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Rural e-commerce platform data analytics for economic development

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ABSTRACT
This paper firstly studies the current situation of rural e-commerce development in China, and then collects the gross output value of agriculture, forestry, animal husbandry and fishery, express delivery volume, rural delivery routes and so on through consulting the relevant official data of the National Bureau of Statistics, which provides an effective and reliable data basis for the construction of econometric model. Through the establishment of a fixed-effects model to analyze the empirical results, to explore the role of rural e-commerce platform development on the promotion of the economy. Finally, with the help of the spatial Durbin model to measure the spatial spillover effect, analyze whether the development of rural e-commerce can reduce the urban-rural income gap. The results show that the number of Taobao villages, kilometers of rural delivery routes, and 10,000 rural broadband access users are the explanatory variables, and the gross output value of agriculture, forestry, animal husbandry and fishery is the explanatory variable, and the coefficients are 0.0156, 0.0781, and 0.0442, with the p-value less than 0.01. Therefore, the better the development of rural e-commerce, the better the economic development is. And the increase in the level of economic development can significantly reduce the urban-rural income gap with an estimated parameter of -0.022.

Keywords: spatial Durbin model, rural e-commerce platform, fixed effect model, economic development

1. Introduction

In rural areas of China, the rise of e-commerce is gradually changing the traditional economic structure and mode of operation. The report of the United Nations Conference on Trade and Development shows that the share of e-commerce in global retail trade continues to grow, and this growth is particularly significant in developing countries [1-3]. The development of rural e-commerce opens a broader

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market for agricultural products, which not only helps to enhance the value of agricultural products, but also can effectively promote the economic development of rural areas [4-6]. For example, through e-commerce platforms, farmers are able to directly reach a wider group of consumers, which not only improves the efficiency of sales, but also helps farmers to obtain higher income. However, despite the great potential of rural e-commerce, its development also faces a series of challenges. The theory of economic development states that technological innovation and industrial upgrading are key factors in promoting economic development [7-8]. In the context of rural e-commerce, this means that attention needs to be paid to the construction of technological infrastructure, the upgrading of farmers' e-commerce skills, as well as the optimization of e-commerce platforms' operation modes [9].

With the progress of science and technology, data is growing explosively, forming a huge data flow, leading to the gradual expansion of the scale of data processing, which brings a certain degree of difficulty to e-commerce data processing. In particular, the e-commerce platform will rely more on data resources in the process of actual development and construction, and enterprises will generate a large amount of data in the process of business activities, in order to further understand the consumer's purchasing behavior, it is necessary to further excavate the relevant data content, so as to promote the development of the e-commerce platform [10-12].

On the other hand e-commerce platform through the collection of such as product data such as product praise rate, advertising click rate, click location, marketing data, user behavior, combined with the market trend of product and marketing strategy analysis, the platform can better understand the market demand, optimize the products and services and enhance the user experience, so as to optimize their own business strategy [13]. Therefore, the platform must choose effective big data analysis technology and apply it scientifically in e-commerce work. Therefore, how to scientifically analyze the product data on the e-commerce platform becomes the key to improve the competitiveness of enterprises.

With the popularization of the Internet and mobile technology, e-commerce activities in rural areas have brought development opportunities to the traditional agricultural market, not only changing the way of selling agricultural products, but also providing new economic growth points in rural areas and creating more jobs for farmers. However, although rural e-commerce shows great potential, its development also faces challenges such as insufficient infrastructure, limited application of technology and uneven market participation capacity [14]. Literature [15] analyzed provincial e-commerce panel data based on linear and panel threshold frameworks and found that e-commerce plays a significant role in narrowing rural and urban incomes in regions with higher public expenditures as well as higher levels of education. Literature [16] conducted a randomized controlled experiment on rural e-commerce and pointed out that the expansion of e-commerce helped villages to overcome the logistical problems of e-commerce and reduced the cost of e-commerce for rural households, and finally mentioned that there is no significant evidence to confirm that e-commerce contributed to the increase in income of the rural population. Literature [17] discusses the association between rural e-commerce entrepreneurship and gender based on a female political economy perspective and reveals that female economic empowerment does not necessarily drive political and cultural empowerment, and that the exploitation of digital capital to a certain extent diminishes the potential for female entrepreneurship. Literature [18] constructed a RECL logistics optimization model and solved it to solve the e-commerce rural logistics transportation and distribution problem, and confirmed the effectiveness of the proposed logistics optimization model with the improved ant colony algorithm as the core by simulation verification in the dataset as well as example analysis. Literature [19] starts from the perspective of resource orchestration and combines it with practical cases to study the problems related to the development of e-commerce capacity in Chinese rural communities, pointing out that the communities are mainly developed through two forms of government support and self-coordination, and the study emphasizes the importance of resource coordination for the development of community e-commerce. Literature [20] examines the development history of Taobao villages in

China as well as the organizational structure of the development, lists the production-oriented and market-oriented development modes. Literature [21] builds a comprehensive framework for analyzing the formation logic of agricultural e-commerce clusters, and analyzes that the development of regional e-commerce is a comprehensive and systematic project, but due to the commercial competition and the speculationism of the local residents, which leads to quality problems of the products of e-commerce clusters, and argues that the government needs to have a correct understanding of the development mode of e-commerce and agriculture combination. Literature [22] used structural equation modeling, and combined with human capital, social capital and other elements, to explore how e-commerce affects the entrepreneurship of rural residents, the results of the study show that the development of e-commerce promotes farmers' entrepreneurial intentions and behaviors, and the level of network infrastructure, the human quality of the region, the e-commerce entrepreneurial intentions are more intense. Literature [23] examined the e-commerce marketing system of enterprises based on big data technology, and concluded that big data technology empowers the e-commerce marketing system, which helps to improve the accuracy and efficiency of e-commerce marketing. Literature [24] discusses the practice and performance of sentiment analysis strategy in e-commerce marketing, and argues that based on sentiment analysis, customer sentiment data can be obtained and then analyzed to gain insights into customer shopping intention and shopping experience, which helps to increase e-commerce sales. Literature [25] talks about the concern for the value of data information in the field of e-commerce, and tries to explore the feasibility of real-time dynamic analysis of e-commerce website operation data based on the analysis and reflection of actual cases. Literature [26] introduces a newly designed e-commerce big data analysis model, which has the function of intelligently analyzing e-commerce product and sales data, and provides e-commerce information to assist e-commerce users in decision-making.

This paper mainly focuses on the role of rural e-commerce platform development in promoting urban and rural economy. Using the fixed effect model to explore from both qualitative and quantitative aspects, firstly, the mechanism of the impact of rural e-commerce development on the growth of the agricultural economy is analyzed from a qualitative perspective, and the relevant variables affecting on the rural economy are selected. Secondly, from a quantitative perspective, the empirical study was launched by collecting and processing relevant data from 348 rural areas across China from 2013 to 2023. The per capita disposable income of urban and rural residents in 11 prefectural-level cities of a province is used as an indicator to measure the level of rural e-commerce development. A spatial Durbin model is used to empirically study the impact of rural e-commerce development on the urban-rural income gap in a province.

2. Fixed effects modeling

2.1. Types of panel data models

1) Mixed cross-section regression model. The general form of the mixed cross-section regression model is as follows:

$$y_{it} = \alpha + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \varepsilon_{it} \tag{1}$$

2) Fixed effects models. An individual fixed effects model is a model that has different intercepts for different individuals.

$$y_{it} = \alpha_i + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \varepsilon_{it} \tag{2}$$

A moment fixed effects model is a model that has different intercepts for different cross-sections (moment points).

$$y_{it} = \gamma_t + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \varepsilon_{it} \tag{3}$$

$$y_{it} = \alpha_i + \gamma_t + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \varepsilon_{it} \tag{4}$$

3) Random effects models. It is assumed that either unobserved effects model can be expressed as:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + v_i + w_{it} \tag{5}$$

If the unobserved effect v_i is assumed to be uncorrelated with each of the explanatory variables, i.e:

$$\mathrm{Cov}(x_{itj}, v_i) = 0, \quad t = 1,2,\ldots,T; j = 1,2,\ldots,k \tag{6}$$

2.2. Tests for Panel Data Model Setting

1) F-test. The F test is primarily used to determine whether a mixed cross-section regression model or a fixed effects model should be chosen.

The F statistic is defined as:

$$\begin{aligned} F &= \frac{(SSE_r - SSE_n)/[(NT-k-1)-(NT-N-k)]}{SSE_n/(NT-N-k)} \\ &= \frac{(SSE_r - SSE_n)/(N-1)}{SSE_n/(NT-N-k)} \sim F(N-1, NT-N-k) \end{aligned} \tag{7}$$

For the test of moment effects, the original hypothesis H_0 and alternative hypothesis H_1 are respectively:

$H_0: \gamma_t = \gamma_0$ The intercepts of the different cross-sections in the model are the same (the true model is a mixed cross-section regression model).

H_1: The intercept terms for the different cross-sections in the model γ_i are different (the true model is a moment fixed effects regression model).

F The statistic is defined as:

$$\begin{aligned} F &= \frac{(SSE_r - SSE_u)/[(NT-k-1)-(NT-T-k)]}{SSE_u/(NT-T-k)} \\ &= \frac{(SSE_r - SSE_u)/(T-1)}{SSE_u/(NT-T-k)} \sim F(T-1, NT-T-k) \end{aligned} \tag{8}$$

2) Hausman test. Hausman test, which can be abbreviated as H-test, is a significance test of the difference between two estimates of the same parameter, and is mainly used to determine whether a fixed effects model or a random effects model should be established.

H_0: Individual effects are not related to the regression variables (individual random effects regression model).

H_1: Individual effects are correlated with the regression variables (individual fixed effects regression model).

H Statistic defined as:

$$H = \frac{(\hat{\beta}_W - \tilde{\beta}_{RE})^2}{s(\tilde{\beta}_{RE})^2 - s(\hat{\beta}_W)^2} \sim \chi^2(k) \tag{9}$$

3. Spatial Durbin modeling

3.1. Theories related to spatial panel modeling

Spatial econometric models differ from traditional econometric models in that spatial econometric models take into account spatial interactions between observed individuals, i.e., spatial effects, in the analysis of displayed economic behavior. Traditional econometric models, on the other hand, default to the spatial independence and homogeneity of individuals.

3.2. Forms of spatial linear regression

The generic form of the spatial linear model can be expressed as:

$$\begin{gathered} y=\rho W_1 y+X\beta+\xi \\ \xi=\lambda W_2\xi+\varepsilon \\ \varepsilon \sim N(0,\sigma^2 I_n) \end{gathered} \tag{10}$$

where y is a $n\times 1$-dimensional vector, β is a vector of parameters $(k\times 1)$ associated with the exogenous (explanatory) variables $X(n\times k)$, and W_1 and W_2 are the spatial weight matrices of $n\times n$ associated with the spatial autoregressive process of y and the spatial autoregressive process of the disturbance term ε, respectively. The spatial weight matrices can be row-normalized matrices, binary matrices or other non-normalized matrices. A number of specific models can be derived from the generalized form of the spatial linear regression model.

First-order spatial autoregressive models can be obtained at $\beta=0$ and $W_2=0$:

$$\begin{gathered} y=\rho W_1 y+\varepsilon \\ \varepsilon \sim N(0,\sigma^2 I_n) \end{gathered} \tag{11}$$

The spatial autoregressive model is usually referred to as this model, or SAR for short, in the following form:

$$\begin{gathered} y=\rho W_1 y+X\beta+\varepsilon \\ \varepsilon \sim N(0,\sigma^2 I_n) \end{gathered} \tag{12}$$

where y is the matrix of dependent variables for $n\times 1$ and X is the matrix of explanatory variables for $n\times k$. W is the spatial weight matrix, usually a first-order adjacency matrix, ρ is the coefficient of the spatially lagged dependent variable W_{1y} which is used to express whether there is a significant spatial correlation between the different sample individuals, and β reflects the effect that the explanatory variables have on the dependent variable y . Only one spatial weight matrix exists in this type of model. The model can be interpreted as a standard regression model integrating the spatially lagged dependent variable. It is important to note that the results of the model parameter estimation only indicate an averaged out externality, and externality effects that differ between individuals cannot be captured by the model When $W_1=0$ in the generalized form, a spatial error model is obtained:

$$\begin{gathered} y=X\beta+\xi \\ \xi=\lambda W_2\xi+\varepsilon \\ \varepsilon \sim N(0,\sigma^2 I_n) \end{gathered} \tag{13}$$

The spatial Durbin model adds the spatial lag term of the explanatory variables and the spatial lag term of the dependent variable to the ordinary spatial panel model as shown below:

$$\begin{gathered} (I-\rho W)y=(I-\rho W)X\beta+\varepsilon \\ y=\rho Wy+X\beta-\rho WX\beta+\varepsilon \\ \varepsilon \sim N(0,\sigma^2 I_n) \end{gathered} \tag{14}$$

The model form commonly used for the spatial Durbin model is obtained by an equivalent transformation:

$$y = \rho W y + X\beta + WX\theta + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{15}$$

Compared to ordinary spatial panel models, spatial Durbin models Spatial Durbin models are able to express the dependence that exists between regions on the independent and dependent variables.

3.3. Spatial weighting matrix

In spatial panel analysis, in order to express the proximity relationship between individual observation spaces, it is necessary to define a binary symmetric spatial weight matrix W of the following form:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{16}$$

A spatial distance matrix is a matrix that takes as its starting point the geographic distances between individuals. Among the spatial distance matrices, one type is the binary neighbor weight matrix. If observation unit i and observation unit j have geographically common boundaries, i.e., are neighboring, then $w_{ij} = 1$, otherwise $w_{ij} = 0$. In addition, there are inverse distance matrices, general accessibility spatial weight matrices, and other matrices based on geographic distances between individuals.

3.4. Spatial autocorrelation test

There are many ways to calculate and test whether the financial agglomeration behavior of a region has shown spatial autocorrelation in geospatial space and whether there is a cluster phenomenon, and this paper adopts the MoranI index, which is commonly used at present, to test it. The composition of the spatial autocorrelation test index MoranI is as follows:

$$MoranI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(e_i - \bar{e})(e_j - \bar{e})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{17}$$

Based on the distribution of the spatial data the expected value of the normal distribution MoranI can be calculated $E_n(I) = -\frac{1}{n-1}$:

$$VAR_n(I) = \frac{n^2 w^1 + n w^2 + 3 w_0^2}{w_0^2 (n^2 - 1)} - E_n^2(I) \tag{18}$$

It is possible to test whether spatial autocorrelation exists in the n regions:

$$Z(d) = \frac{MoranI - E(I)}{\sqrt{VAR(I)}} \tag{19}$$

3.5. Tests for random effects

Similar to ordinary panel models, spatial panel models are distinguished between spatial fixed effects models and spatial random effects models. In the ordinary panel, the Hausman test is used to determine whether to build a random effects model or a fixed effects model, and the Hausman test is extended to the spatial panel model with the original hypothesis that there is no correlation between the individual effects and the explanatory variables, that is to say, the random effects model is accepted, and the test takes the following form:

$$H_0 : h = 0 \tag{20}$$

$$h = d'[var(d)]^{-1} d, d = \left[\hat{\beta}' \hat{\delta}\right]'_{FE} - \left[\hat{\beta}' \hat{\delta}\right]'_{RE} \tag{21}$$

$$var(d) = \sigma^2_{RE} \left(X_1' X_1\right)^{-1} - \sigma^2_{FE} \left(X^{*'} X^*\right)^{-1} \tag{22}$$

$$X^* = X - \overline{X}, X_1 = X - (1-\theta)\overline{X}, \theta^2 = \sigma^2 f(T\sigma^2_\mu + \sigma^2) \tag{23}$$

In addition, Elhorst extends the likelihood ratio LR test to spatial panel models. Thus, the LR statistic can be obtained:

$$LR = -2^* (\log liklag - \log liklag_{FE}) \tag{24}$$

3.6. Estimation of direct and spillover effects

Direct and spillover effects are easily obtained from the Durbin spatial model mentioned above. The spatial social bin model is of the form:

$$\begin{gathered} y = \rho W y + X\beta + WX\theta + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I_n) \end{gathered} \tag{25}$$

Thus, the partial differential matrix of the explained variable y for the knd of the explanatory variables ($x_{ik}, i = 1, \cdots, N, i$ denotes the ith spatial observation unit) at moment t is:

$$\begin{bmatrix} \frac{\partial Y}{\partial x_{1k}} & \cdots & \frac{\partial Y}{\partial x_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_k & W_{12}\theta_k & \cdots & W_{1N}\theta_k \\ W_{21}\theta_k & \beta_k & \cdots & W_{2N}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1}\theta_k & W_{N2}\theta_k & \cdots & \beta_k \end{bmatrix} \tag{26}$$

4. Layout of rural e-commerce platform industry development

Rural e-commerce industry development layout shown in Figure 1, rural e-commerce platform also from the past vigorously promote the development of agricultural products on the development strategy gradually shifted to the layout of agricultural products industry development, from research and development, industry chain, sales of several aspects of multi-dimensional assistance to the region to build brands of agricultural products to enhance the value-added of agricultural products in the R & D end of the rural e-commerce platform to set up tens of billions of agricultural research special to improve the quality of agricultural products and scientific production by promoting the wisdom of agriculture. Scientific production, in the supply chain, rural e-commerce platform vigorously promote the development of “more farm” mode, joint government, farmers, new farmers to optimize the rural industry chain, the establishment of regional characteristics of agricultural products brand, in the sales side, the rural e-commerce platform to “more food”, “community group purchase”, “100” and “100”. On the sales side, the rural e-commerce platform expands the sales channels of regional specialty agricultural products with channels such as “DuoDuoBuy”, “Hundred Counties Live” and “Farmers' Festival of Origin”.

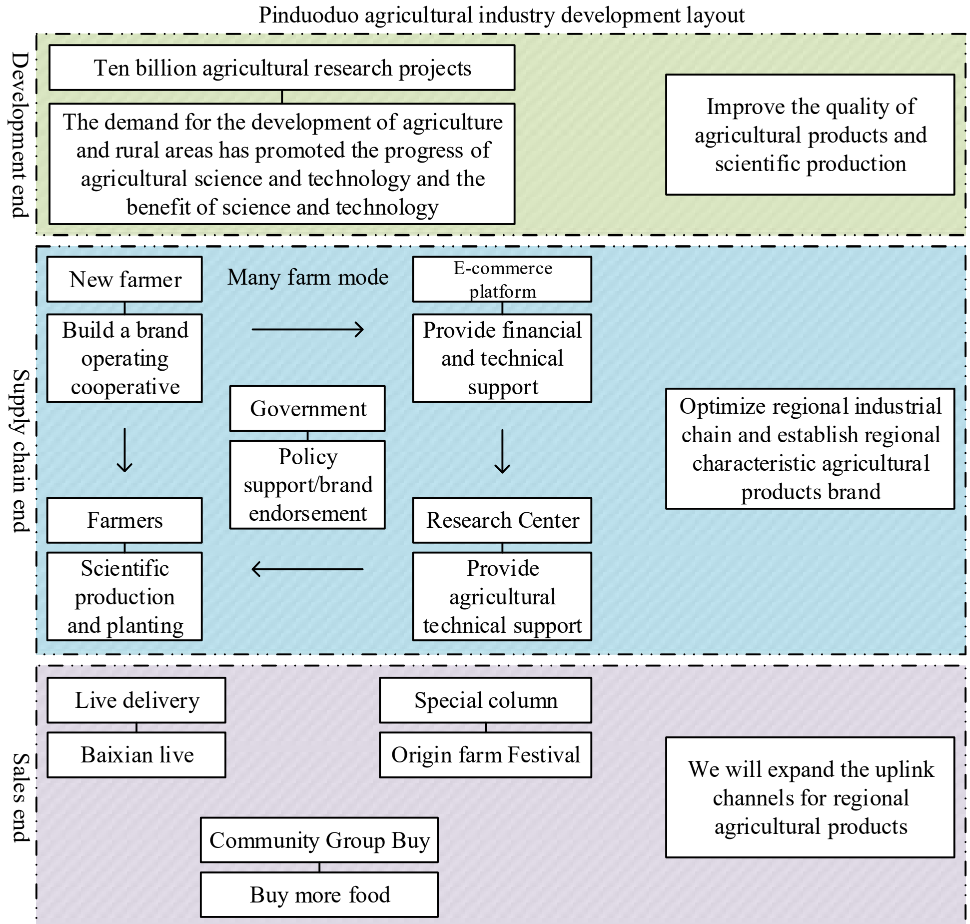

Fig. 1. Rural e-commerce industry development layout

5. Data analysis of the role of rural e-commerce development as an economic driver

5.1. Development of rural e-commerce platforms

China's urban and rural Internet penetration in each half year of the past five years, as shown in Figure 2, China's hardware and software infrastructure development is unbalanced, but with the growth of time, the information barriers between urban and rural areas have been broken down, and the advantageous resources of the city have been gradually spreading to the rural area, which has gradually narrowed this gap. As can be seen from the figure, the growth rate of Internet penetration in rural areas in the past five years is significantly higher than that in urban areas, in which the rural Internet penetration rate has doubled, and as of June 2023, the Internet penetration rate in urban areas is 82.19%, while that in rural areas is 58.48%.

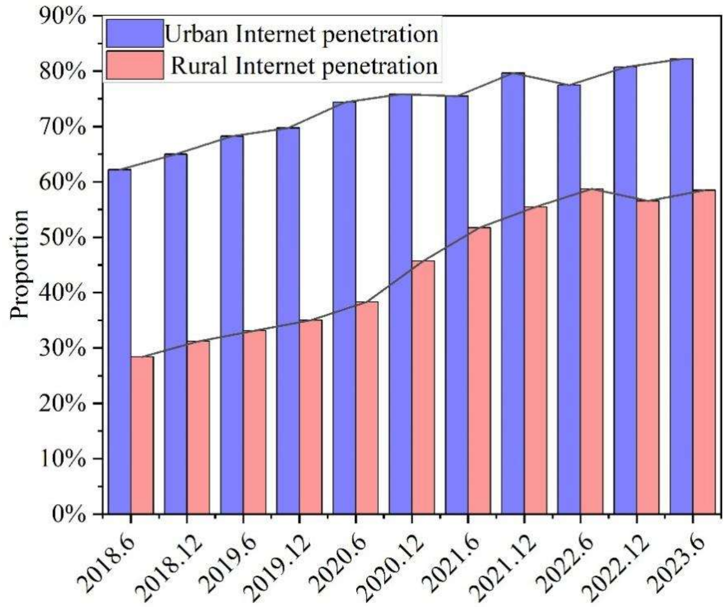

Fig. 2. The popularization of urban and rural Internet in China

By analyzing the development statistics of Taobao villages and Jinduoduo villages in China from 2013 to 2023, as shown in Figure 3, the development of Taobao villages has gone through three phases. 2013-2017 is the budding period of Taobao villages and Jinduoduo villages, rural areas have just been exposed to e-commerce, and Taobao villages and Jinduoduo villages have formed a large-scale and very slow growth. The growth rate is extremely slow. 2017-2020 period, the expansion rate is multiplied, through the government's orderly guidance and people's recognition of e-commerce, Taobao Village and Pinduoduo Village is developed in a cluster mode, the industrial development and the gradual improvement of supporting facilities, the trend of full expansion. As the government's support for rural e-commerce continues to increase, more and more rural e-commerce platforms have emerged. For example, Alibaba's “Village Amoy”, Jingdong's “Jingdong Rural”, etc., the number of e-commerce platforms show a year-on-year increase in the trend. Commodity varieties continue to increase, rural e-commerce involves more and more varieties of commodities, including not only traditional agricultural products and local specialties, but also daily necessities, clothing, home appliances, etc., to meet the diversified consumption needs of rural residents. The service scope is expanding, with the continuous development of rural e-commerce platform, the service scope is also becoming more and more extensive, including not only the sale of goods, but also logistics and distribution, after-sales service, etc., which provides rural consumers with a more convenient shopping experience. To summarize, the scale of rural e-commerce is expanding, which is manifested in the growth of transaction volume, the number of e-commerce platforms, the variety of commodities, the expansion of the scope of services, etc. In the future, rural e-commerce is expected to usher in a more broad space for development.

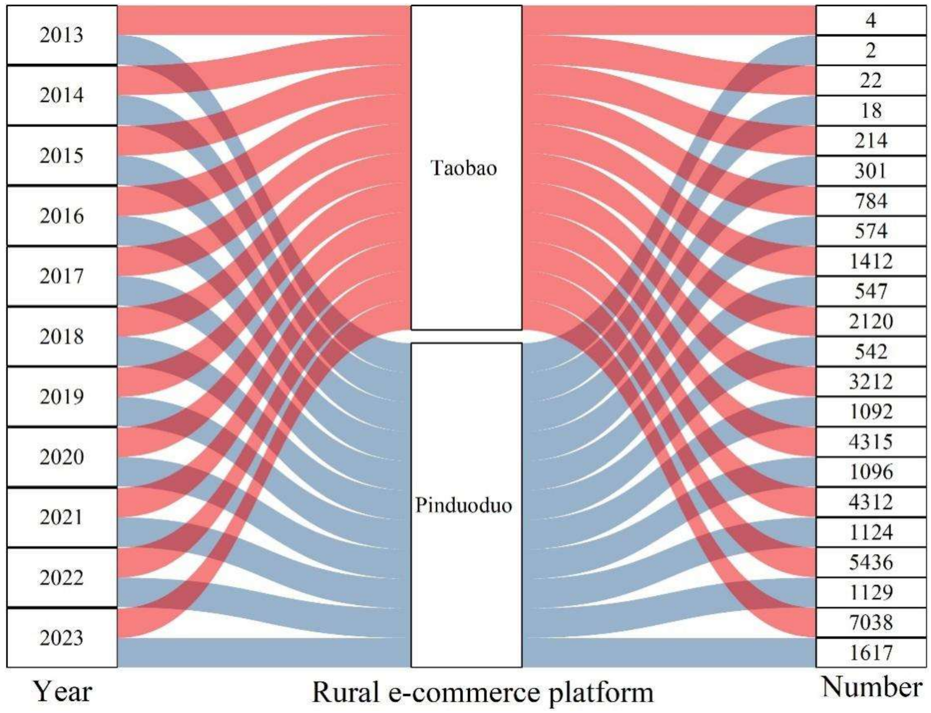

Fig. 3. Development trend of rural e-commerce platform

5.2. Empirical analysis of the economic impact of rural e-commerce development

5.2.1. Preliminary Estimates of Fixed Effects Models. Fixed effects used in this paper: the fixed effects model, also known as the fixed effects regression model, which is an analytical method based on the manifestation of the panel data form. The e-commerce development and agricultural economy of 348 rural villages nationwide from 2013-2023 from the National Bureau of Statistics is selected as the research object. lnGDP indicates the total output value of agriculture, forestry, animal husbandry and fishery in billions of yuan, lntb is the number of Taobao villages, lntd is the kilometers of rural delivery routes, and lnkdjr is the 10,000 users of rural broadband access, and the variables of lntb, lntd, and lnkdjr The direction of the coefficient $\beta 1$ coefficient is the main observation of this paper and indicates the coefficient of the impact of rural e-commerce on rural agricultural income affecting income, Xit denotes the control variable, which may affect the impact on rural agricultural income, ui denotes that the individual effect of each province does not change over time, and γi denotes the time fixed effect that does not change with individual differences between cities, εit denotes a random perturbation term, ***P<0.01,**P<0.05,*P<0.1, and the results are shown in Table 1.

The impact of the number of Taobao villages, kilometers of rural delivery routes, and 10,000 rural broadband access users on rural agricultural income. Model (1) takes the total output value of agriculture, forestry, animal husbandry and fishery of 100 million yuan as the explanatory variable, the number of Taobao villages as the explanatory variable, model (2) takes the total output value of agriculture, forestry, animal husbandry and fishery of 100 million yuan as the explanatory variable, the kilometer of rural delivery routes as the explanatory variable, model (3) takes the total output value of agriculture, forestry, animal husbandry and fishery of 100 million yuan as the explanatory variable, and 10,000 users of rural broadband access as the explanatory variable, and the coefficients are now used to analyze whether there are favorable impacts of the development of e-commerce on the rural agricultural income Whether there is a favorable impact. The coefficients of model (1)-(3) are 0.0156, 0.0781, 0.0442, all significant at 1%. From these coefficients, we can see that the better the development of rural e-commerce on rural agricultural income brings more and more obvious benefits, more favorable to the development of agriculture.

Table 1. Preliminary estimate of the fixed effect model

	(1)	(2)	(3)
	r1	r2	r3
VARIABLES	InGDP	InGDP	InGDP
Intb	0.0156*** (3.26)		
intd		0.0781*** (2.76)	
Inkdjr			0.0442*** (3.25)
Inrj	0.6782*** (12.58)	0.2193 (0.98)	1.3028*** (5.24)
Inls	0.3280 *** (6.29)	0.3174 *** (5.02)	0.2815*** (5.22)
Inwd	-0.0145 (-1.12)	-0.0231 (-1.34)	-0.0028 (5.22)
Inpjl	-0.0125 (-0.76)	0.1374 (1.32)	-0.4120*** (-5.03)
Innyjx	0.1495*** (4.38)	0.1266*** (3.08)	0.1349*** (3.92)
Inyxgg	0.0865 (0.98)	0.1885*** (3.05)	0.1357*** (3.96)
Indfcz	-0.0324 (-0.79)	0.0378 (0.68)	0.0396 (0.98)
Inrgel	0.1648*** (8.29)	0.1768*** (7.45)	0.1352*** (7.04)
Constant	-3.3012*** (-6.38)	-1.1715 (-0.69)	-8.3452*** (-5.47)
Observation	348	348	348
R-squared	0.876	0.825	0.896
Number of code	32	32	32
R2_a	0.865	0.775	0.874
F	213.2	70.74	128.10

5.2.2. Robustness Tests. The results of the robustness test are shown in Table 2. This paper used lag one period, delete the sample size and replace the model OLS to do, the results are as follows: from the lag one period of the results can be seen, in the lag one period of all the explanatory variables to carry out the study and the results of the study are positive and significant (0.0156, 0.0635, 0.0563), there is no reverse causality of the possibility of the development of rural e-commerce, the better the development of rural agriculture, the income of rural agriculture each year The better the development of rural e-commerce the better the income of rural agriculture every year. The faster the development of e-commerce in the countryside, the more farmers are exposed to the network, the more they know about e-commerce.

Table 2. Robustness test results

	(1)	(2)	(3)
	r1	r2	r3
VARIABLES	InGDP	InGDP	InGDP
L intb	0.0156*** (2.85)		
L intd		0.0635** (2.45)	
L inkdjr			0.0563*** (4.13)
Inrj	0.5427*** (6.58)	0.3206 (1.46)	1.2475*** (6.32)
Lnls	0.3875*** (6.25)	0.3252*** (4.62)	0.2668*** (4.58)
Inwd	-0.0130 (-72)	-0.0202 (-1.08)	0.0032 (0.19)
Inpjl	0.1578*** (2.78)	0.2405 (1.02)	-0.9028*** (-4.32)
Innyjx	0.1805*** (4.56)	0.1429*** (3.16)	0.1416*** (3.95)
Inyxgg	0.2306** (2.15)	0.1925 (1.49)	0.2136** (2.25)
Indfcz	-0.0254 (-0.56)	0.0054 (0.09)	0.0054 (0.12)
Inrgcl		0.1536*** (6.28)	0.1248*** (6.45)
Constant	-3.3875*** (-4.79)	-2.3462* (-1.89)	-6.2036*** (-5.39)
Observation	348	348	348
R-squared	0.820	0.795	0.885
Number of code	32	32	32
R2_a	0.805	0.756	0.863
F	154.8	56.63	110.8

5.3. Study on the impact of rural e-commerce development on urban-rural income gap

5.3.1. Spatial Durbin model regression results. Data on per capita disposable income of urban and rural residents as well as regional population of 11 prefecture-level cities in a province are collected. Where theil denotes the urban-rural income gap, X denotes the level of rural e-commerce development (tbc) and five control variables, which are the level of economic development (gdp), communication infrastructure (cinfra), the level of human resources (edu), the degree of openness to the outside world (exp), and transportation infrastructure (tinfra). Local effects are first analyzed based on the regression results of the spatial econometric model. The regression results of the spatial Durbin model are shown in Table 3, and the coefficient of the core explanatory variable rural e-commerce development level is -0.640, and it is significant at 1% level. There may be the following reasons for this conclusion: the development of rural e-commerce allows agricultural products to be directly oriented to consumers, which reduces intermediate links and improves farmers' income. Secondly, e-commerce provides more employment opportunities in rural areas and increases farmers' income sources. In addition, e-commerce has led to the upgrading of rural industries and technological progress, improving the added value of agricultural products and increasing farmers' income. Finally, e-commerce also promotes the flow and exchange of information between urban and rural areas, broadening farmers' horizons and opportunities. Among the five control variables, the level of economic development has a significant contribution to the reduction of the urban-rural income gap, with an estimated parameter of -0.022. Analyzing the reasons for this may be: prefecture-level cities in a province with a high level of economic development can provide farmers with more employment opportunities, which will lead to better development of rural areas, better in all aspects, and better able to raise the income of rural residents. The inhibitory effect on the reduction of the urban-rural income gap is communication infrastructure, transportation infrastructure, the estimated parameters of which are 0.004, 0.005, significant at the 1% level and 10% level, respectively, indicating that the improvement of either communication infrastructure or transportation infrastructure will widen the urban-rural income gap. This paper suggests that the reason for this may be that infrastructure improvement in cities is faster, while infrastructure development in rural areas is relatively slow, thus creating an imbalance that leads to the widening of the gap.

Table 3. The spatial measurement model returns

VARIABLES	Main effect
The development level of rural e-commerce	-0.640** (-10.550)
Economic development level	-0.022*** (-7.038)
Communication infrastructure	0.004*** (3.320)
Human resource level	0.002 (0.956)
Openness	-0.002 (-1.152)
Transportation infrastructure	0.005* (1.928)
WX	
The development level of rural e-commerce	2.446*** (5.586)
Economic development level	0.002 (0.647)
Communication infrastructure	0.009*** (13.436)
Human resource level	-0.032*** (-3.745)
Openness	-0.001 (-1.063)
Transportation infrastructure	-0.012** (-2.087)
Spatial: rho	0.389*** (6.506)
sigma2_e	0.001*** (5.611)
N	120
R2	0.232

5.3.2. Effect decomposition. The effect decomposition is shown in Table 4, the direct effect of the level of rural e-commerce development on the urban-rural income gap is -0.293, which is significant at the 1% level, i.e., the enhancement of the level of rural e-commerce development reduces the urban-rural income gap in a certain province, which is consistent with the results of the model estimation in Table 3. The indirect effect of rural e-commerce development on the urban-rural income gap is 2.875, which is significant at the 1% level, indicating that an increase in the level of e-commerce development in this region can widen the urban-rural income gap in neighboring regions, which is still consistent with the results in Table 3. The enhancement of the level of human resources in neighboring regions contributes to the reduction of the local urban-rural income gap. Among the other control variables, the direct and indirect effects of communication infrastructure are both significantly positive, indicating that the improvement of communication infrastructure in both the region and neighboring regions will expand the local urban-rural income gap.

Table 4. Effect decomposition

Variable name	Direct effect	Indirect effect	Total effect
The development level of rural e-commerce	-0.293*** (-4.532)	2.875*** (6.432)	2.583*** (5.553)
Economic development level	-0.017*** (-7.115)	-0.008* (1.912)	-0.024*** (-4.716)
Communication infrastructure	0.004*** (5.982)	0.014*** (2.947)	0.016*** (3.876)
Human resource level	-0.004 (-0.903)	-0.042*** (-4.311)	-0.040*** (-3.623)
Openness	-0.003 (-0.614)	-0.005 (-0.175)	-0.005 (-0.242)
Transportation infrastructure	0.002 (0.546)	-0.022 (-4.583)	-0.015 (-1.072)

6. Conclusion

This study measured the impact effect of the development of rural e-commerce platforms on economic development by using fixed effect model and spatial Durbin model qualitative analysis and quantitative simulation. Through empirical analysis and research, the following conclusions are drawn:
1) The rural Internet penetration rate and the number of e-commerce villages grow significantly over time, with Taobao villages reaching 7,038 in 2023.
2) Rural e-commerce has a significant contribution to agricultural economic growth. Rural e-commerce increases the sales channels of rural products, while increasing the income of rural residents.
3) The coefficient of the level of rural e-commerce development is significantly negative, implying that increasing the level of rural e-commerce development in a province can reduce the urban-rural income gap.

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