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Smart Tourism Cities and Income Equity: How Digital Economy Reshapes Urban-Rural Disparities

Jia Wang[1], Hangdi Zhao[1,*]

[1] Macau University of Science and Technology, Macau, China

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ABSTRACT

In the context of the rapid rise of the digital economy, comprehending its role in shaping urban-rural income dynamics has become increasingly critical. This study focuses on smart tourism cities (a hallmark of the digital economy) to examine how the digital economy influences the urban-rural income gap from a tourism perspective. Despite the growing prominence of the digital economy, its specific impact on urban-rural income disparities in tourism-dependent regions remains underexplored, motivating this investigation. This study selects 71 key tourism cities over the period 2012–2019 and employs advanced analytical methods, including mediating effects analysis, multi-period Difference-in-Differences (DID) testing, instrumental variable approaches, robustness testing, and heterogeneity analysis. The findings indicate that: first, the digital economy significantly reduces the urban-rural income gap in tourism cities; second, tourism serves as a key mediating variable in this process; third, after conducting an exogenous shock test using a multi-period DID econometric model based on the "Broadband China" initiative, the conclusions remain robust; fourth, the digital economy's impact on narrowing the income gap is particularly pronounced in second-tier and lower-tier cities, especially in third-tier and lower-tier cities, while no significant effect is observed in first-tier cities. In summary, the development of the digital economy effectively narrows the urban-rural income gap in tourism cities. Therefore, governments should prioritize enhancing the construction of smart and digital tourism cities to further promote balanced regional development.

1.Introduction

1.1 Research Background

The Digital Economy (DE) has become a global catalyst for reshaping economic growth, productivity, and social inclusion. Technologies like high-speed internet, e-commerce, mobile platforms, and digital finance are widely recognized as tools for promoting sustainable development and addressing structural challenges such as income inequality, market inefficiencies, and geographic

* *Corresponding author.*
E-mail address: z18538012698@163.com

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isolation [1]. Globally, the DE has enhanced service delivery, expanded entrepreneurship, and promoted financial inclusion, particularly in bridging urban-rural divides. However, its impact varies significantly across countries, depending on digital infrastructure, policy support, and ecosystem maturity.

With the accelerated innovation of technology, deep integration of the DE and the substantial economy, has received a strong boost to China's economy. Specifically, by 2020, the value added of China's DE had soared to 39 trillion yuan, accounting for approximately 39% of the Gross Domestic Product [2]. This value has been steadily expanding at a growth rate close to 10% in recent years. By 2022, this number is expected to reach 50.2 trillion yuan, constituting a significant 41.5% of the GDP and placing second globally in overall volume [3]. These findings collectively suggest that the DE has emerged as a crucial element within the framework of China's economic progression and a pivotal force propelling sustained economic expansion.

Meanwhile, in China, there is an urgent need to transform from a traditional-type economic development model to a more advanced one. The DE is seen as the main driving force. But does DE really promote it? If the effect does exist, what is its mechanism? In response to the above questions, current empirical studies in pertinent literature generally focus on the influence of the DE on entrepreneurial activity [4,5], the level of innovation [6], total factor productivity [7], inclusive growth [8], and corporate governance [9]. However, high-quality economic development involves various aspects of society, including but not limited to the above. As one of its important components, tourism has intricate connections with the DE.

1.2 Research Purpose

The DE and tourism have seen the former's swift expansion present fresh opportunities for the latter [10]. However, has the advancement of the digital realm truly catalyzed the flourishing of tourism? Moreover, has it succeeded in diminishing the inequality between urban and rural communities in tourism cities? If this effect is confirmed, what is the underlying mechanism?

Conventional theoretical research has deduced that the influence of the DE on the income gap of urban-rural (Theil) is far-reaching and comprehensive: firstly, for micro perspective, the development of electronic information and other emerging technologies disperses the information barriers, reduces transaction costs, increases the number of jobs, and creates more opportunities for entrepreneurship [9], which narrows the inequality of urban and rural; second, at the macro level, the overall efficiency of societal inputs has been increased [11,12], and thus the inequality of urban and rural has been reduced, through technological factor progress [9], the modification of industrial composition [4,13], and the reconfiguration of labor and capital [14]. However, from the perspective of tourism, through what path does DE mainly affect the levels of urban and rural inequality? This existing literature does not provide a complete framework for explaining the issue. In this regard, this study considers rural tourism and selects China's major tourist cities as the research object, to analyze and discuss the DE, tourism and urban-rural income gap in a more comprehensive manner.

1.3 Research Methodology

This study employs a combination of theoretical analysis, literature review, and empirical modeling to examine the relationship between the digital economy, tourism development, and urban-rural income disparity in Chinese tourism cities. It synthesizes existing research and economic data to establish the context of the study and identify gaps in the literature. The research hypotheses were developed on the basis of theoretical insights from economic development, digital transformation, and tourism impact studies. Empirically, the study used panel data from 71 key tourism cities (2012–2019) and applied econometric techniques, including fixed effects regression, mediation analysis, robustness tests, heterogeneity analysis, instrumental variable methods, and multi-period Difference-in-Differences (DID) analysis based on the "Broadband China" policy, to rigorously test the proposed hypotheses and explore causal relationships.

In detail, this study establishes an analytical framework through the lens of rural tourism, assessing the progress of the DE and the current state of the urban-rural income disparity (Theil) in key tourism cities nationwide from 2012 to 2019, and empirically analyzes the influence of the DE on the disparity between urban and rural incomes in tourism cities and its path using mediation effect, robustness test, heterogeneity test, and multi-period DID.

1.4 Research Innovations

The potential incremental contributions of this study encompass the following: first, it re-measures the degree of DE and Theil in tourism cities and explores the relationship between the two from a more detailed perspective. Second, this article investigates the mechanisms through which the DE influences Theil, viewed through the lens of rural tourism. This study validates the intermediary function of rural tourism in the DE's influence on Theil, thereby expanding the scope of current scholarly work. Finally, this study conducts an exogenous shock test with the help of the "Broadband China" policy. The same conclusion is reached, which enhances the credibility of the research findings.

2. Literature Review

2.1 Research on the Correlation between DE and Income Inequality between Urban and Rural Areas

Current scholarly works broadly concur that the DE fosters increased income for all residents via multiple approaches, such as incentivizing entrepreneurship, increasing employment, and regional synergistic development [15]. However, has the DE contributed more to the rise in urban or rural incomes? How does it ultimately affect income inequality between urban and rural areas? Academics have yet to reach a unified conclusion on this question.

Based on electronic information technology, DE integrates artificial intelligence and other new business forms with traditional rural industries, allowing the digital dividend to penetrate rural areas [16]. Its impact on the disposable income of rural residents can be divided into direct and indirect effects [9,17]. First, the direct effect is manifested in the fact that DE, by virtue of its high integration ability, not only reshapes the sales and transportation patterns of products in rural areas, but also effectively integrates different factors of production and breaks down the barriers to the flow of factors of production [11]. Second, the indirect effect is that the DE promotes the improvement of tourism production efficiency through different channels by relying on e-information technology [8].

Therefore, certain academics posit that the digital dividend accruing to rural regions significantly exceeds that of urban counterparts, thereby facilitating the DE's role in diminishing the income inequality between urban and rural areas.

However, several scholars have noted that the development of the DE is inextricably linked to the construction of digital infrastructure and the ability to collect, process, and analyze data. Compared with urban areas, rural regions have weaker digital infrastructure. For the ability to analyze data, rural workers are much lower than urban workers, which means the problem of the "digital divide" has not yet been effectively avoided [18]. Because the problem has not been effectively circumvented [19], it may trigger a series of inequities that affect rural revitalization. As a result, urban regions can reap greater digital benefits, thereby expanding the income disparity between urban and rural areas.

In short, from different perspectives, the outcomes of DE's influence on the urban-rural income disparity vary. Therefore, drawing from the preceding analysis, the following hypotheses are proposed in this research:

H1: DE's growth impacts income disparity between urban and rural areas.

2.2 Linkage between DE and Rural Tourism

The existing challenges within China's rural tourism include a lack of intrinsic motivation, variability in the quality of attractions, and scarcity of cultural preservation efforts. These factors collectively hinder the sector's development and its ability to attract and satisfy tourists. Addressing these multifaceted problems is crucial for enhancing the overall appeal and sustainability of rural tourism in the country. Electronic information technology can upgrade the traditional rural tourism industry, enhance its endogenous power, and open new opportunities for its development. Specifically, DE influence on rural tourism is delineated into four distinct dimensions:

First, for economic development, DE fosters the increase of the local GDP and increases the disposable income of residents. An increase in income has boosted consumer demand for tourism [8], accelerating the growth of rural tourism.

Next, for technological advancement, the information-sharing function brought by DE accelerates the technological innovation of the tourism industry [8]. In line with the theory of endogenous economic growth, technological innovation will further promote the growth of the tourism economy.

Finally, from the output efficiency perspective. By virtue of its own characteristics, the DE breaks the boundaries to the movement of production inputs [20], reallocates and utilizes resources, promotes the structural upgrading of the tourism sector, improves the overall productivity of inputs in the tourism sector, and then promotes the economic growth of the tourism industry [21].

The digital economy acts as a catalyst for industrial upgrading from the perspective of industrial economics by reducing transaction costs, enhancing market efficiency, and promoting innovation-driven competition [22]. The integration of digital technologies into traditional sectors such as tourism reshapes industry structures by lowering information asymmetries, broadening market reach, and improving resource allocation [23]. Furthermore, digital platforms foster new business models and value chains, stimulating dynamic adjustments within the tourism industry and driving regional economic development [24].

In short, DE can spur the expansion of the tourism sector via a range of mechanisms, including the wealth effect and technological advancements, efficiency improvement, and industrial upgrading. Consequently, the following hypotheses are proposed in this study:

H2: DE can foster the tourism sector's advancement.

2.3 Study on Correlation between Rural Tourism and the Urban-rural Income Disparity

First, seen from the angle of regional industrial integration, rural tourism is based on natural scenery, cultural monuments, local customs, and agriculture. Concurrently, the technology and economy generated through the advancement of rural tourism industry feedback to agriculture, driving agricultural development and thus fostering an increase in farmers' earnings [25].

Secondly, for regional industry coordination, the advancement of rural tourism is inextricably linked to the establishment of infrastructure, which requires substantial financial investment. Therefore, the advancement of rural tourism is beneficial for enriching regional foreign exchanges, broadening regional investment and financing channels, and driving the development of rural tourism with investment. The economic spillover brought about by tourism development drives the growth of rural tourism aids in the progression of other regional industries, fosters the harmonized advancement of primary, secondary, and tertiary sectors in rural regions [26], alleviates problems such as unreasonable distribution of rural resources, promotes the all-round development of rural economy, and further increases farmers' income.

Finally, from the perspective of labor demand: first, as a service sector, the robust growth of rural tourism has the capacity to draw in a multitude of labor forces [8], including a significant number of high-caliber talents who return to their hometowns to launch enterprises, to promote employment and raise the average income level of rural inhabitants [27]; Second, rural tourism can promote the growth of clothing, food, housing, transportation, entertainment and other industries in rural areas, leading to a rise in labor demand [14]. Therefore, it promotes the career transformation of residents from farmers to workers and increases the income of rural residents.

The digital economy reshapes markets by lowering transaction costs, expanding access, and promoting industrial upgrading, thus influencing income distribution between urban and rural areas [22,28,29]. Digital platforms enable rural producers to access wider markets, fostering entrepreneurship and employment [17]. International research has shown that digital technologies, such as mobile banking and e-commerce, can reduce income inequality by integrating rural economies with infrastructure and skills [30,31]. However, scholars warn that if access is unequal, the digital divide may worsen disparities [32]. Thus, the effect DE's on the urban-rural income gap hinges on both opportunity creation and equitable digital access [9].

Due to regional restrictions, the growth of rural tourism exerts a significantly less influence on the earnings of urban dwellers compared to rural inhabitants. Therefore, drawing on the foregoing analysis, this study proposes the following hypothesis:

H3: Rural tourism has the potential to reduce the income gap between urban and rural areas.

2.4 Mechanism through which DE Influences the Urban-rural Income Divide

The digital economy reshapes production, distribution, and consumption by leveraging information technology to reduce transaction costs, enhance transparency, and improve resource allocation [22,21]. At the macro level, industrial upgrading and technology diffusion are promoted, extending economic opportunities to rural areas through better market access and services. At the micro level, digital platforms lower entry barriers for rural entrepreneurs, create jobs, and integrate small producers into larger value chains, effects that depend on access to infrastructure and skills [9,32].

Rural tourism acts as a key channel for transferring the benefits of the digital economy to rural communities by expanding market reach, increasing efficiency, and attracting investment [8,16]. This supports local employment, stimulates related industries, and helps integrate rural areas into regional economies, contributing to narrowing the urban-rural income gap.

Promoting rural tourism development through digital technology benefits by upgrading urban and rural tourism industry structure and economic development [33], enhancing the urban and rural digital level and material economic prosperity, thus narrowing the urban-rural income gap [34,35]. Therefore, this study proposes the following hypothesis:

H4: Indirect effect is that the DE can narrow it by promoting rural tourism development.

3. Research Design

The study's methodology followed a structured framework, beginning with the establishment of a Theoretical Framework and subsequent Data Collection. Variable Construction and Model Building led to the core analysis, which included rigorous Robustness Checks and an Endogeneity Test. The final analysis incorporated Heterogeneity Analysis and a DID Test to evaluate specific impacts, with the entire process culminating in the Interpretation & Recommendations section (see figure 1).

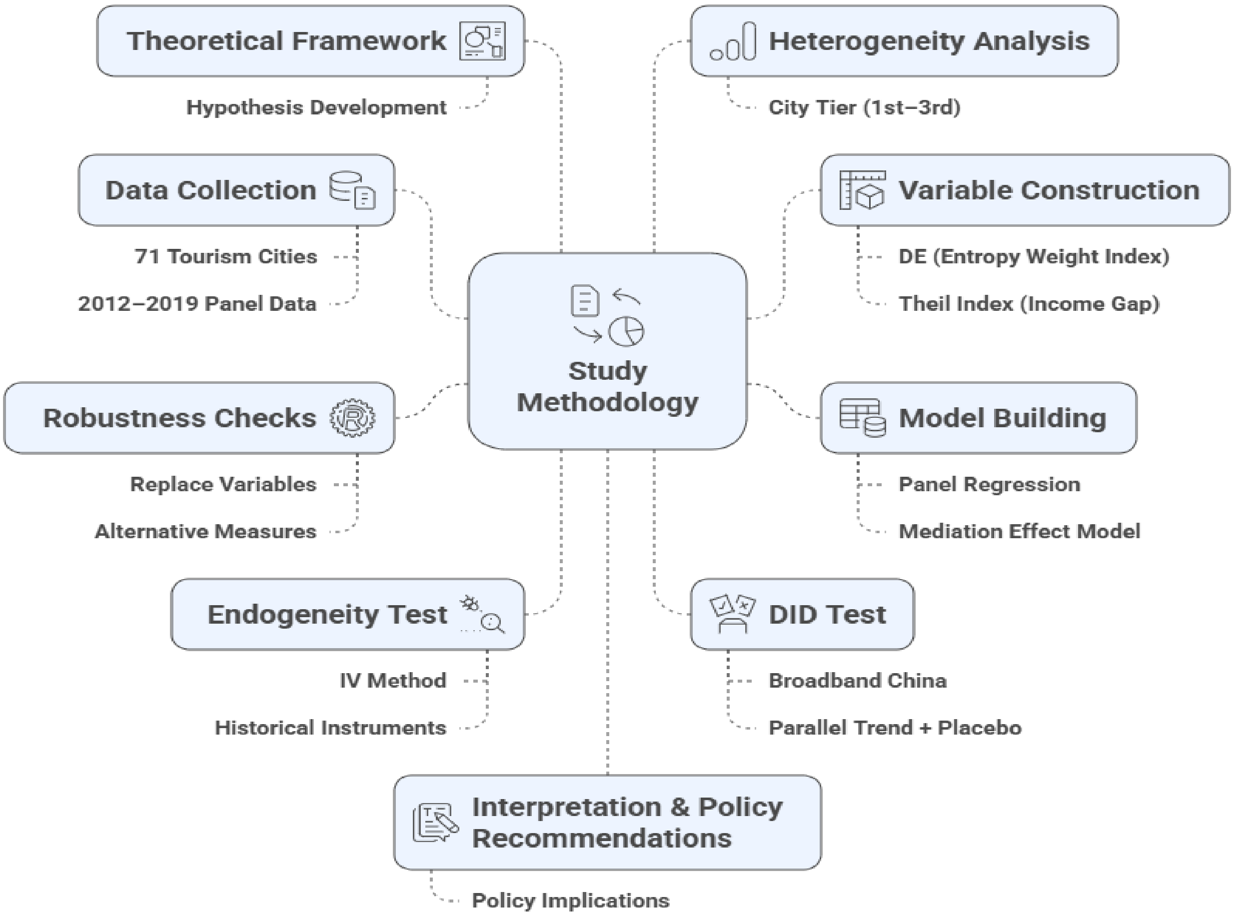

Fig. 1. Study Methodology Flowchart

3.1 Models

Grounded in the above research hypotheses, this study constructs the model presented below based on a three-step method of mediating effect. First, the formula depicting DE's direct contribution to the urban-rural income divide is provided hereafter:

$$Theil_{i,t} = \alpha_0 + \alpha_1 Dige_{i,t} + \alpha_2 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{1}$$

About the equation, $Theil_{i,t}$ denotes the urban-rural income disparity, $Dige_{i,t}$ signifies the extent of DE, the vector$Z_{i,t}$ represents the ith control variable in period t, μ_i represents individual fixed effect, δ_i means time effect; $\varepsilon_{i,t}$ is the random error, i is city, t is year.

Secondly, based on the research hypothesis, the model is constructed as shown below:

$$Lntr_{i,t} = \beta_0 + \beta_1 Dige_{i,t} + \beta_2 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{2}$$

$$Theil_{i,t} = \gamma_0 + \gamma_1 Dige_{i,t} + \gamma_2 Lntr_{i,t} + \gamma_3 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{3}$$

Combined with equation (1), the specific validation idea is as follows: first of all, regress the DE with the income imbalance between urban and rural communities, and when the regression coefficient α_1 is significant, continue to construct the regression equation between the DE and the tourism development index, as well as the regression equation between the DE and the tourism development index on the urban-rural earnings discrepancy, and lastly, through the importance of regression coefficient values of the equations (1-3) to determine whether the level of tourism development is a mediating variable.

3.2 Measurement and Description of Variables

3.2.1 Dependent Variables: indicators of urban-rural income disparity

The earnings gap between the city and the countryside is measured in three ways: the income ratio between city and countryside residents, the Theil index, and the Gini coefficient. Among them, only the Theil index considers the impact of population change. It decomposes the earnings gap between city and countryside into the gap between urban and rural, urban and urban, and rural and rural, more representative of the urban-rural income difference. Hence, this study utilizes the Theil index to quantify the urban-rural income difference. The relevant equation is presented as:

$$Theil_{i,t} = \sum_{i=1}^{2}\left(\frac{y_{i,t}}{y_t}\right) \times ln\left[\frac{y_{i,t}}{y_t} / \frac{x_{i,t}}{x_t}\right] \tag{4}$$

The higher the value, the more pronounced the disparity between urban and rural income, where, t represents year, $i = 1$ & $i = 2$ denotes respectively urban and rural, y represents disposable income, x represents population.

3.2.2 Explanatory Variables: indicators of the DE's level

Liu Jun [36] indexed the DE’s status in Chinese provinces through three aspects of informatization, the Internet, & digital transactions. On this basis, Zhao Tao [4] indexed the degree of DE in China's cities by using the PCA (principal component analysis) method.

Building on this foundation, this study takes the accessibility of data into consideration and draws on the methods of previous scholars, and will re-measure the degree of tourist cities’ DE. The detailed assessment indicator framework is illustrated in Table 1 below.

Table 1
DE level index framework

			Measurement	Unit	Properties
Level of the DE	Internet level	Internet usage rate	Internet broadband access for every 100 people	Classifier for households	Positive
		Practitioners	percentage of staff in IT services compared to all employees in businesses	%	Positive
		Relevant outputs	Telecommunication services output per inhabitant	Yuan	Positive
		Cell phone penetration rate	Number of cell phone subscribers per 100 population	Classifier for households	Positive
	Digital finance	DFI	Digital Financial Inclusion Index (DFII)	-	Positive

The determination of the evaluation index system of the DE index is only the first step; to accurately calculate the level of DE development, it must be combined with the corresponding weights. Determining the weights involves choosing between two main methods of empowerment: qualitative and quantitative. The qualitative method relies on personal judgment and experience, which can be highly subjective and less scientific. Conversely, the quantitative method uses objective, mathematical techniques like entropy weighting and Principal Component Analysis (PCA) to assign weights more systematically and accurately.

Owing to the relatively recent advancement of the DE, this study employs an objective weighting technique to calculate the weights from the perspective of the data itself [37]. Specifically, this study utilizes entropy weight method to ascertain the weighting of every indicator within framework, which is based on the principle of entropy value and the calculation formula to determine the indicator's importance.

Before determining the weights, to remove the impact of indicator units as well as positive and negative, the data must be positively oriented first, and the specific processing equation is presented as:

Positive indicators:

$$Z_{\theta ij} = \frac{x_{\theta ij} - min\{x_{.j}\}}{max\{x_{.j}\} - min\{x_{.j}\}} \times 40 + 60 \tag{5}$$

Negative indicators:

$$Z_{\theta ij} = \frac{max\{x_{.j}\} - x_{\theta ij}}{max\{x_{.j}\} - min\{x_{.j}\}} \times 40 + 60 \tag{6}$$

Among these,$X_{\theta ij}$denotes the number of i city's j indicator in θth year,$Z_{\theta ij}$denotes the result of the normalization process. $max\{x_{.j}\}$ represents peak value of j indicator, $min\{x_{.j}\}$ represents opposite side.

Once the data has been normalized, calculating the weight of the *j*th individual indicator for the *i*th city becomes necessary, as detailed in the following formula:

$$P_{\theta ij} = \frac{Z_{\theta ij}}{\sum_{i=1}^{m} Z_{\theta ij}} \tag{7}$$

Next, calculate data entropy e_j and coefficient of variation g_j via the following formulas:

Information entropy:

$$e_j = \frac{\sum_{\theta=1}^{r}\sum_{i=1}^{m} P_{\theta ij} \ln P_{\theta ij}}{ln(\theta \times m)} \tag{8}$$

Coefficient of variation:

$$g_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} \tag{9}$$

among these, when$0 \le g_j \le 1, \sum_{j=1}^{n} g_j = 1$

Indicator weight is derived as:

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{10}$$

After determining the weights, they are weighted and summed with the indicator data obtained from equations (5) and (6) to obtain the DE degree score of ithcity's jth indicators in the θ year, as shown in the following formula

Once weights are determined, then calculate DE score via the following formula:

$$y_{\theta i} = \sum_{j=1}^{n} w_j Z_{\theta ij} \tag{11}$$

3.2.3 Mediating Variable: measurement of rural tourism development level

Rural tourism broadens farmers' income through regional industrial integration, coordination, and labor demand and improves farmers' income levels. The more advanced the degree of rural tourism, the greater the benefits it brings. Based on this, this study chooses total tourism income as the criterion for assessing the development stage of rural tourism.

3.2.4 Control Variables

It is essential to manage a range of factors that could influence the dependent variable (the Theil index) to maintain the objectivity and reliability of empirical outcomes. The control variables chosen for this study include, as in Table 2.

Table 2
Variable definitions

Categories	Variables' name	Variable abbreviation	Explanation of indicators
Explained variable	Income inequality of urban-rural	Theil	Theil index
Core explanatory variable	Degree of DE	DE	Entropy weight method
Intermediate variable	Rural tourism	tr	(Domestic tourism revenue + international tourism revenue exchange rate)/Gross regional product
Control variables	Urbanization level	Urban	Urban resident population/total population
	Educational level	Edu	the enrollment rate of pupils in colleges, averaging per ten thousand individuals
	Openness to the outside world	Open	Total imports and exports /GDP
	Industrial structure	Tertiary	Value contribution of the service sector to GDP
	Financial support	Finance	The year-end balances of deposits and loans held by financial entities
	Fiscal expenditure	Gov	Government expenditure /GDP

The six control variables were chosen for their proven influence on income distribution in economic studies. The level of urbanization affects labor shifts and income structures [8], whereas industrial structure influences labor absorption and regional disparities [26]. Educational level shapes human capital and wage gaps and the level of openness serves as an indicator of trade's influence on regional income [38]. Fiscal expenditure affects redistribution and poverty, and financial development influences investment, growth, and income equality [39]. Together, these variables control for key economic and structural factors relevant to the urban-rural income gap.

(1) Industrial composition (tertiary). The tertiary industry is the service industry, which mostly belongs to the labor-intensive industry, and can absorb a significant surplus of labor in villages, reduce rural unemployment rate, enhance the earnings of people living in villages, improve the structure of national income distribution, and diminish earnings disparity between city and countryside. The specific calculation way is: "the proportion of contribution of the service sector to the Gross Domestic Product". The higher the ratio, the stronger the ability of the tertiary industry to absorb the employment of rural surplus labor, and the greater its function in enhancing the structure of national income distribution, the greater its role in narrowing the difference in earnings between urban and rural regions.

(2) Level of openness (OPEN). Foreign trade activities occur more often in cities, which can affect the Theil index by influencing the employment opportunities of urban residents, wage levels, and other mechanisms. Its specific calculation is the "total value of the share of imports and exports in GDP."

(3) Fiscal expenditure (gov). Fiscal expenditures redistribute national income through transfer payments, subsequently impacting the Theil index. The specific calculation method is: "fiscal social security expenditure as a percentage of all government's fiscal spending."

(4) Urbanization level (urban). The influence of urbanization's progression on economic expansion cannot be overlooked, and the changes in the Theil index brought about by economic growth should naturally be considered. The index is quantified by "the proportion of urban residents to the total population."

(5) Educational level (edu). China is still at a stage where the education level has increased, and earnings disparity exists. Concurrently, Benhabib [40] points out that there is educational inequality across the divide between city and countryside in China, and the inequality in education will be exacerbated and reflected in the inhabitants' income level, which in turn affects the Theil index. In this study, "the enrollment rate of pupils in colleges, averaged per ten thousand individuals," is used to measure.

(6) Financial support (finance), using the year-end balances of deposits and loans held by financial entities. Because the capital market can promote shifts in industrial composition, job market dynamics, and other aspects, thereby affecting the Theil index.

3.3 Data Sources

This study examines 71 key tourism cities in China from 2012 to 2019, using data from authoritative sources. Urbanization, industrial structure, and demographic data were sourced from the China Urban Statistical Yearbook (2013–2020) by the National Bureau of Statistics [2]. Trade openness figures came from the China Trade and External Economic Statistical Yearbook (2013–2020) [41], while fiscal data were obtained from the China Financial Yearbook (2013–2020) [42]. Educational indicators were drawn from the China Educational Statistical Yearbook (2013–2020) [43]. Financial development data were collected from the Wind Economic Database (2012–2019) [44]. These sources are recognized for their accuracy and have been widely used in economic research.

3.3.1 Results`

The empirical statistical findings of the key variables are illustrated in the following Table 3.

Table 3
Descriptive statistics

VarName	Obs	Mean	SD	Min	Max	Median
theil	568	0.065	0.039	0.000	0.227	0.057
de1	568	0.188	0.131	0.039	0.875	0.153
lntr	568	10.894	1.146	6.373	13.341	10.936
ur	568	0.640	0.160	0.276	1.000	0.664
open	568	0.293	0.372	0.003	2.185	0.162
tertiary	568	50.970	10.285	20.680	83.520	50.430
lnedu	568	2.483	1.409	-0.622	4.748	2.588
gov	568	0.191	0.086	0.086	0.541	0.167

The findings indicate that the maximum value of Theil is 0.227, the opposite side is 0, the range is 0.227, the mean is 0.065, and the SD is 0.039, which means that the Theil index and the differences among various tourism cities are quite significant. Similarly, the level of DE development has the highest value of 0.875, the lowest value of 0.039, DE's range is 0.836, the mean is 0.188, and SD is 0.131. The Max, Min, Range, Mean, and SD of the rural tourism development level of the intermediate variable are 13.341, 6.373, 6.968, 10.894, and 1.146. Both have the same "small mean and large SD."

3.3.2 Discussion

These findings suggest that DE's level and the extent of rural tourism growth show a notable discrepancy across various tourist cities. Considering controlling variables, different tourist cities have obvious differences in urbanization rate (ur), degree of openness (open), industrial composition (tertiary), education level (lnedu), fiscal expenditure (gov), and financial development (finance).

3.4. Empirical Test

3.4.1 Results and Discussion of Unit Root Test

This test must be performed on each variable before panel regression. If the data has a unit root, it will be unstable, and there will be false regression. Only stable data can ensure the correctness of subsequent regression. The detailed test outcomes are presented in Table 4 following this section. Except for the urbanization rate and industrial structure, the other variables do not have a unit root; that is, the data is stable.

Table 4
Unit root test

VarName	Statistic	z	p-value	stationarity
theil	0.0099	-4.8884	0.0000	stable
de1	0.1179	-2.6901	0.0036	stable
lntr	-0.0319	-5.7388	0.0000	stable
ur	0.2189	-0.6336	0.2632	Unstable
open	-0.0178	-5.4528	0.0000	stable
tertiary	0.4376	3.8189	0.9999	Unstable
lnedu	0.1526	-1.9830	0.0237	stable
gov	-0.0092	-5.2776	0.0000	stable
finance	0.1026	-3.0007	0.0013	stable

3.4.2 Results and Discussion of Co-integration Test

To analyze and solve the quantitative relationship between non-stationary economic variables, Granger puts forward the co-integration test. Cointegration implies that when two or more variables are non-stationary, the new sequence shows stationarity after a linear combination. Its purpose is to examine the causality, as their regression equations indicate, which is pseudo-regressive. If there is a co-integration relationship between non-stationary variables, then it is proved that the series after the linear combination is stationary, and there is no pseudo-regression. Based on this, to solve the problem of the instability of urbanization rate and industrial structure data, the author tested whether there is a co-integration relationship between the two. The detailed outcomes are presented in Table 5. After testing, the P-value is 0, falling below the 0.05 threshold. Thus, the null hypothesis of the co-integration test is rejected. So, a co-integration relationship exists between variable urbanization rates and industrial structure.

Table 5
Test of cointegration

	Statistic	p-value
Variance ratio	9.0849	0.0000

3.4.3 Results and Discussion of Choosing Model

This study establishes OLS, fixed effect, and random effect models, respectively, with Theil as the explained variable, and then determines which model to use according to different tests. On the basis of the F-test outcomes, the P-value is 0.000, less than 0.01, which means the rejection of the null hypothesis. Consequently, as in Table 6, the fixed effect model is chosen between OLS and the fixed effect model. Further, as in Table 7, in the outcomes of the Hausman Test, the P-value for the Hausman Test, with Theil as the dependent variable, is 0.0007, which is less than 0.01. That means the rejection of the null hypothesis, favoring the selection of the fixed effect model over the random effects model.

Table 6
Regression results of different models

Regression model	OLS		Fixed effect		Random effect	
Explained variable	Theil		Theil		Theil	
de1	-0.0088		-0.0198		-0.0242	**
	(-0.59)		(0.104)		(0.032)	
lntr	-0.0067	***	-0.0148	***	-0.0130	***
	(0.000)		(0.000)		(0.000)	
ur	-0.1564	***	-0.0631	***	-0.0916	***
	(0.000)		(0.000)		(0.000)	
tertiary	0.0004	**	6.39e-05		0.0000	
	(0.042)		(0.739)		(0.911)	
open	-0.0045		-0.00562		-0.0056	
	(0.317)		(0.216)		(0.167)	
lnedu	0.0072	***	-0.00429	**	0.0017	
	(0.000)		(0.021)		(0.448)	
gov	0.1040	***	-0.0548		-0.0072	
	(0.000)		(0.301)		(0.735	
finance	-0.0011		0.00622	***	0.0039	
	(0.625)		(0.010)		(0.078)	
Constant	0.1870	***	0.280		0.2610	***
	(0.000)		(0.000)	***	(0.000)	
Individual fixation effect	NO		YES		YES	
Time-fixed effect	NO		NO		NO	
N	568		568		568	
R-squared	0.5810		0.3356		0.4625	

Table 7
Hausman Test results

Explained variable	Theil
chi2(8)	26.96
Prob	0.0007
Conclusion	Fixed effect

3.4.4 Results and Discussion of Benchmark Regression Results

As depicted in Table 8, model (1) reveals a negative coefficient for the DE, suggesting that the DE's advancement contributes to reducing urban-rural income inequality. This conclusion is still valid in model (2). In model (2), the coefficient of urbanization(ur) is negative, which means that the expansion of urban size narrows the income inequality of urban-rural. The coefficient for the tertiary sector is significantly negative, signifying that improving the proportion of the tertiary industry can reduce the income inequality of urban-rural. The coefficient for external openness is negative yet statistically insignificant, suggesting that foreign capital has not significantly reduced the Theil index, which could be that foreign trade activities are more likely to occur in cities and exert a more significant influence on the income of city dwellers. The coefficient of educational attainment (edu) is negative and significant, confirming that the need to expand education has a broad impact on long-term strategies to reduce the Theil index in the future. The coefficient for government spending (gov) is notably negative, suggesting that fiscal regulation of income distribution is crucial in diminishing income inequality. The coefficient of financial development level is positive and significant, indicating that the advancement of the capital market does not favor the reduction of urban-rural income inequality.

Table 8
Regression results

Variables	Theil			
	(1)		(2)	
de1	-0.0865	***	-0.0361	***
	(0.000)		(0.004)	
ur			-0.0795	***
			(0.000)	
tertiary			-0.007	***
			(0.000)	
open			-0.0040	
			(0.407)	
lnedu			-0.0116	***
			(0.006)	
gov			-0.6183	**
			(0.013)	
finance			0.0054	**
			(0.032)	
Constant	0.0813	***	0.1938	***
	(0.000)		(0.000)	
Individual fixation effect	YES		YES	
Time-fixed effect	NO		NO	
N	568		568	
R-squared	0.2802		0.3416	

To verify the DE mechanism on urban-rural income inequality (Theil) in tourism cities, this study adopts an intermediary effect, and the specific results are shown in Table 9. First, in model (1), it is confirmed that DE can reduce the Theil index; second, model (2) confirms that DE indeed enhances tourism development. Subsequently, the level of tourism development is incorporated into the regression equation assessing the impact of DE on the Theil index, thereby constructing model (3), wherein the impact coefficient of DE has decreased compared with model (1) and has changed from significant in model (1) to insignificant in model (3). It shows that the improvement of tourism is indeed a mechanism of DE to narrow the gap between urban-rural income, and the empirical results support the research hypothesis.

Table 9
Test results of the mechanism of DE affecting urban-rural income inequality

Var	Theil		Lntr		Theil	
	(1)		(2)		(3)	
de1	-0.0361	***	1.1011	***	-0.0198	
	(0.004)		(0.000)		(0.104)	
lntr					-0.0148	***
					(0.000)	
ur	-0.0795	***	1.1128	***	-0.0631	
	(0.000)		(0.001)		(0.000)	
tertiary	-0.007	***	0.0544	***	6.39e-05	***
	(0.000)		(0.000)		(0.739)	
open	-0.0040		-0.1123		-0.00562	**
	(0.407)		(0.274)		(0.216)	
lnedu	-0.0116	***	0.4957	***	-0.00429	**
	(0.006)		(0.000)		(0.021)	
gov	-0.6183	**	0.4740		-0.0548	
	(0.013)		(0.375)		(0.301)	
finance	0.0054	**	0.0536		0.00622	***
	(0.032)		(0.322)		(0.010)	
Constant	0.1938	***	5.8309	***	0.280	
	(0.000)		(0.000)		(0.000)	
Individual fixation effect	YES		YES		YES	
Time-fixed effect	NO		NO		NO	
N	568		568		568	
R-squared	0.3416		0.5799		0.3356	

3.4.5 Results and Discussion of Robustness Test

This study conducts some robust tests to further verify the reliability of all conclusions, including adding new control variables, replacing core explanatory variables, and replacing explained variables.

As in Table 10, in model (1), the author added the structure of the primary industry as a new control variable and found that the substantial inverse correlation between the DE and the income disparity of urban-rural remains consistent. Additionally, it's worth mentioning that the DE can be measured in numerous ways, and each method may yield different numerical results. This diversity in measurement approaches highlights the importance of choosing a method that best fits the specific objectives and context of the analysis. This study alters the computation approach for the key explanatory variable, the DE, substituting the original entropy weight method with the PCA method for its estimation and adding the original model for regression. The detailed outcomes are presented in the model (2) in the following table, where the coefficient of de2 is -0.0905, and it is statistically significant at a 1% confidence level or higher, which means that there is no substantial change in the conclusion after replacing the calculation method of DE. In addition, various academics have also put forward different opinions on the measurement of income inequality in urban-rural areas. Table 9 selects the ratio of urban and rural residents' income. The detailed outcomes are presented in the following model (3). The core variable coefficient is -0.5152, and significance is observed at a confidence level of no less than 1%. This means that differences in the measurement of explanatory variables do not lead to substantial changes to the conclusions, which once again proves the stability of the model.

Table 10
Robustness test

Variables	Exclude macroscopic factors and systemic changes		Replace the core explanatory variable (de2)		Replace the explained variable (g)	
	(1)		(2)		(3)	
de1	-0.0325	***			-0.5152	***
	(0.010)				(0.003)	
de2			-0.0905	***		
			(0.001)			
First	0.0020	***				
	(0.000)					
ur	-0.0698	***	-0.0801	***	0.0691	
	(0.000)		(0.000)		(0.707)	
tertiary	-0.007	***	-0.0007	***	-0.0093	***
	(0.000)		(0.000)		(0.000)	
open	-0.0040		-0.0042		-0.0377	
	(0.399)		(0.376)		(0.584)	
lnedu	-0.0085	**	-0.0112	***	-0.1541	***
	(0.047)		(0.008)		(0.003)	
gov	-0.0722	***	-0.0667	***	-0.8386	***
	(0.004)		(0.008)		(0.006)	
finance	0.0047		0.0056	**	0.0766	**
	(0.061)		(0.026)		(0.014)	
Constant	0.1629	***	0.2410	***	3.3213	***
	(0.000)		(0.000)		(0.000)	
Individual fixation effect	YES		YES		YES	
Time-fixed effect	NO		NO		NO	
N	568		568		568	
R-squared	0.3770		0.3417		0.0035	

3.4.6 Results and Discussion of Endogeneity Test

Applying the IV technique to confront the issues of endogeneity that might occur due to potential backward causality and unaccounted-for variables.

Drawing on Huang Qunhui's [11] findings, this study selects the fixed-line telephone penetration rate per 100 individuals and the volume of post-business per person in 1984. The interaction terms between these factors, along with the national Internet investment from the preceding year, are utilized as instrumental variables for DE.

The specific empirical outcomes are shown in Table 11 below. The F-statistic value is 14.1595, which exceeds 10, which proves that this instrumental variable is not weak. Secondly, the P-value derived from the test for overidentifying restrictions is 0.1624, exceeding the threshold of 0.05. The original hypothesis is accepted; that is, there is no over-recognition phenomenon. In the results of the endogenous test, the coefficient for DE is -0.2181, which once more suggests that the advancement of DE can reduce the income gap between urban and rural areas.

Table 11
Endogenous test

Variables	IV method	
de1	-0.2181	**
	(0.022)	
ur	-0.1097	***
	(0.000)	
tertiary	-0.0008	**
	(0.018)	
open	-0.0260	*
	(0.099)	
lnedu	-0.0044	***
	(0.008)	
gov	-0.0706	**
	(0.026)	
finance	0.0023	
	(0.294)	
Constant	0.1003	***
	(0.000)	
Individual fixation effect	YES	
Time-fixed effect	NO	
N	560	
R-squared	0.3654	
GMM C statistic chi2(1)	12.6695	
	(0.0004)	
Weak instrumental variable F test	14.1595	
	(0.000)	
Overrecognition test	1.95128	
Hansen’s J chi2(1)	(0.1624)	

3.4.7 Results and Discussion of Heterogeneity Test

There is marked heterogeneity at the stage of economic progress across various cities. Therefore, the impact of DE on the Theil index may also have regional heterogeneity. Based on this, considering the varying stages of economic growth, categorizes cities into first-tier, second-tier, and third-tier cities or lower.

In Table 12, the analysis of regional heterogeneity using regression methods is performed. The outcomes of the model (1) show that in first-tier cities, DE does not exert a significant influence on the Theil index; models (2) and (3) indicate that DE significantly influences the income gap of urban-rural in second-tier, third-tier cities, and the impact on third-tier cities is greater than that on second-tier cities. The likely explanation for this finding is that China's first-tier cities attain a superior level of economic development and urbanization, resulting in a negligible gap between urban and rural residents’ income. Therefore, the growth of DE does not significantly affect them. In second-tier, third-tier, and lower-tier cities, the advancement of DE has yielded dividends, significantly reducing the income inequality of urban-rural.

Table 12
Heterogeneity test

Variables	First-tier city		Second-tier city				Tier 3 and below cities			
	(1)		(2)		(3)		(4)		(5)	
de1	0.0075		-0.0342	*	-0.0227		-0.0831	**	-0.0406	
	(0.201)		(0.087)		(0.259)		(0.017)		(0.176)	
lntr					-0.0107	***			-0.0195	***
					(0.005)				(0.000)	
ur	-0.009		-0.1034	***	-0.0897	***	-0.0481		-0.0334	
	(0.699)		(0.000)		(0.000)		(0.119)		(0.202)	
tertiary	0.00003		-0.0005	*	-0.00002		-0.0005		0.0009	**
	(0.841)		(0.088)		(0.965)		(0.261)		(0.044)	
open	-0.0060	**	-0.0001		-0.0011		-0.0285		0.0002	
	(0.026)		(0.988)		(0.881)		(0.177)		(0.991)	
lnedu	-0.0059		-0.0126		-0.0076		-0.0150		-0.0045	
	(0.505)		(0.194)		(0.434)		(0.051)		(0.502)	
gov	-0.0150		0.0110		-0.0083		-0.1620	***	-0.1604	***
	(0.595)		(0.857)		(0.891)		(0.010)		(0.003)	
finance	-0.0023		0.0010		0.0039		0.0170		0.0036	
	(0.570)		(0.801)		(0.329)		(0.018)		(0.371)	
Constant	0.0574		0.2075	***	0.2684	***	0.1796	***	0.2899	***
	(0.177)		(0.000)		(0.000)		(0.000)		(0.000)	
Individual fixation effect	YES		YES		YES		YES		YES	
Time-fixed effect	NO		NO		NO		NO		NO	
N	32		264		264		88		88	
R-squared	0.6679		0.4319		03843		0.2060		0.0394	

3.4.8 Results and Discussion of Exogenous Shock Test

This study is grounded on the "Broadband China" policy and tested using the multi-period DID method to more comprehensively verify the impact of DE on the gap of urban-rural income.

(1) Policy background and DID model setting

Throughout 2014, 2015, and 2016, a total of 120 cities were designated in three phases as demonstration areas for the "Broadband China" initiative. The selected cities will increase their network infrastructure. Selected cities will strengthen network infrastructure, expand broadband subscriber scale, and broaden coverage. Over time, their network development will reach national leading standards.

The DID model formula is as listed: where i denotes the city, t means the year; DID represents whether the city was included in the "Broadband China" pilot list for that particular year, and "yes" takes "1", & "no" takes "0"; vector Z is the control variables; μ controls the individual effect; ε is random error.

$$Theil_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{12}$$

$$Lntr_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{13}$$

$$Theil_{i,t} = \gamma_0 + \gamma_1 DID_{i,t} + \gamma_2 Lntr_{i,t} + \gamma_3 Z_{i,t} + \mu_i + \delta_i + \varepsilon_{i,t} \tag{14}$$

(2) Benchmark DID regression results

Before the Basic DID regression, a parallel trend test is necessary. This study uses an ex-ante test, with results shown in Figure 2, confirming the model passes the test.

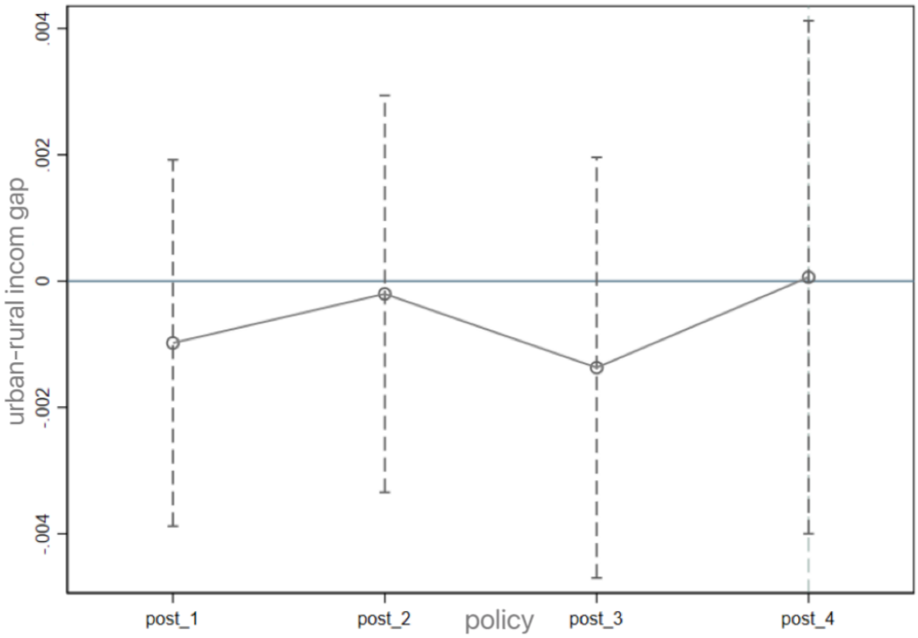

Fig. 2. Parallel trend test

Since the chosen cities are not entirely random, their determination must consider the area's economic development status, resource endowment, and other factors of the area. The above factors may have different influences on the income inequality of urban-rural areas; therefore, to control the impact of these factors, this study adds them to the control variables. Specifically, adopting the initial economic level of the city, the initial level of urbanization as a proxy variable for these antecedent factors mitigates the estimation bias resulting from the experimental group's non-random sampling to a certain extent. The regression outcomes are displayed in Table 13: In model (1), DID significantly contributed to narrowing the income inequality of urban-rural. Model (2) demonstrates that DID significantly promotes the tourism industry. Based on DID significantly reducing the income inequality of urban-rural, the model (3) with the addition of tourism development level shows that the coefficient of the differential term of DID has changed from significant to insignificant, and the coefficient associated with the degree of tourism is significantly negative, suggesting that an increase in tourism development significantly contributes to decreasing the rural-urban income disparity and is the intermediate variable.

Table 13
Test results based on "Broadband China"

Variables	Theil		Lntr		Theil	
	(1)		(2)		(3)	
DID	-0.04368	*	3.4333	***	0.0011	
	(0.038)		(0.000)		(0.960)	
lntr					-0.1304	***
					(0.000)	
Control variables	YES		YES		YES	
Individual fixation effect	YES		YES		YES	
Time-fixed effect	NO		NO		NO	
N	568		568		568	
R-squared	0.5043		0.2677		0.5096	

However, other unobservable factors may still be present in the regression and may have different effects over time. Therefore, this study conducted a placebo test. The specific steps are, first, through the ‘Broadband China’ pilot, randomly generate a list of experimental groups, and second, according to the list of experimental groups, randomly generate a list of time points when the policy occurs to generate the coefficient estimate of the error multiplicative term, and the process is repeated 500 times, and observe the distribution, and ultimately get the results. As shown in Figure 3, it can be observed that it passes the placebo test.

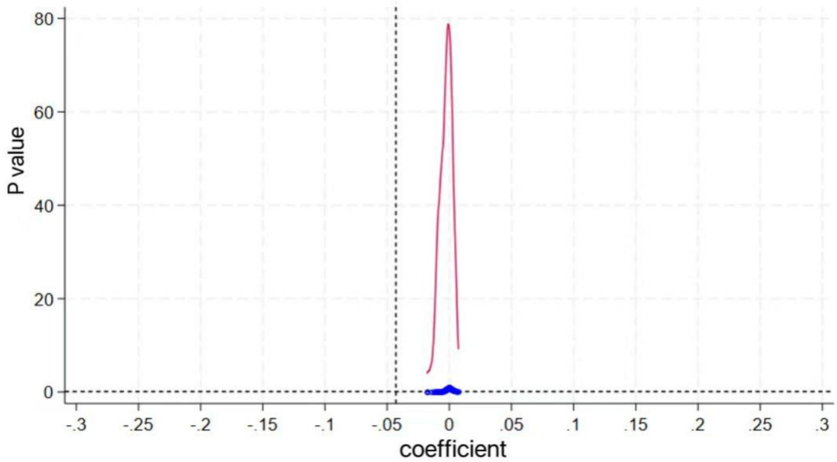

Fig. 3. Placebo test result

5. Theoretical and Practical Implications

This study makes several key theoretical contributions. First, it extends the understanding of the digital economy's role in regional development by integrating perspectives from industrial economics and income distribution theory. While this study focuses on China, its findings have broader relevance for other emerging economies where urban-rural inequality persists and digital infrastructure is rapidly expanding. Countries in South and Southeast Asia, Latin America, and Africa are similarly exploring smart city initiatives and rural tourism as strategies for equitable development. The identified mechanism whereby the digital economy facilitates tourism-led rural revitalization offers a transferable policy framework, contingent on local conditions such as internet access, digital literacy, and tourism potential. Unlike prior studies that focus separately on digitalization or income inequality, this research establishes a clear theoretical linkage between the digital economy, rural tourism development, and the narrowing of the urban-rural income gap [45]. Second, by identifying rural tourism as a transmission channel, the study enriches the mediating mechanism theory, showing how sectoral dynamics in tourism serve as conduits for the digital economy’s broader economic effects [23]. Finally, the research contributes to the literature on economic geography and regional inequality by providing empirical evidence of how digitalization’s impact varies across city tiers, reinforcing theories of spatial heterogeneity in economic development. These insights offer a more integrated theoretical framework for analyzing digital economy-driven regional equity.

4. Conclusions

The study confirms significant variation in the levels of digital economy development and rural tourism growth across different tourist cities in China. For instance, cities like Hangzhou and Guangzhou, known for their advanced digital infrastructure and strong e-commerce ecosystems, show high digital economy scores and a rapid expansion of rural tourism, driven by digital platforms and smart tourism initiatives. Although rooted in the Chinese context, the conclusions drawn here offer insights applicable to other developing nations undergoing digital transformation. Policymakers in these regions can adapt the lessons on digital-tourism linkages to design inclusive strategies for narrowing spatial income gaps. Future research can extend this analysis through cross-country comparisons or regional case studies to further test the generalizability of the findings. In contrast, cities such as Lijiang and Guilin, despite their tourism appeal, exhibit lower digital economy indices and slower rural tourism growth due to weaker digital infrastructure and limited digital entrepreneurship. This contrast highlights how differences in digital readiness and infrastructure significantly affect the capacity of tourism cities to leverage digital tools for rural economic development. Such disparities suggest that digital economy-driven rural tourism growth is highly context-dependent, reinforcing the need for tailored policy interventions based on local digital capacities.

Focusing on the perspective of rural tourism development and empirically examining the influence of the DE on the gap between urban-rural income and the underlying mechanisms. The primary findings can be summarized as follows. First, the DE clearly reduces the gap, and the conclusion still holds by replacing DE and other robustness tests. Second, in terms of heterogeneity, the impact of DE on narrowing the gap of urban-rural income in first-tier cities is smaller than in second-tier and third-tier cities. Third, elevating the degree of tourism serves as the mechanism through which DE diminishes the income inequality of urban-rural. Finally, the enforcement of the "Broadband China" pilot policy plays a pivotal role in mitigating the urban-rural income disparity within China.

This study has certain limitations that should be acknowledged. Its findings are based solely on Chinese tourism cities, which may limit generalizability to other countries with different digital and economic contexts. Additionally, some unobserved factors such as digital literacy, governance quality, or informal employment were not fully controlled for. Future research could explore cross-country comparisons, incorporate micro-level data, or examine how local conditions influence the relationship between the digital economy, tourism, and income inequality.

Author Contributions

Conceptualization, H.Z.; methodology, H.Z.; software, J.W.; validation, J.W.; formal analysis, H.Z.; investigation, H.Z.; resources, H.Z.; data curation, J.W.; writing—original draft preparation, H.Z.; writing—review and editing, J.W.; visualization, H.Z.; supervision, J.W.; project administration, J.W. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets generated during and/or analyzed during the current study are available in the China Urban Statistical Yearbook & Wind database repository, https://www.wind.com.cn

Conflicts of Interest

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

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