1 Intermediary effect test

In the theoretical analysis section of the previous text, this article delves into the impact mechanism of platform economy on narrowing the urban–rural income gap by improving land use efficiency. To verify the validity of this theoretical mechanism, further testing is conducted based on the mediation effect model. According to the mechanism verification steps, the first step is to verify the direct impact of platform economy on narrowing the urban–rural income gap, which has been fully discussed in the previous text and will not be repeated here. The second step is to examine the intrinsic relationship between platform economy and land use efficiency. The results in column (1) of Table 10 indicate that at the 1% statistical level, platform economy can be considered to have a significant positive impact on land use efficiency. The results in columns (2), (3), and (4) show that after controlling for other variables, platform economy still significantly promotes the construction of land use efficiency H3, which is verified. The platform economy serves as an intermediary mechanism to narrow the income gap between urban and rural areas by improving land use efficiency. Its core lies in converting potential land resources in rural areas into sustainable monetary benefits. The operating mechanism is that the platform integrates scattered land with market demand to drive the intensive use of idle or inefficient rural land (such as homesteads and farmland) for the construction of production warehouses, processing workshops, or rural tourism facilities, thereby enhancing its unit output value. This directly creates local non-agricultural employment opportunities and connects agricultural products directly to the urban consumer market through e-commerce live streaming and other channels, reducing intermediate links and enabling farmers to more fully share the benefits of land appreciation and industrial chain profits. In the end, this process broadened farmers' income channels and achieved diversification and growth in their income structure through the transformation of resources into assets and farmers into shareholders/employees/shop owners.

7.2 Heterogeneity analysis

To analyze the impact of platform economy's characteristics and infrastructure on its development speed, this paper divides the average platform economy development level index of 31 provinces from 2015 to 2024 into three groups: East, Central, West, and conducts spatial econometric regressions separately (Zhao, 2020). Limitations of the traditional east-central-west regional classification and the use of the spatial Durbin model, this study refers to existing research and conducts heterogeneity analysis based on the platform economy development level index. Columns (1)–(3) in Table 11 show the results of spatial econometric regressions for provinces with east, central, west platform economy development levels, respectively (Yang and Li, 2023). Except for the spatial spillover effect coefficient of the low-level group, the coefficients and spatial spillover effect coefficients of the three groups are significant. The coefficients of pfed are negative, and those of pfed2 are positive, showing a "U"-shaped relationship between platform economy development and urban–rural income gap, consistent with the overall sample model. Provinces with high platform economy development have significant spatial spillover effects, similar to the overall sample regression results. Those with medium platform economy development have significant spatial spillover effect coefficients with larger absolute values than the overall sample regression coefficients, indicating stronger spatial spillover effects. In provinces with low platform economy development, the spatial spillover effect coefficient of the core explanatory variable is significantly negative, showing a negative spillover effect, where an increase in the platform economy development level in neighboring provinces widens the urban–rural income gap in the local province. Provinces with high and medium platform economy development should assist those with low development, while the latter also need to adopt development strategies.

8 Conclusions and implications

Based on panel data from 31 Chinese provinces spanning 2015 to 2024, this study quantifies the development of the platform economy across two dimensions—platform infrastructure and platform transaction activity—using 14 tertiary indicators and the entropy method. A spatial Durbin model is constructed to examine the impact of platform economy development on the urban–rural income gap, with particular attention to its spatial spillover effects and developmental heterogeneity. The main findings are as follows:

(1) Both the urban–rural income gap and the level of platform economy development exhibit significant positive spatial autocorrelation across provinces. The spatial distribution is non-random, showing clear clustering patterns, notably "high-high" and "low-low" agglomerations.
(2) The relationship between platform economy development and the urban–rural income gap follows a "U-shaped" pattern, initially narrowing and later widening the disparity. Currently, most provinces lie on the left side of the U-shaped curve,

TABLE 11 Heterogeneity test results.

	(1) Eastern region		(2) Central region		(3) Western region	
	Explanatory variable	Spatial variable	Explanatory variable	Spatial variable	Explanatory variable	Spatial variable
pfed	−0.033*** (−0.234)	−0.172*** (−1.985)	−0.713*** (−2.442)	−1.897*** (−3.768)	−1.715*** (−2.678)	−3.461*** (−3.897)
$pfed^2$	0.079*** (3.246)	0.441*** (4.837)	2.257*** (2.976)	7.987*** (3.768)	11.215** (2.379)	7.167 (0.728)
lnpgdp	0.031*** (3.917)	−0.031 (−1.234)	−0.021 (−0.899)	0.068*** (1.976)	0.035*** (2.167)	−0.031 (−0.921)
Urban	−0.255*** (−8.887)	−0.188*** (−3.222)	−0.156** (−2.012)	−0.061 (−0.432)	−0.617*** (−7.897)	0.156 (1.178)
Is	−0.011*** (−0.523)	0.187*** (3.797)	0.027 (0.668)	−0.075 (−0.867)	−0.005 (−0.021)	0.142 (1.567)
Gov	0.112*** (3.771)	0.087 (0.678)	−0.08 (−1.432)	0.321** (2.156)	−0.151*** (−5.789)	−0.178*** (−2.824)
ρ		−0.008 (−0.467)		0.713*** (0.162)		−0.073** (0.741)
R^2	0.921		0.761		0.789	
Sample size	310		310		310	

, * indicates significance at the 5%, 1% level.

indicating that platform economy development generally helps reduce urban–rural income inequality at this stage.

(3) Platform economy development generates significant positive spatial spillover effects. A higher level of platform development in one province is associated with a wider urban–rural income gap in neighboring provinces. The direct effect within a province is negative, whereas the indirect effect (spillover) on other provinces is positive.

(4) The impact of the platform economy on the urban–rural income gap displays regional heterogeneity. Its effect is more pronounced in the eastern region compared to the central and western regions, while the central region shows a smaller promoting effect relative to the western region. This suggests that the central region represents a key area where the platform economy can effectively narrow the urban–rural divide.

Based on these findings, the study proposes the following policy recommendations:

(1) Strengthen weaker areas of urbanization to amplify the platform economy's contribution to common prosperity. Enhancing urbanization provides essential infrastructure, reinforcing the network and radiation effects of the platform economy and helping narrow urban–rural income disparities. Regions with lagging urbanization should implement targeted plans to advance high-quality urban development and better support the platform economy's inclusive growth.

(2) Promote integrated urban–rural development through digital transformation. Leveraging digital technologies—such as high-speed connectivity, integrated systems, and green solutions—can modernize rural governance, improve public services, cultivate local talent, and foster new business models. Accelerating the construction of rural digital infrastructure, including big data, IoT, and digital finance systems, will help build modular networks that support urban–rural synergy, industrial upgrading, and specialized division of labor. Extending the platform economy into rural areas can mitigate the "big-city suction effect" and help bridge the urban–rural gap.

(3) Guide rural labor toward high-quality employment to counteract potential job displacement caused by industrial upgrading. Facilitating skill development and enabling quality employment will further help narrow income disparities.

(4) Encourage local governments to design tailored and adaptive policies according to regional platform economy development levels and urban–rural income conditions, so as to foster platform-driven growth while reducing inequality.

(5) Promote e-commerce live streaming to empower rural specialty industries. Revitalize underutilized rural land and homesteads by establishing standardized production warehouses, processing workshops, and live-streaming bases. By reducing intermediate distribution links, platform-based direct sales can retain more value-added income in rural areas, directly expanding farmers' income channels.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

WH: Supervision, Writing – review & editing, Methodology, Investigation, Visualization, Validation. JZ: Writing – original draft, Data curation, Methodology, Resources, Formal analysis, Project administration.

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Conflict of interest

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

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