sustainability

Article

Rural Tourism, Economic Growth, and Environmental Sustainability: Empirical Evidence Based on County-Level Data in China

Jiahui Li [1], Yu Yang [1] and Yuqi Ye [2,*]

[1] China Academy of Public Finance and Policy, Central University of Finance and Economics, Beijing 100081, China; 2022110223@email.cufe.edu.cn (J.L.); yangyu@email.cufe.edu.cn (Y.Y.)
[2] School of Economics, Dongbei University of Finance and Economics, Dalian 116025, China
* Correspondence: yeyuqi@stumail.dufe.edu.cn

Abstract

Rural tourism is widely recognized as a key pathway for sustainable development by balancing economic growth with environmental protection. Utilizing an interdisciplinary analytical framework combining tourism, economy, and environment, this study applies a difference-in-differences (DID) approach to examine the economic effects and environmental costs of rural tourism policies in China, based on a sample of 1399 counties from 2007 to 2023. The empirical results reveal that rural tourism policies significantly boost per capita GDP, with effects significantly driven by the increase in newly registered tourism-related enterprises and expanded land transfer for tourism development. The impact is more pronounced in non-poor counties, those near city centers, and those with better transportation infrastructure. Further analysis demonstrates that while rural tourism development contributes to economic growth, the associated environmental costs are much lower than the economic gains. This study contributes to the literature by combining tourism policy evaluation with environmental performance, demonstrating an underlying significant role of rural tourism in achieving a sustainable development pattern. And for the policymakers who seek to achieve rural revitalization, it is imperative to embed the principles of environmental sustainability into rural tourism initiatives to ensure long-term sustainability.

Keywords: rural tourism; difference-in-differences model; rural revitalization; environmental sustainability

Academic Editor: Eduardo Parra-López

Received: 26 August 2025
Revised: 24 September 2025
Accepted: 15 October 2025
Published: 17 October 2025

Citation: Li, J.; Yang, Y.; Ye, Y. Rural Tourism, Economic Growth, and Environmental Sustainability: Empirical Evidence Based on County-Level Data in China. *Sustainability* **2025**, *17*, 9215. https://doi.org/10.3390/su17209215

1. Introduction

With the rapid development of the global economy and the increasing environmental pressures, how to balance economic growth with environmental protection has become a central issue widely discussed by academia and policymakers [1–3]. Traditional industrial development patterns often trade environmental degradation for economic benefits too aggressively. Although this "high pollution for high growth" model has led to productivity improvements in the short term, it has exacerbated ecological pressures in the long run [3,4]. This contradiction is particularly prominent in developing countries, especially in rural areas, where the pursuit of rapid growth to improve livelihoods poses significant challenges to the ecological vulnerability and sustainability of the environment. With the deepening promotion of sustainable development concepts, finding new development patterns that balance economic development and ecological protection has become increasingly important for academia and policymakers.

Against this backdrop, tourism has emerged as a new green development pattern in the global discourse. Compared to industrial development patterns, tourism, with its multiple functions such as economic growth, cultural heritage preservation, and ecological utilization [5,6], has gradually been seen as one of the key pathways to achieving the United Nations Sustainable Development Goals (SDGs). In particular, with the growing public demand for environmentally friendly travel experiences, rural tourism, as a vital component of the tourism industry, has gradually become a new economic growth point for regions due to its unique cultural and ecological resources, playing a key role in promoting sustainable development. Meanwhile, the application of rapidly developing technologies, such as artificial intelligence (AI) and large language models (LLMs), is driving rural tourism towards greater efficiency [7]. While these technologies enhance the visitor experience and improve businesses' data analysis and targeted marketing [8–10], they also inject more momentum into the green development of rural tourism, propelling it toward a more efficient and sustainable future.

Rural tourism is generally defined as tourism that takes place in rural areas, offering visitors experiences deeply tied to the rural environment, culture, and lifestyle. According to the United Nations World Tourism Organization (UNWTO), rural tourism encompasses a broad range of products and activities rooted in rural life and nature, including nature-based activities, agricultural experiences, rural sightseeing, and more [11]. In both developed and developing countries, rural tourism has been increasingly seen as a key strategy for driving local economic growth and promoting rural development [12,13], while also serving as an important tool for balancing economic modernization and preserving rural heritage [14]. As more countries recognize the role of tourism in sustainable development, corresponding rural tourism policies are being increasingly implemented [15–17]. Effective rural tourism policies aim to promote the alignment of tourism development with broader rural development goals. The core of these policies is ensuring a balance between economic benefits, environmental sustainability, cultural heritage preservation, and so on through scientific planning [18–20]. Therefore, rural tourism policies are inherently interdisciplinary, linking economic, social, and environmental dimensions, and thus require an interdisciplinary analytical framework.

Existing studies indicate that rural tourism can significantly foster rural economic development, for instance, increasing farmer income and enhancing regional sustainability [12,13]. However, tourism development is not entirely "green", as this process can also lead to resource depletion, environmental pollution, and ecological damage [21–23]. This contradiction has sparked academic debates regarding whether tourism development is "truly sustainable." On the one hand, tourism is seen as a crucial lever for driving economic transformation and promoting high-quality social development; on the other hand, its potential environmental costs have attracted widespread concern. In light of this, the paper raises the following questions: Can rural tourism policies stimulate regional economic development? What are the underlying mechanisms? Furthermore, can rural tourism policies achieve a sustainable development model that synergizes economic growth with environmental protection?

To answer these questions, this study integrates interdisciplinary perspectives from tourism studies, economics, and environmental science and uses county-level data from China spanning 2007 to 2023. By treating the Chinese rural tourism "demonstration zone" policy as a quasi-natural experiment, this study employs a DID approach to evaluate the economic and environmental impacts of this rural tourism policy. Compared to existing literature, the marginal contribution of this paper lies as follows: First, this study integrates rural tourism, economic development, and environmental quality into a unified theoretical framework, and conducts multi-dimensional mechanism and heterogeneity tests from several different perspectives, such as newly registered enterprises and land transfer that have not been previously systematically discussed. The results help deepen academics' and policymakers' understanding of rural tourism policies. Second, as implied by the Environmental Kuznets Curve (EKC) theory [24,25], economic growth in the early stages inevitably leads to increased environmental pollution. Therefore, focusing separately on one aspect of the effects of policies may prove incomplete. When examining only the economic impacts of policies, the overall effectiveness is likely overestimated due to the neglect of environmental costs. Conversely, when focusing solely on impacts, the adverse effects of policies may be exaggerated. Therefore, this paper differs from previous literature that treats economic and environmental impacts separately [21,26,27]. Instead, it integrates both dimensions by introducing the environmental efficiency ratio (EER) concept. Through quantitative methods, the "conversion rate" between the environmental costs and economic benefits can be assessed, and the role of rural tourism policies in establishing a sustainable development path can be further revealed.

2. Theoretical Analysis and Research Hypotheses

2.1. Rural Tourism on Economic Growth

The implementation of rural tourism policies has a positive impact on regional economic growth. First, on the demand side, implementing rural tourism policies effectively stimulates tourism demand by attracting tourists and promoting the development of the rural tourism industry. Tourists' direct spending on accommodation, food, transportation, and local products generates new cash inflows for rural households in the tourism area, effectively increasing their disposable income levels [13,28]. Once tourist spending is converted into income for local businesses and residents, the additional income will further stimulate residents' re-spending on local goods and services, amplifying the tourism industry's economic stimulation effects through the "multiplier effect" and fostering sustained regional economic growth [29]. Second, the popularity of rural tourism typically leads to increased public and private capital investment in infrastructure such as transportation, electricity, and communications. Such infrastructure investments can effectively reduce transportation costs, enhance resource allocation efficiency, and improve regional carrying capacity, thus promoting local economic growth [30]. Third, from an invisible perspective, the development and productization of the rural tourism industry help shape and strengthen regional brands, increase the visibility and credibility of destinations, attract subsequent capital and tourists, expand market bargaining power, and sustain local economic revitalization through residents' identity recognition and community participation. As a result, this positive promotion effect is sustained over time.

Hypothesis 1. *Implementing rural tourism policies can positively affect regional economic growth.*

Hypothesis 2. *Implementing rural tourism policies can positively affect regional economic growth by increasing household income, stimulating regional consumption, and boosting infrastructure investment.*

2.2. Rural Tourism on Newly Registered Enterprises

A possible pathway through which the implementation of rural tourism policies promotes regional economic growth is by increasing the number of newly registered tourism-related enterprises. Policy measures typically include fiscal incentives, simplified administrative procedures, market promotion, and infrastructure improvements, all of which significantly lower the costs of entrepreneurship and reduce market entry barriers. This, in turn, stimulates entrepreneurs to enter the rural tourism market and drives the growth of new tourism-related enterprises [17,31]. The increase in the number of registered tourism enterprises then has a positive impact on regional economic development through multiple effects. First, new tourism enterprises generate local income and employment, which spread throughout the region through local multiplier effects, stimulating the development of related supporting industries. Moreover, the emergence of new entrepreneurs in rural tourism destinations helps enhance the market competitiveness and attractiveness of the tourism destination [32]. By offering innovative services, differentiated products, and personalized experiences, individual entrepreneurs increase the region's tourism appeal and drive the overall upgrade of the tourism ecosystem. Additionally, the spatial concentration of multiple enterprises helps form industrial clusters [33], promoting resource sharing, division of labor, and efficiency improvements, further enhancing the industry's overall competitiveness. Finally, the business activities of new enterprises may also promote regional knowledge and innovation spillovers, such as the diffusion of management experience, service skills, and marketing models [34], which contribute to the overall development of the rural tourism industry and further promote regional economic growth.

Hypothesis 3. *Implementing rural tourism policies promotes regional economic development by promoting newly registered enterprises in the tourism industry.*

2.3. Rural Tourism on Land Transfers

Another possible pathway through which the implementation of rural tourism policies positively promotes regional economic growth is expanding the extent of land transfers for tourism development. (In the Chinese context, "land transfer" refers to the process through which the state grants the use rights of state-owned land to land users for a specified period through market mechanisms such as bidding or auction. The land users are required to pay a transfer fee and obtain legally protected usage rights. The land designated for tourism or commercial development typically has a usage period of 40 years) for tourism development. Under the implementation of rural tourism policies, local governments, through precise planning, simplified approval processes, and land use guarantees, facilitate the conversion of rural land from agricultural production to tourism development, providing legal protection and institutional support for the growth of the tourism industry. The supply of land for transfer is crucial for the growth of the tourism industry [35]. Land is an irreplaceable fundamental resource for tourism development and serves as the basis for constructing tourism infrastructure and developing tourism products. Increasing the land transfer for tourism can provide the necessary physical space for infrastructure construction and tourism project investment, such as hotels, scenic areas, and supporting facilities, thus directly creating employment and income during the construction and operation phases. Furthermore, the allocation and development of tourism land also help expand the local fiscal revenue base through land transactions or tourism taxes. This expanded fiscal capacity, in turn, can further promote economic development and investments in ecological protection, forming a virtuous development cycle.

Hypothesis 4. *Implementing rural tourism policies promotes regional economic development by increasing the extent of land transfer to the tourism industry.*

2.4. Rural Tourism on Environmental Quality

While rural tourism contributes to regional economic development, it may also have specific negative environmental impacts. Theoretically, based on the EKC theory, economic growth in the early stages inevitably leads to increased environmental pollution, an unavoidable "development cost" during the initial phase of modernization [24,25]. In relatively underdeveloped rural areas, developing the rural tourism industry can drive economic growth and rapidly enhance the degree of regional modernization. However, it also inevitably incurs some environmental costs. In practice, these impacts may manifest in several ways: First, many rural areas have limited natural environmental carrying capacity and inherent vulnerabilities. When the development of rural tourism leads to an increase in the number of tourists and the intensity of tourism beyond the threshold that the local ecosystem can support, it may result in a decline in environmental quality [36]. Second, during the development process, rural tourism destinations may experience physical damage to ecosystems and infrastructure overload [37]. Dust from roads and vehicle emissions caused by tourists' travel and transportation, energy consumption from catering and accommodation industries related to rural tourism, and commercial and construction activities during the development of scenic spots may further exacerbate regional air pollution. Third, the construction of tourism infrastructure occupies a significant amount of rural land, which may lead to deforestation, reduced vegetation coverage, and changes to the original land cover structure. Improper planning may damage topography and landscapes, causing soil erosion and other environmental damage [38].

However, the environmental costs can be lower than its economic gains. From an industrial perspective, as a service industry, tourism has advantages such as lower resource input and market access thresholds compared to capital- and technology-intensive, high-pollution industries [39]. In particular, rural tourism primarily relies on the natural scenery and cultural features of rural areas [40], enabling local economic vitality to be quickly stimulated with relatively low investment, thereby increasing residents' income. This development pattern demonstrates a high "pollution conversion rate," where economic output per unit of environmental pollution is much higher than in traditional industries. Moreover, the environmental issues related to rural tourism are mostly controllable and localized problems, rather than systemic, irreversible global pollution. In the long term, as the tourism industry grows and specializes, its negative environmental impacts can be further mitigated [41]. Lastly, economic benefits and fiscal revenues from rural tourism also enable local governments to invest more in advanced environmental technologies and green management practices, hence better promoting sustainable development and a "low pollution, high growth" model that balances regional economic development and environmental protection.

Hypothesis 5. *The economic benefits of rural tourism policies can offset their environmental costs.*

The Figure 1 gives a visual summary of the theoretical analysis in diagram form.

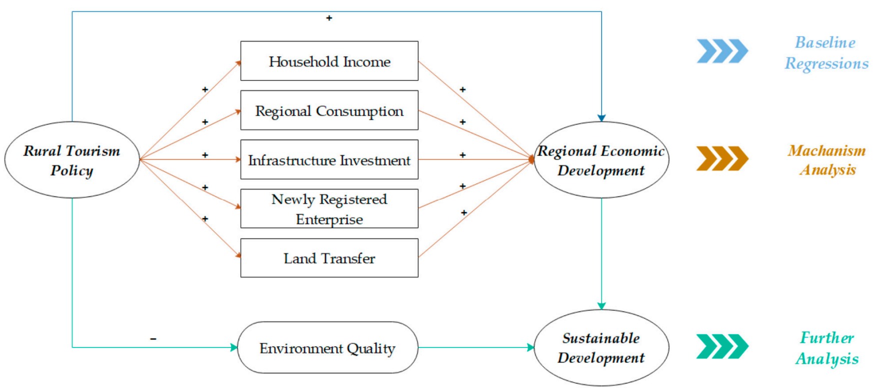

Figure 1. A visual summary of the theoretical analysis in diagram form.

3. Data and Methods

3.1. Data

Due to the data availability, this study uses county-level cities in China from 2007 to 2023, as the research sample and applies the following treatments: (1) For individuals with missing statistical data, missing values are filled using the moving average method. (2) Samples with significant missing data or extreme values are excluded. (3) All continuous variables are winsorized at the 1% upper and lower tails to reduce the potential impact of extreme values on the results. After these treatments, a balanced panel of 1399 county-level cities, consisting of 23,783 observations, is obtained.

In terms of data sources: (1) County-level city characteristic data comes from the China County Socio-Economic Statistical Yearbook, China Regional Economic Statistical Yearbook, the China Economic Information Network statistical database, and county-level statistical bulletins. (2) Information on newly registered enterprises comes from the China National Industrial and Commercial Enterprise Registration Database, which includes the registered address, registration year, and industry classification of newly registered enterprises. The number of new enterprises is aggregated at the county-level city to form a city-year panel dataset. (3) Land transfer data comes from the China Land Market Network (Data resource: https://www.landchina.com/#/givingNotice, accessed on 14 October 2025), which includes information on land parcel locations, transfer area, industry classification, etc. The number of land transfers is aggregated at the county-level city to form a city-year panel dataset. (4) County-level PM2.5 comes from the China High-Resolution PM2.5 Dataset [42], which has a spatial resolution of 1 km. This study averages the data at the county level using ArcGIS to form a city-year panel dataset. The county-level PM10 data comes from the official website of the Ministry of Ecology and Environment of China (Data resource: https://www.openstreetmap.org, accessed on 14 October 2025). (5) The Landsat normalized difference vegetation index (NDVI) comes from the China regional 250 m fractional vegetation cover dataset [43], which is a satellite-derived indicator widely used in environmental and ecological studies to measure vegetation activity, density, and growth conditions, providing a consistent proxy for vegetation coverage over time and space. The raster data were further processed in ArcGIS through spatial aggregation and mapping to generate county-level indicators. (6) Data on land cover types, including water, forests, and grassland areas, come from the 30 m annual land cover datasets [44], which provide consistent and spatially explicit measurements of land cover. Similarly, the ArcGIS is used to generate county-level indicators. (7) Road network data comes from the OSM website (Data resource: https://www.openstreetmap.org, accessed on 14 October 2025). The total length of the road network is aggregated at the county level using ArcGIS, while the number of high-speed rail stations and airports comes from the National Railway Administration (Data resource: https://www.nra.gov.cn, accessed on 14 October 2025) and the China National Space Administration (Data resource: https://www.caac.gov.cn/index.html, accessed on 14 October 2025), respectively.

3.2. Variable Definition

3.2.1. Dependent Variable

This study selects per capita GDP (*per_GDP*) as the dependent variable for regional economic development. Per capita GDP refers to the gross domestic product of a region over a specified period, divided by the total population of that region. It reflects the region's residents' average economic output and living standards [45]. In further analysis, the study introduces a series of environmental indicators, trying to consider environmental effects more comprehensively: (1) For the air dimension, the annual average concentrations of PM2.5 (*pm2.5*) and PM10 (*pm10*) are used as the dependent variables to assess regional air environmental quality. PM2.5 refers to particulate matter with an aerodynamic diameter less than or equal to 2.5 per micrometer, and the definition is similar to PM10. It has been widely employed as a key indicator of ambient air pollution and regional environmental quality [46–48]. (2) For the land and biodiversity dimension, vegetation cover is critical in providing habitats that sustain species survival. Accordingly, the NDVI (*NDVI*), forest coverage (*Forest*), and grassland coverage (*Grassland*) are used to capture land conditions and vegetation health, and serve as proxies to some extent for the potential influence of policies on biodiversity. (3) For the water dimension, water body coverage (*Water*) is employed to measure the availability of surface water resources, which are essential for ecological sustainability and human well-being.

3.2.2. Core Independent Variable

This study employs a DID approach for causal identification, with the dependent variable being a 0–1 dummy variable (*DID*). Following the approach used in previous literature [49], the dummy variable is defined as follows: based on the list of rural tourism policies published on the official website of the Ministry of Culture and Tourism of China (Data resource: https://www.mct.gov.cn, accessed on 14 October 2025), if a county-level city implemented a rural tourism policy in a given year, the dummy variable for that year and subsequent years takes the value of 1; otherwise, it takes the value of 0.

3.2.3. Control Variable

To control for other possible regional factors, this study includes the following variables as control variables: industrial structure (*ind*), fiscal expenditure (*fis*), communication level (*com*), healthcare level (*med*), industrial foundation (*fac*), agricultural foundation (*agr*), and human capital (*hum*). The definitions and descriptive statistics of the variables are presented in Table 1. Among these, the mean value of the core explanatory variable (*DID*) is 0.171. In the sample of 1399 county-level cities, there are 647 observations in the treatment group and 752 in the control group.

Table 1. Variable Definitions and Descriptive Statistics.

Symbol	Definition	Obs.	Mean	Std.
per_GDP	Per capita GDP (10,000 yuan)	23,783	3.816	3.977
pm2.5	Annual average PM2.5 value ($\mu g/m^3$)	23,783	44.764	19.307
pm10	Annual average PM10 value ($\mu g/m^3$)	23,783	80.698	40.710
NDVI	Landsat normalized difference vegetation index	23,783	0.734	0.137
Forest	The logarithmic forest coverage area of the county land	23,783	5.201	2.747
Grassland	The logarithmic grassland coverage area of the county land	23,783	2.634	2.940
Water	The logarithmic water coverage area of the county land	23,783	2.642	1.472
DID	Policy implementation dummy variable	23,783	0.171	0.376
ind	Proportion of the tertiary industry added value	23,783	0.383	0.112
fis	Per capita fiscal expenditure (10,000 yuan)	23,783	0.242	0.175
com	Per capita fixed-line telephone users	23,783	0.119	0.102

Table 1. *Cont.*

Symbol	Definition	Obs.	Mean	Std.
med	Per capita hospital beds	23,783	0.004	0.002
fac	Per capita number of large-scale factories (per 10,000 people)	23,783	2.241	2.690
agr	Per capita total agricultural machinery power	23,783	0.938	0.736
hum	Per capita number of students in ordinary secondary schools	23,783	0.050	0.016

Specifically, to represent potential interrelationships among the multidimensional environmental indicators considered in this study, Table 2 reports their correlation coefficient matrix.

Table 2. Correlation Coefficient Matrix for Environment Indicator.

	pm2.5	*pm10*	*NDVI*	*Water*	*Forest*	*Grassland*
pm2.5	1					
pm10	0.850 ***	1				
NDVI	−0.096 ***	−0.437 ***	1			
Water	−0.507 ***	−0.572 ***	0.473 ***	1		
Forest	−0.212 ***	0.137 ***	−0.577 ***	−0.017 ***	1	
Grassland	−0.133 ***	−0.139 ***	−0.139 ***	0.048 ***	−0.086 ***	1

Note: *** indicates significance levels of 1%.

Table 2 reports the correlation coefficient matrix for the environment indicators used in this study. It can be noticed that the PM2.5 and PM10 exhibit a strong and positive correlation (0.850), suggesting that these two indicators are closely related in capturing air quality conditions. Additionally, vegetation coverage (*NDVI*) is negatively correlated with both PM2.5 (−0.096) and PM10 (−0.437), indicating that higher vegetation levels are generally associated with lower air pollutant concentrations. Similarly, forest coverage demonstrates strong negative correlations with PM2.5 (−0.507) and PM10 (−0.572), while being positively associated with vegetation coverage (0.4730), thereby underscoring the role of forest ecosystems in mitigating air pollution and enhancing ecological balance. Then, water area coverage shows a significant negative correlation with both PM2.5 and PM10, while representing a positive correlation with vegetation coverage (*NDVI*), indicating that higher water coverage is associated with a higher environmental level.

3.3. Empirical Model

This study uses a DID approach to examine the impact of policy implementation on regional outcomes. The baseline model is set as follows:

$$Y_{it} = \alpha_0 + \alpha_1 DID_{it} + X_{it} + \delta_i + \nu_t + \varepsilon_{it} \quad (1)$$

In Equation (1), the subscript i denotes the county-level city, and t represents the year. Y_{it} is the dependent variable for city i in year t, while the core explanatory variable DID_{it} represents the policy implementation indicator for city i in year t. X_{it} includes the control variables, δ_i represents the individual fixed effects for city i, ν_t represents the year fixed effects for year t, and ε_{it} is the random error term. The coefficient of interest in this study is α_1, which measures the policy effect. If α_1 is significantly positive, it suggests that the rural tourism policy has a significant positive effect, vice versa. Standard errors in all multi-period panel regressions are clustered at the county level to address potential heteroscedasticity and serial correlation issues.

4. Results

4.1. Baseline Model Results

Table 3 reports the regression results for Equation (1). Column (1) sets the clustering level of robust standard errors at the county level, testing for heteroscedasticity and serial correlation. Column (2) builds on Column (1) by adding city and year fixed effects, effectively controlling for time-invariant city characteristics and national time trends. Column (3) further adds city-level control variables such as industrial structure, fiscal expenditure, and communication levels to enhance the model's identification capability.

Table 3. Baseline model results.

	(1) *per_GDP*	**(2)** *per_GDP*	**(3)** *per_GDP*
DID	2.302 ***	0.449 ***	0.462 ***
	(0.188)	(0.108)	(0.098)
Control Variable	NO	NO	YES
Individual Fixed Effects	NO	YES	YES
Year Fixed Effects	NO	YES	YES
N	23,783	23,783	23,783
R^2	0.047	0.847	0.872

Note: *** indicates significance levels of 1%. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

The regression results indicate that, after controlling for a range of factors that may affect regional per capita GDP, the coefficient of the core explanatory variable *DID* remains significant at the 1% level, suggesting that the policy implementation has a stable positive effect on regional per capita GDP. From an economic significance perspective, after implementing the rural tourism demonstration zone policy, per capita GDP increased by an average of 0.46 thousand yuan, accounting for approximately 12% of the sample average (3.82 thousand yuan), demonstrating a significant policy effect. Implementing rural tourism policies increased regional income and created numerous job opportunities, driving the extension and development of the regional tourism industry chain, thus promoting the increase in regional per capita GDP. The results support Hypothesis 1.

4.2. Parallel Trend Test

The parallel trends assumption is a prerequisite for the DID approach to be effective. If the treatment group did not receive the policy intervention, the trend in the dependent variable changes for the treatment group should be the same as that of the control group. This study follows the prior research [50,51] and uses an event study approach to test the differences in the trends of the dependent variable for both the treatment and control groups over different years. The test results are shown in Figure 2.

Figure 2 presents the results of the parallel trend test. As shown, in the 15 periods prior to the implementation of the policy, the estimated coefficients of the dependent variable are consistently near zero and not significantly different from zero, which suggests that there are no significant pre-existing differences between the treatment and control groups, supporting the parallel trends assumption. At the policy implementation period (at x = 0), the estimated coefficient shows a significant increase, indicating an immediate impact of the policy on the dependent variable. Moreover, this effect remains elevated in the subsequent periods (from x = 1 to x = 13), demonstrating that regional per capita GDP significantly improved after the policy was implemented, with the effect being persistent rather than a one-time occurrence. The results of the parallel trend test are consistent with the baseline regression, further strengthening the causal identification of the baseline regression.

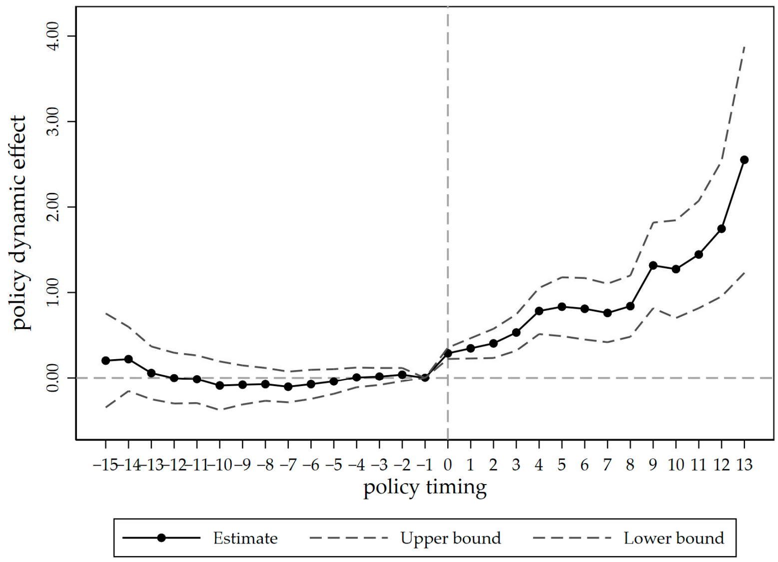

Figure 2. The *X*-axis represents the relative time of the sample observations to the year of policy implementation, with the gray vertical dashed line (x = 0) indicating the time of policy implementation. The period immediately before the policy implementation (x = −1) is selected as the baseline for the parallel trend test. The *Y*-axis shows the trend of the changes in the estimated coefficients for the dependent variable, with the dashed lines representing the 95% confidence intervals of the estimated coefficients.

4.3. Placebo Test

After confirming the assumption of parallel trends, unobservable time-varying confounding events may still affect both the dependent variable and the implementation of rural tourism policies. In this case, the estimated policy effect may be partially driven by these time-varying confounders, leading to endogeneity and estimation bias. To rule out the influence of such confounding events, and following the prior approaches [52], this study performs both "unconstrained" and "constrained" DID mixed placebo test.

For the "unconstrained" DID mixed placebo test, since the sample includes 1399 individuals, with 647 in the treatment group and 752 in the control group, as illustrated in Section 3.2.3, this study randomly selects 647 individuals from the 1399 county-level city individuals and randomly assigns a policy implementation time to them, along with a randomly selected placebo treatment time. This results in a placebo sample, which is then subjected to DID estimation. After repeating this process 500 times, statistical inference is made using the distribution of the placebo results.

For the "constrained" DID mixed placebo test, given that 24 county-level cities implemented the policy in 2010, 21 in 2011, 24 in 2012, and so on, this study first randomly selects 24 county-level cities and assigns the policy implementation time as 2010, then randomly selects 21 cities from the remaining cities and assigns the policy implementation time as 2011, and continues this process until all the virtual treated individuals are assigned with a policy implementation time, forming the placebo sample. DID estimation is then performed, and after repeating the process 500 times, statistical inference is made using the distribution of the placebo results. The results of the "unconstrained" and "constrained" DID mixed placebo tests are reported below.

Figures 3 and 4 report the results of the "unconstrained" and "constrained" DID mixed placebo tests, respectively. The estimated coefficient of the core explanatory variable *DID*

(0.462) in the baseline regression is greater than most of the estimated coefficients in both placebo tests, passing the placebo test. It suggests that the conclusion that implementing rural tourism policies promotes per capita GDP growth is not driven by unobservable time-varying confounding events, further strengthening the causal identification of the baseline regression.

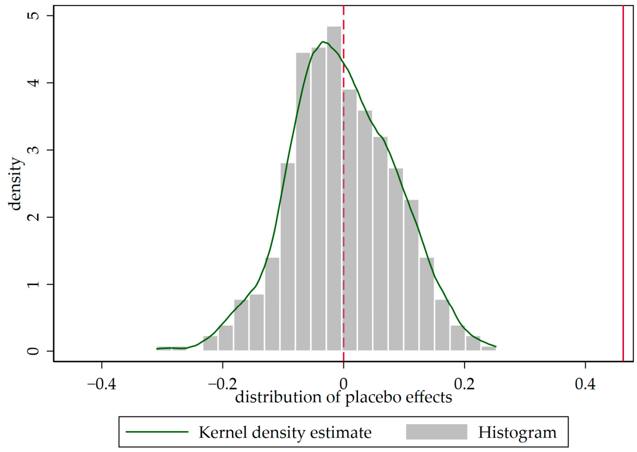

Figure 3. The unconstrained mixed placebo test for DID.

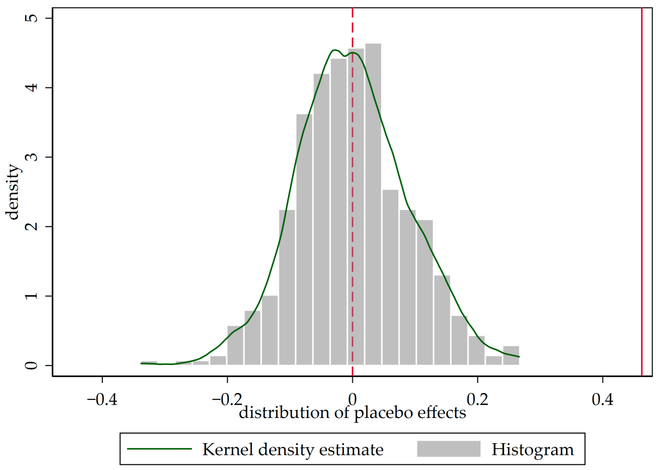

Figure 4. The constrained mixed placebo test for DID.

Note: For Figures 3 and 4, the *X*-axis represents the distribution of the coefficient of the core explanatory variable *DID* from 500 placebo tests, with the solid red vertical line (x = 0.462) representing the baseline regression, which is the estimated coefficient of the core explanatory variable *DID* from Column 3 of Table 3, and the dashed red vertical line (x = 0) representing as assumed no-effect policy. The *Y*-axis represents the frequency density of the coefficients of the core explanatory variable *DID* from the 500 placebo tests, with the gray rectangle representing the frequency histogram and the red solid line representing the kernel density curve.

4.4. Heterogeneous Treatment Effects

Given that the policy implementation times vary across different county-level cities, the estimated coefficients of the DID model are essentially a weighted average of all possible two-group DID estimations in the data. When some group weights are negative, a “negative weight” phenomenon may occur, potentially causing the estimated results to have the opposite sign from the actual policy effect [53]. When the same treatment event produces different treatment effects on different individuals—i.e., when there are heterogeneous treatment effects—this can lead to issues where earlier-treated samples may become the control group for later-treated samples, causing the "negative weight" problem and resulting in biased estimates [54]. Therefore, this study uses Bacon decomposition to test for heterogeneous treatment effects, with the results presented below:

Table 4 reports the results of the Bacon decomposition. As seen, the weight of the "Treated later vs. earlier" component, which could potentially lead to the "negative weight" issue and cause estimation bias, is only 8.6%, much smaller than the weights of 77.2% and 14.2% for the "Treated vs. never treated" and "Treated earlier vs. later" components, respectively. The bias in the estimated coefficients can be considered negligible after weighting. Figure 5 shows the estimated coefficients and weights of all possible two-group DID estimations. Most of the policy effect comes from the counterfactual analysis of the control group, which has not been treated, indicating that the regression results are not severely affected by heterogeneous treatment effects and estimation bias. The results of Bacon decomposition further confirm the robustness of the baseline regression findings.

Table 4. Bacon decomposition.

ATET Decomposition Summary	ATET Component	Weight
Treated vs. never treated	0.519	0.772
Treated earlier vs. later	0.399	0.142
Treated later vs. earlier	−0.102	0.086

Note: This table summarizes the results of the ATET (Average Treatment Effect on the Treated) decomposition based on the DID method. The decomposition is presented in three components: "Treated vs. Never Treated", "Treated Earlier vs. Later" and "Treated Later vs. Earlier.".

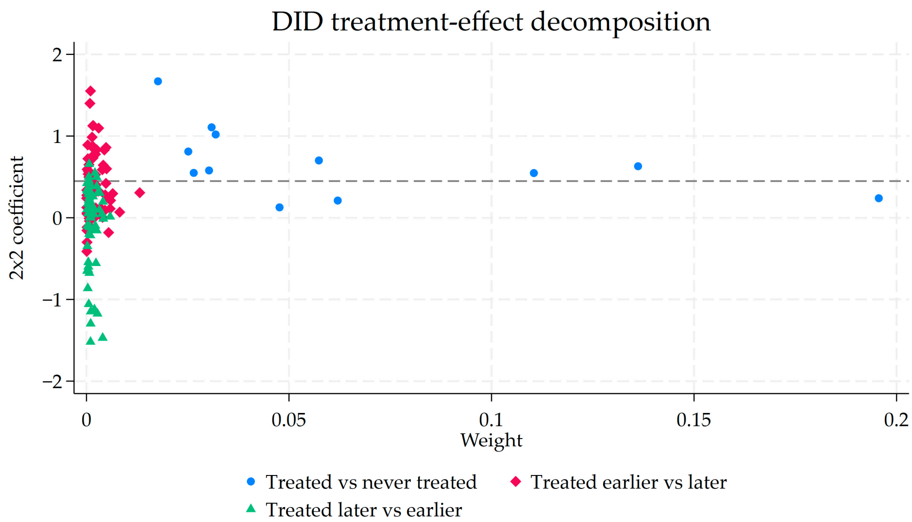

Figure 5. This figure illustrates the distribution of treatment effects for the three components of the ATET decomposition from Bacon's method. The *X*-axis represents the weight of each component, while the *Y*-axis shows the corresponding 2 × 2 DID coefficient. The blue points represent the "Treated vs. Never Treated" component, the green triangles correspond to "Treated Later vs. Earlier" and the red diamonds depict "Treated Earlier vs. Later".

4.5. PSD-DID and SDID

In this part, the PSM-DID and SDID are used to mitigate the potential selection bias problem embedded in the baseline model and serve as robustness tests to provide more empirical support to the DID approach. Specifically, although the DID method estimates the average treatment effect of the rural tourism policy, the policy implementation may not be strictly a quasi-natural experiment. Before policy implementation, individual differences could exist across counties in various dimensions, implying that the counties may develop their rural tourism industries based on different baselines. If these baseline differences lead to systematic differences between the treatment and control groups, it could result in sample selection bias, leading to biased estimates. To address this, this study employs the PSM-DID and SDID methods where the control groups are technically constructed with characteristics more similar to the treatment group, significantly mitigating the potential systematic differences between the control and treatment groups, and generating more robust policy effects estimation.

Specifically, in the PSM-DID method, this study follows the prior research [55,56], using 1:1, 1:3 nearest neighbor matching with replacement, as well as kernel matching, to find the optimal control group that satisfies the common support condition, removing samples that do not meet the common support condition, and generating a new dataset for the DID estimation. The results are presented in Columns (1)–(3) of Table 5. In the SDID method, following prior research [57], the synthetic control method is used to construct a virtual synthetic control group for the treatment group with a similar pre-treatment trend, and further DID estimation is performed by removing individual and time fixed effects. After obtaining the synthetic control DID estimate, this study uses placebo tests and the bootstrap method, sampling 500 times to calculate the standard errors. The results are presented in Columns (4) and (5) of Table 5. As shown, the coefficient of the core explanatory variable *DID* remains significantly positive, further indicating that the results obtained from the baseline regression are robust.

Table 5. Estimation results of the PSM-DID and SDID method.

	(1)	(2)	(3)	(4)	(5)
		PSM-DID			**SDID**
	per_GDP	*per_GDP*	*per_GDP*	*per_GDP*	*per_GDP*
DID	0.280 ***	0.389 ***	0.462 ***	0.442 ***	0.442 ***
	(0.109)	(0.097)	(0.098)	(0.112)	(0.084)
Control Variable	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
N	12,650	20,957	23,772	23,783	23,783
R^2	0.881	0.875	0.873		

Note: *** indicates significance levels of 1%. Columns (1)–(3) present results based on 1:1 nearest neighbor matching with replacement, 1:3 nearest neighbor matching with replacement, and kernel matching, respectively. Due to differences in the removal of non-common support samples in each matching process, the sample sizes vary. In Columns (4)–(5), the standard errors of the estimated coefficients are calculated using the placebo method and the bootstrap method, sampling 500 times. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process.

4.6. Double Machine Learning

In this part, double machine learning is used to mitigate the potential bias from high-dimensional covariates, complex nonlinear relationships, and the model specification problem, serving as robustness tests for the DID approach. Specifically, when the empirical model involves multiple control variables, traditional regression methods may struggle to handle the potential relationships between these variables effectively. For instance, many economic phenomena and policy effects may exhibit nonlinear interactions under different conditions, which traditional linear models may fail to capture, leading to biased estimates. And the model misspecification is another potential factor that may cause bias in the policy effect estimations.

The double machine learning method offers an effective solution. Machine learning algorithms can efficiently handle high-dimensional control variables by automatically selecting the most important ones while avoiding omitting relevant information and controlling for multicollinearity. Through a two-stage process, machine learning algorithms first estimate the effects of control variables in the initial stage, and then these estimates are used as instrumental variables in the second stage regression analysis. This approach helps to avoid estimation bias caused by high-dimensional control variables, effectively identifies potential nonlinear relationships among variables, and reduces bias from model specification. As a result, DML improves the accuracy of policy effect estimation.

To conduct this method, following the prior research [58,59], the control variables are included in linear and quadratic terms to capture potential nonlinear relationships better. At the same time, in the cross-fitting procedure, the number of sample splits is set to 5 to balance estimation stability and computational efficiency. To test the sensitivity of the results to different machine learning algorithm choices, the study uses Ordinary Least Squares (OLS), Lasso regression, Ridge regression, Random Forest, and Elastic Net algorithms in the first-stage prediction model. The regression results are shown in Table 6.

Table 6. Estimation results of double machine learning.

	(1)	(2)	(3)	(4)	(5)
	OLS	**Lasso Regression**	**RidgeCV**	**Random Forest**	**ElasticNet**
	per_GDP	*per_GDP*	*per_GDP*	*per_GDP*	*per_GDP*
DID	0.439 ***	0.462 ***	0.439 ***	0.288 ***	0.464 ***
	(0.045)	(0.044)	(0.045)	(0.040)	(0.044)
Control Variable (linear terms)	YES	YES	YES	YES	YES
Control Variable (quadratic terms)	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783	23,783

Note: *** indicates significance levels of 1%. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

As observed, after accounting for potential issues such as high-dimensional covariates, complex nonlinear relationships, and model specification, the estimated coefficients of *DID* remain positive at the 1% significance level, with the economic significance showing no substantial deviation from the baseline model results. These results demonstrate that the influence of these potential issues on the estimates can be negligible, and the results obtained from the baseline model are robust.

4.7. Excluding Other Policy Interference

To avoid the impact of other concurrently implemented policies on the estimation results, this study further controls for several policy variables that may influence the dependent variable. During the period of rural tourism policy implementation, other policies, such as the development of rural complex projects, the establishment of national all-area tourism demonstration zones, and the construction of national key ecological zones, may have also promoted tourism development or ecological protection in the regions, thereby exerting effects on the dependent variable. If not controlled for, the effects of these policies might be incorrectly attributed to the rural tourism policy, leading to estimation bias. Based on this, the study incorporates these three policies into the regression model one at a time, as shown in Columns (1) to (3) of Table 7, and considers all three policies simultaneously in Column (4) of Table 7. The regression results indicate that after controlling for these potential competing policies, the coefficient of the core explanatory variable remains significantly positive, demonstrating that the main conclusion of this study remains robust after excluding the influence of other policies.

Table 7. Estimation results after excluding other policy interference.

	(1) *per_GDP*	(2) *per_GDP*	(3) *per_GDP*	(4) *per_GDP*
DID	0.478 ***	0.458 ***	0.475 ***	0.482 ***
	(0.098)	(0.100)	(0.098)	(0.099)
Rural Complex	0.426 ***			0.424 ***
	(0.108)			(0.107)
All-round Tourism		0.086		0.149
		(0.190)		(0.185)
Ecological Zones			−0.569 ***	−0.570 ***
			(0.090)	(0.089)
Control Variable	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783
R^2	0.873	0.872	0.873	0.874

Note: *** indicates significance levels of 1%. The values in parentheses represent the robust standard errors, with standard errors clustered at the county-level city level during the regression process. *Rural Complex*, *All-round Tourism*, and *Ecological Zones* represent dummy variables for implementing the rural complex projects, national all-area tourism demonstration zones, and national key ecological zones policies, respectively. Constructing these dummy variables follows the same methodology as the core explanatory variable *DID*.

4.8. Intensity DID

It can be argued that the specification of the *DID* variable in the baseline regression may not be able to capture more detailed information regarding the intensity or strength of policy implementation, which could potentially affect the assessment of the policy's impact. To improve this limitation, we draw on existing literature and introduce an Intensity DID framework to more accurately capture the variation in policy implementation strength, thus enhancing the precision of our policy effect evaluation [60].

Specifically, we construct a policy intensity indicator, interact it with the core explanatory variable *DID*, and regress the interaction term based on Equation (1). In terms of constructing the policy intensity indicator, we utilize four key metrics: the total number of newly registered tourism enterprises in the county in a given year (*NRE*), the number of newly registered tourism enterprises per 1000 people (*per_NRE*), the total area of land allocated for tourism in a given year (*Land*) and the per capita land allocation for tourism (*per_Land*). We divide the districts into five equal groups based on the values of these indicators. The group with the highest value for each indicator is assigned a policy intensity value of 1, indicating the strongest policy implementation, with the second-highest group assigned a value of 0.9, and so on, down to the lowest group, which is assigned a value of 0.6. We then interact this policy intensity measure with the DID variable and include the interaction term in our regression model. By employing multiple indicators rather than a single one, a more comprehensive variation in policy implementation across districts can be reflected, and a more precise assessment of the policy's effects can be made.

Table 8 reports the results obtained from the intensity DID. It can be noticed that after introducing the policy intensity indicator, the coefficient of the interaction term remains significantly positive when changing the construction ways of the policy intensity indicator, which indicates that higher policy implementation intensity is associated with a more substantial positive effect of the policy intervention. Districts with higher policy intensity levels experience greater per GDP improvements, thus a more significant economic effect.

Table 8. Estimation results of Intensity DID.

	(1) *per_GDP*	**(2)** *per_GDP*	**(3)** *per_GDP*	**(4)** *per_GDP*
Policy Intensity Indicator	*NRE*	*per_NRE*	*Land*	*per_Land*
DID × *Policy Intensity Indicator*	0.569 ***	0.625 ***	0.600 ***	0.608 ***
	(0.111)	(0.115)	(0.119)	(0.121)
Control Variable	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Time Trend Term	NO	YES	NO	YES
Provincial and Year Fixed Effects	NO	NO	YES	YES
N	23,783	23,783	23,783	23,783
R^2	0.872	0.873	0.873	0.872

Note: *** indicates significance levels of 1%. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

4.9. Other Robustness Tests

This study also conducts a series of additional robustness checks: (1) Excluding specific years: To eliminate the potential interference of the COVID-19 pandemic on the regression results, we exclude the years after 2020 from the sample and re-estimate the model. The results are presented in Column (1) of Table 9. (2) Introducing time trend term: Pre-existing characteristic differences between the treatment and control groups may lead to differences in subsequent development. Following prior research [61], we introduce an interaction term between the treatment variable and the year to control the time trend differences between the treatment and control groups. The regression results are shown in Column (2) of Table 9. (3) Considering time-varying provincial influences: Provincial governments can significantly influence the development of county-level cities within their jurisdiction through policy reforms and pilot projects. We add provincial and year-fixed effects to Equation (1) to further control for these effects. The results are presented in Column (3) of Table 9. (4) Simultaneously including time trend variables and time-varying provincial influences: The results are reported in Column (4) of Table 9. (5) Considering different baselines: Counties may have started the rural tourism policy from varying baselines, which may introduce the sample selection bias into the model. To control this potential issue, we introduce a set of time trend variables, where each time trend variable is constructed as the interaction between the value of the control variables in 2007 (the start year of the sample period) and the year indicators. By adding these pre-implementation variables, the baseline variation can be controlled, and the results are reported in Column (5) of Table 9.

Table 9. Estimation results of other robustness tests.

	(1) *per_GDP*	**(2)** *per_GDP*	**(3)** *per_GDP*	**(4)** *per_GDP*	**(5)** *per_GDP*
DID	0.342 ***	0.248 ***	0.290 ***	0.232 ***	0.307 ***
	(0.096)	(0.068)	(0.098)	(0.061)	(0.087)
Control Variable	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Time Trend Term	NO	YES	NO	YES	YES
Provincial and Year Fixed Effects	NO	NO	YES	YES	NO

Table 9. *Cont.*

	(1) *per_GDP*	(2) *per_GDP*	(3) *per_GDP*	(4) *per_GDP*	(5) *per_GDP*
N	18,174	23,783	23,766	23,766	23,783
R^2	0.924	0.872	0.895	0.895	0.899

Note: *** indicates significance levels of 1%. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

As shown, the coefficient of the core explanatory variable *DID* remains significantly positive across all five specifications, further confirming the robustness of the baseline results.

5. Mechanism Analysis

Based on the empirical results discussed earlier, it is evident that implementing rural tourism policies significantly enhances regional per capita GDP. To empirically explore the mechanism behind this promotional effect and test Hypothesis 2, this study follows prior research [62] and sets up the following specification for the mechanism analysis:

$$M_{it} = \gamma_0 + \gamma_1 DID_{it} + X_{it} + \kappa_i + \varrho_t + \vartheta_{it} \tag{2}$$

In Equation (2), M_{it} represents the mechanism variable for county-level city i in year t, with γ_1 and γ_0 being the estimated coefficients of the core explanatory variable DID_{it} and the constant term, respectively. κ_i represents the individual fixed effects for city i, and κ_i represents the year fixed effects for year t, while ϑ_{it} is the random error term, and the other terms are consistent with those in Equation (1). In the mechanism analysis, this study focuses on γ_1, which measures the impact of policy implementation on the mechanism variable. The analysis examines the mechanism from two perspectives: the number of newly registered tourism enterprises and the land transfer for tourism.

5.1. Household Income, Consumption, and Infrastructure Investment

This study employs the following five indicators for analysis: rural residents' disposable income (*RDI*, in thousands of yuan), total consumption goods at the county level (*TCG*, in billions of yuan), Per Capita consumption goods at the county level (*per_CG*, in thousands of yuan), total infrastructure investment at the county level (*TII*, in billions of yuan), and Per Capita infrastructure investment at the county level (*per_II*, in thousands of yuan). Based on Equation (2), a regression analysis is conducted to test H2 empirically. The results are presented in Table 10.

Table 10. Mechanism analysis of income, consumption, and infrastructure.

	(1) *RDI*	(2) *TCG*	(3) *per_CG*	(4) *TII*	(5) *per_II*
DID	0.381 **	0.875 ***	1.503 ***	2.618 ***	2.618 ***
	(0.162)	(0.328)	(0.349)	(0.771)	(0.771)
Control Variable	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783	23,783
R^2	0.895	0.824	0.836	0.835	0.835

Note: ** and *** indicate significance levels of 5% and 1%, respectively. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

The findings indicate that after the implementation of rural tourism policies, the disposable income of rural residents at the county level significantly increased, suggesting that the policy effectively enhanced the income levels of residents. Furthermore, both consumer goods retail sales and fixed asset investment exhibit significant positive coefficients at the 1% significance level, demonstrating that rural tourism policies have a spillover effect, which can stimulate consumption and fixed asset investment at the county level, thereby promoting regional economic development and increasing Per Capita GDP.

5.2. Newly Registered Tourism Enterprises

This study further analyzes the issue from the perspective of the number of newly registered tourism enterprises. The number of new registered enterprises directly reflects the ability of rural tourism policies to encourage market participants to enter the market. It demonstrates the actual effect of the policy in reducing market entry barriers through improvements in infrastructure, business environment, and other factors. Therefore, following prior research [63], this study uses the total number of newly registered tourism enterprises in the county in a given year (*NRE*) and the number of newly registered tourism enterprises per 1000 people (*per_NRE*) as mechanism variables, and performs regression based on Equation (2), with the results presented in Table 11.

Table 11. Mechanism analysis of enterprises and land transfer.

	(1) *NRE*	(2) *per_NRE*	(1) *Land*	(2) *per_Land*
DID	0.945 ***	0.117 ***	0.747 **	0.029 **
	(0.310)	(0.035)	(0.344)	(0.014)
Control Variable	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783
R^2	0.626	0.657	0.301	0.298

Note: ** and *** indicate significance levels of 5% and 1%, respectively. The values in parentheses represent the robust standard errors, with standard errors clustered at the county level during the regression process.

As can be seen, rural tourism policies significantly promote the total number of newly registered tourism enterprises and the Per Capita number of these enterprises in the county. After the policy implementation, the increase in registered tourism enterprises enhanced the supply of tourism products and services in the county. This effectively boosted the vitality of the tourism market and contributed to the agglomeration and development of related industries, such as accommodation, catering, and transportation. These developments help form industrial chain effects and economies of scale, further driving local economic growth and increasing Per Capita GDP. The H3 is empirically supported.

5.3. Land Transfer for Tourism

This study lastly analyzes the issue from the perspective of land allocation for tourism. Land transfer is a fundamental prerequisite for tourism development, particularly for constructing large-scale tourism facilities, such as resorts, hotels, and infrastructure for tourist attractions, all requiring substantial land. Therefore, land allocation is not only one of the necessary conditions for driving the development of the tourism industry but also an important indicator for measuring the expansion and growth potential of the tourism sector. In light of this, following prior research [64], this study uses the total area of land allocated for tourism in a given year (*Land*) and the Per Capita land allocation for tourism (*per_Land*) as mechanism variables. The regression results are presented in Table 11. As shown, rural tourism policies significantly promote the extent of land allocation for tourism in the county. After the policy implementation, land allocation for tourism increased significantly, enhancing the spatial resources required for tourism projects. This enabled counties to utilize limited space to drive the development of the tourism industry, thereby promoting an increase in Per Capita GDP. The H4 is empirically supported.

6. Heterogeneity Analysis

The effect of rural tourism policies may vary due to inherent regional characteristics. To further explore this heterogeneity, this study conducts an analysis based on whether the county is a poverty-stricken county, the geographic location of the county, and the level of transportation infrastructure development. Finally, Figure 6 provides a visual summary of all results of the heterogeneity analysis.

6.1. Poverty-Stricken County

This study conducts a heterogeneity analysis based on whether the county is poverty-stricken. Poverty-stricken and non-poverty-stricken counties differ in resource endowment, industrial foundation, and infrastructure levels, which may affect the implementation effectiveness of rural tourism policies. Therefore, based on the list of national poverty-stricken counties published by the Office of the Leading Group for Poverty Alleviation and Development of the State Council of China, counties are classified according to whether they have ever been on this list, and the sample is divided into poverty-stricken and non-poverty-stricken counties for group regressions. The results are presented in Table 12. In addition, to test the statistical significance of the coefficient differences between the groups, this study uses Fisher's Permutation test and conducts statistical inference through Bootstrap self-sampling with 500 iterations to obtain empirical *p*-values.

Table 12. Heterogeneity analysis of the poverty-stricken county.

	Poverty-Stricken County	**Non-Poverty-Stricken County**
	(1)	**(2)**
	per_GDP	***per_GDP***
DID	0.590 ***	0.090
	(0.133)	(0.056)
Control Variable	YES	YES
Individual Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
N	15,572	8211
R^2	0.874	0.874
Fisher's Permutation Test	0.501 ***	

Note: *** indicates significance levels of 1%. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process. Fisher's Permutation test reports the economic and statistical significance of the difference in coefficients between the two groups, with the statistical significance level based on Fisher's Permutation test, and empirical *p*-values calculated through Bootstrap self-sampling with 500 iterations.

The results indicate that the impact of rural tourism policies is significantly greater in non-poverty-stricken counties than in poverty-stricken ones. A possible explanation for this disparity lies in the differences across regions in China regarding the accessibility of resource endowments, infrastructure, and market integration, which collectively influence the effectiveness of these policies. In poverty-stricken counties, the benefits of rural tourism policies are often less pronounced due to weaker economic foundations and underdeveloped infrastructure.

Specifically, while poverty-stricken areas have tourism resources—such as natural resources, intangible cultural heritage, and traditions—comparable to non-poverty areas, their accessibility is hindered by inadequate transportation infrastructure. Underdeveloped transportation systems will increase travel time and costs for tourists and diminish the tourism experience. Additionally, these areas often have lower commercialization, poor market integration, and gaps in tourism infrastructure and services, further limiting their attractiveness. One of the underlying reasons for this disparity is that China just achieved the goal of eradicating absolute poverty by 2020 (Data resource: http://english.scio.gov.cn/whitepapers/2021-04/06/content_77380652.htm, accessed on 14 October 2025), which implies that some poverty-stricken areas only recently completed poverty alleviation, starting marketization and commercialization later, which slowed their development. Due to weak economic foundations, these areas are still in the early stages of infrastructure development, market integration, and commercialization. Consequently, their ability to attract external capital and tourism enterprises is limited, thus weakening the effectiveness of rural tourism policies.

6.2. Geographic Location

This study further analyzes heterogeneity based on the spatial distance between counties and regional central cities. Theoretically, location distance not only affects the accessibility of local tourism resources and market potential but also determines transportation costs, information flow efficiency, and the degree of factor agglomeration during policy implementation. Counties near the city center of a prefecture-level city or provincial capital can typically benefit more from the infrastructure, market development, and other resources in central cities, thereby amplifying the policy's economic effects. To examine the heterogeneity of rural tourism policy effects under different spatial conditions, the study groups counties based on their distance to the central city. The operations are as follows: (1) Distance to the prefecture-level city center: Counties are grouped into "near" and "far" based on the average straight-line distance to the capital of their prefecture-level city. (2) Distance to provincial capital: Counties are grouped into "near provincial capital" and "far provincial capital" based on the average distance to their provincial capital. The regression results are presented in Table 13.

Table 13. Heterogeneity analysis on geographic location.

	Instance to the City Center		**Instance to the Provincial Center**	
	(1)	**(2)**	**(3)**	**(4)**
	Near	**Far**	**Near**	**Far**
DID	0.499 ***	0.410 ***	0.618 ***	0.201 *
	(0.140)	(0.137)	(0.148)	(0.118)
Control Variable	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
N	12,478	11,305	12,750	11,033
R^2	0.872	0.873	0.870	0.880
Fisher's Permutation Test	0.089		0.417 ***	

Note: * and *** indicate significance levels of 10% and 1%, respectively. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process. Fisher's Permutation test reports the economic and statistical significance of the difference in coefficients between the two groups, with the statistical significance level based on Fisher's Permutation test, and empirical *p*-values calculated through Bootstrap self-sampling with 500 iterations.

The results indicate that rural tourism policies have a more significant effect in counties closer to the regional central cities, reflecting spatial heterogeneity in policy impacts. The underlying cause of this disparity could primarily stem from the differences in tourism resource endowments driven by geographic advantages.

Firstly, from the perspective of resource endowments, China's current regional development pattern is imperfect, where infrastructure construction, market development, and other resources are more geographically concentrated in central cities. Counties closer to the more developed urban centers can benefit more from superior infrastructure, market access, and enhanced capital acquisition capabilities, enabling the policy's effects to be more effectively translated into economic growth. Furthermore, from the perspective of tourist resources, proximity to urban centers enables these counties to attract higher-income visitors, yielding greater returns even with similar investments. Finally, from the perspective of information dissemination, counties closer to central cities typically enjoy stronger media coverage and more efficient information transmission, enabling them to effectively reduce information asymmetry between rural areas and potential visitors, attracting more tourists, and boosting tourism performance.

The disparity in Fisher's Permutation test results further supports this observation. When using distance to the provincial capital as the grouping criterion, the test value is 0.417 at the 1% significance level, significantly contrasting with the value of 0.089 when using distance to the prefecture-level city center. This contrast highlights the advantages of provincial capitals, as higher-level central cities, in infrastructure development, capital access, and information flow, enabling nearby counties to use rural tourism policies more effectively to increase economic growth.

6.3. Transportation Infrastructure

Transportation infrastructure is crucial for the accessibility of rural tourism resources. Rural tourism often relies on natural resources, cultural heritage, and ecological environments, which are typically located in remote areas with limited transport access. While these areas offer unique attractions, poor accessibility would increase tourist travel costs, weakening the effectiveness of rural tourism policies. Therefore, the quality of transportation directly impacts the realization of policy outcomes.

From the perspective of the characteristics of rural tourism, transportation infrastructure plays a critical role in the accessibility of rural tourism resource endowments. Rural tourism typically relies on abundant natural resources, cultural heritage, and ecological environments, which are often located in relatively remote areas with limited transportation accessibility. While these areas possess unique tourist attractions, if the accessibility of their tourism resource endowments is low, it results in higher travel costs for tourists, which weakens the effectiveness of rural tourism policies. Therefore, the quality of transportation directly determines the sustainable development of rural tourism and the realization of policy outcomes.

To further explore the differences in the effects of rural tourism policies driven by transportation infrastructure, this study uses three modes of tourism transportation—road, rail, and air—as classification criteria. For the road classification, the study employs road network density, which is calculated as the total length of roads in the county adjusted for the county's area. The sample is divided into two groups based on the average road network density: "dense road network" and "sparse road network" counties. For the rail classification, counties are grouped based on whether they have high-speed rail stations. For the air classification, counties are grouped based on whether the prefecture-level city in which the county is located has an airport. Table 14 reports the regression results based on these three modes of transportation.

Table 14. Heterogeneity analysis on transportation infrastructure.

	Road		High-Speed Rail Station		Airport	
	(1) Intensive	(2) Sparse	(3) YES	(4) NO	(5) YES	(6) NO
DID	0.885 ***	0.301 ***	0.613 ***	0.372 ***	0.479 ***	0.407 ***
	(0.212)	(0.100)	(0.173)	(0.116)	(0.142)	(0.135)
Control Variable	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
N	7157	16,626	6239	17,544	12,206	11,577
R^2	0.876	0.874	0.867	0.877	0.880	0.858
Fisher's Permutation Test	0.584 ***		0.241 **		0.072	

Note: ** and *** indicate significance levels of 5% and 1%, respectively. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process. Fisher's Permutation test reports the economic and statistical significance of the difference in coefficients between the two groups, with the statistical significance level based on Fisher's Permutation test, and empirical *p*-values calculated through Bootstrap self-sampling with 500 iterations.

Overall, in counties with higher levels of transportation infrastructure, the promotion effects of rural tourism policies are more significant, which can be attributed to the fact that rural tourism depends a lot on the actual arrival of tourists. Improvements in transportation infrastructure can significantly enhance the accessibility of tourist destinations, facilitating the movement of tourists and market expansion, thereby strengthening the effectiveness of policy benefits.

Moreover, Fisher's Permutation exact test for the between-group differences shows varying statistical and economic significance levels when using different types of transportation as the grouping criterion. Specifically, the most pronounced differences in the group comparisons appear in the road network density grouping, with the coefficient difference in the core explanatory variable *DID* being significantly positive at the 1% significance level. This is followed by the high-speed rail station grouping, with the most minor differences observed in the airport grouping.

A possible explanation for this is that the road system is the most commonly used and flexible mode of transportation for rural residents and tourists. A well-developed road network significantly reduces the "last mile" travel costs, making it easier for tourists to reach destinations and enhancing the policy effect. While high-speed rail can improve interregional connectivity, its impact on rural tourism is limited by the few stations, creating more of a node-radiation effect than widespread coverage. Lastly, the airports are constrained by high costs and infrequent services, making them a less significant driver for county-level rural tourism development. The differences in the between-group coefficients further confirm the impact of transportation infrastructure on the accessibility of rural tourism resources and the mobility of tourists. In remote areas, poor transportation severely limits rural tourism development, while in areas with better infrastructure, the potential for rural tourism is more easily realized, amplifying the policy effect.

Figure 6 summarizes this heterogeneity analysis, visually representing the results.

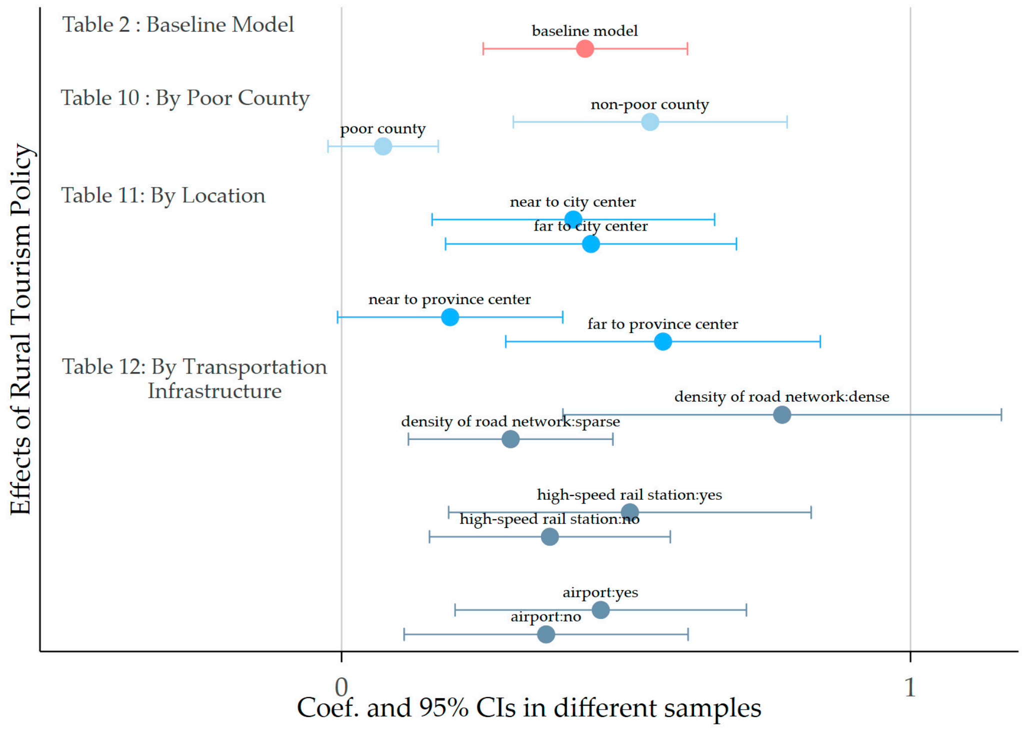

Figure 6. This figure presents the estimated effects of rural tourism policies across different samples. The *X*-axis represents the estimated coefficients of the policy effects, along with their corresponding 95% confidence intervals (CIs). The *Y*-axis lists various subgroups based on the baseline model as well as the sub-sample with different characteristics, including "Poor County," "Location" (near city center, near province center), and "Transportation Infrastructure" (road network density, high-speed rail station, airport), with each subgroup showing the variation in the policy effect across those specific categories.

7. Further Analysis

This section further analyzes the environmental effects of rural tourism policies. As introduced in Section 3.2.1, and drawing on existing studies [43,44,46–48] as well as data availability, PM2.5 (*pm2.5*) and PM10 (*pm10*) are employed as proxy variables for the air quality levels of counties and districts. The *NDVI* and the coverage of county-level forests (Forest) and grasslands (Grassland) are used as a proxy for land environment and biodiversity levels. Similarly, the coverage of county-level water bodies (*Water*) serves as a proxy for water resource levels. Each environmental indicator is treated as a dependent variable and regressed based on Equation (1).

The results are presented in Table 15.

Table 15. Results of further analysis.

	(1) *pm2.5*	(2) *pm10*	(3) *NDVI*	(4) *Forest*	(5) *Grassland*	(6) *Water*
DID	1.022 ***	1.495 ***	−0.002	−0.015 *	0.001	−0.014
	(0.305)	(0.447)	(0.001)	(0.008)	(0.012)	(0.010)
Control Variable	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783	23,783	23,783
R^2	0.937	0.963	0.973	0.998	0.996	0.989

Note: * and *** indicate significance levels of 10% and 1%, respectively. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process.

As can be observed in Table 14, the deterioration of county-level air quality indicators is the most pronounced. The annual average PM2.5 concentration increased significantly by 1.02 μm/m^3, accounting for 2.28% of its sample mean (44.76). Similarly, PM10, which is closely associated with PM2.5, also rose significantly after implementing the policy. The decline in forest coverage is the most significant regarding land and biodiversity indicators. By contrast, the impacts of rural tourism policies on the other two indicators are weaker in terms of both economic and statistical significance when compared with the forest indicator. Regarding water resources, rural tourism policies exert a specific adverse effect on county-level water environment conditions, but this effect is not statistically significant. Overall, after the implementation of rural tourism policies, various environmental indicators at the county level experienced different degrees of deterioration, with air quality and forest land coverage being the most adversely affected.

Rural tourism development, while driving regional economic growth, inevitably leads to environmental degradation. This finding is consistent with the arguments of prior research [21,26,27]. At the same time, this study tries to reveal that such environmental degradation exhibits a relatively high economic conversion rate. In other words, counties that implemented rural tourism policies achieved growth in Per Capita GDP while generating a comparatively lower level of environmental pollution, thereby realizing a "low pollution for high growth" development path. Moreover, this high-efficiency conversion relationship still holds even in the environmental dimensions most adversely affected by rural tourism development. While empirically testing H5, this study further integrates DID approaches with empirical data and provides evidence from the following two perspectives to substantiate this point.

First, since the economic and environmental indicators employed in this study differ in their units of measurement, a simple comparison of regression coefficients may be confounded by variations in scale across indicators. To address this issue, the economic and environmental indicators are standardized to eliminate unit-related discrepancies. After this transformation, the study obtains the standardized Per Capita GDP (*z_per_GDP*) and a set of standardized environmental indicators (*z_pm2.5, z_pm10, z_NDVI, z_Forest, z_Grassland, z_Water*), which are then substituted as dependent variables for regression based on Equation (1).

$$z\_per\_GDP_{it} = \beta_0 + \beta_1 DID_{it} + X_{it} + \pi_i + \tau_t + \epsilon_{it} \tag{3}$$

$$z\_EI_{it} = \gamma_0 + \gamma_1 DID_{it} + X_{it} + \rho_i + \varphi_t + \vartheta_{it} \tag{4}$$

where the subscript i denotes the county-level city, and t represents the year; $z\_per\_GDP_{it}$ and z_EI_{it} represent the standardized *per_GDP* and standardized environment indicators for city i in year t, respectively; β_1 and ψ_1 are the coefficients for the core explanatory variable DID_{it}, measuring the policy implementation effects; X_{it} are control variables; π_i and ρ_i are the individual fixed effects for city i; τ_t and φ_t are the year fixed effects for year t; ϵ_{it} and ϑ_{it} are the random error terms.

Additionally, based on the results of the standardized indicators, this study constructs the EER to estimate the impact of the policy on economic output and environmental performance:

$$EER = \frac{|\beta_1|}{|\gamma_1|} \tag{5}$$

When EER = 1, the increase in standardized Per Capita GDP is equal in magnitude to the variation in standardized environmental indicators, indicating that the policy implementation has achieved a balanced growth path between the economy and the environment. When EER < 1, it suggests that while the policy stimulates economic growth, it simultaneously leads to a higher level of pollution, representing a growth trajectory that is less environmentally friendly. Conversely, when EER > 1, the pollution induced by policy implementation exhibits a higher economic conversion rate, thereby enabling a more environmentally sustainable path of economic growth. To obtain the sampling distribution of EER, this study follows prior research [65] and performs 500 non-parametric bootstrap repetitions, re-estimating both equations in each repetition and recording the estimated EER. The overall EER is inferred through the bootstrap variance-covariance matrix, and the Wald test is used to test whether EER is statistically significantly different from 1.

After standardization to remove dimensional interference, it can be observed in Table 16 that the implementation of rural tourism policies led to a significant 11.6% increase in Per Capita GDP, the magnitude of which substantially exceeds the deterioration observed in other environmental indicators. Among the three most pronounced environmental indicators, PM2.5, PM10, and forest land coverage, the policy implementation resulted in statistically significant increases of 5.3% and 3.7% for PM2.5 and PM10, respectively, and a decline of 0.5% in forest coverage. In contrast, the effects of rural tourism policies on other environmental indicators are neither statistically nor economically significant.

Table 16. Results of further analysis.

	(1) *z_per_GDP*	(2) *z_pm2.5*	(3) *z_pm10*	(4) *z_NDVI*	(5) *z_Forest*	(6) *z_Grassland*	(7) *z_Water*
DID	0.116 ***	0.053 ***	0.037 ***	−0.012	−0.005 *	0.000	−0.010
	(0.025)	(0.016)	(0.011)	(0.007)	(0.003)	(0.004)	(0.007)
Control Variable	YES	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
N	23,783	23,783	23,783	23,783	23,783	23,783	23,783
R^2	0.872	0.937	0.963	0.973	0.998	0.996	0.989

Note: * and *** indicate significance levels of 10% and 1%, respectively. The values in parentheses represent robust standard errors, with standard errors clustered at the county level during the regression process.

Furthermore, based on Equation (4), the EER values corresponding to these three environmental indicators are calculated as 2.32, 3.17, and 21.52, respectively—all greater than 1. This result demonstrates that the high-efficiency conversion relationship between environmental degradation and economic growth remains evident even in the dimensions most adversely affected by rural tourism development. This study conducts statistical tests using the bootstrap method to examine whether these EER values differ significantly from 1. Figure 7 presents the visualization of 500 nonparametric bootstrap replications based on PM2.5. It is evident that across all 500 replications, the observed EER values lie significantly above the red reference line corresponding to EER = 1. The bootstrap standard error of the EER is estimated at 0.389, with a 95% bootstrap confidence interval of [1.434, 2.960]. A Wald test confirms that the null hypothesis of EER equal to 1 can be rejected at the 1% significance level. Similarly, Figures 8 and 9 report the visualization results of 500 nonparametric bootstrap replications based on PM10 and forest coverage, respectively. In both cases, the null hypothesis of EER = 1 is rejected at the 1% significance level.

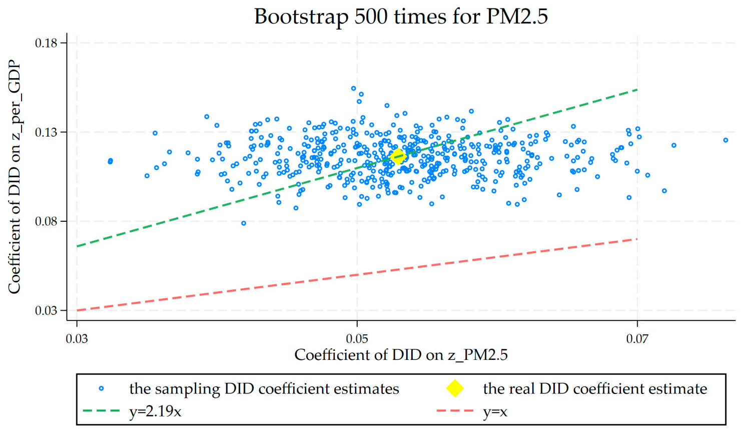

Figure 7. The blue circles represent the distribution of the *DID* coefficient estimates obtained from 500 bootstrap repetitions. The *X*-axis represents the coefficient of the policy effect on the standardized annual average PM2.5 concentration (*z_pm2.5*), while the *Y*-axis represents the coefficient of the policy effect on the standardized Per Capita GDP (*z_per_GDP*). The yellow diamond represents the estimate for the full sample. The green dashed line corresponds to the ratio reference line based on the EER obtained from the actual sample estimate, i.e., y = 2.32x. The red dashed line represents the baseline (EER = 1), i.e., y = x.

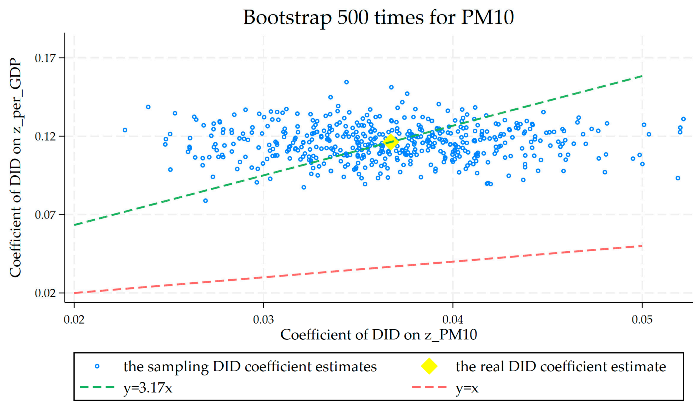

Figure 8. The *X*-axis represents the coefficient of the policy effect on the standardized annual average PM10 concentration (*z_pm10*), while the yellow diamond represents the estimate for the full sample, with the green dashed line corresponding to the ratio reference line based on the EER obtained from the actual sample estimate, i.e., y = 3.17x. The others remain the same as in Figure 7.

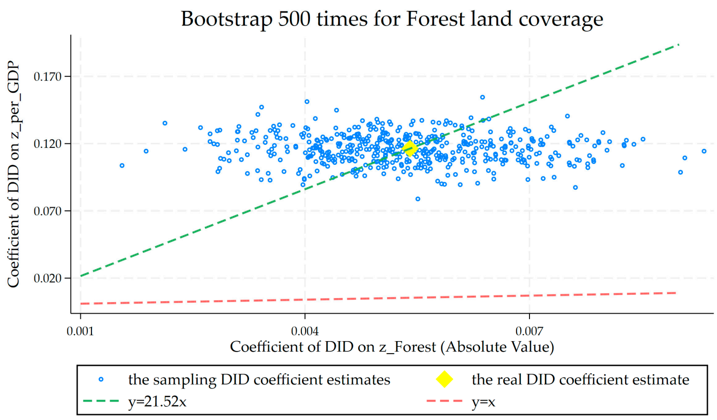

Figure 9. The *X*-axis represents the coefficient (absolute value) of the policy effect on the standardized county forest land coverage (*z_Forest*), while the yellow diamond represents the estimate for the full sample, with the green dashed line corresponding to the ratio reference line based on the EER obtained from the actual sample estimate, i.e., y = 21.52x. The others remain the same as in Figure 7.

These findings imply that, even in the most pronounced dimensions of environmental degradation, the policy-induced changes in economic output can still be substantially larger to offset the adverse effect. This further proves that rural tourism policies, while stimulating regional economic growth, impose relatively lower environmental costs and thus constitute a viable pathway toward sustainable development.

The potential underlying causes can be multifaceted. Firstly, from the perspective of resource endowments, rural tourism relies mainly on natural landscapes and cultural features, which can be more sustainable than the resources used by traditional industries like coal and oil. This low-pollution characteristic enables rural tourism to generate economic benefits while avoiding too much pollution associated with traditional industries. Second, regarding the environmental pollution it generates, the environmental issues related to rural tourism are mostly controllable and localized. These problems are typically confined to specific areas and can be managed and mitigated through environmental management. Third, from a dynamic perspective, the economic benefits and fiscal revenues from rural tourism provide local governments with more fiscal resources that can be reinvested in advanced environmental technologies and green management, which can reduce the regional environmental pollution and further facilitate a "low pollution, high growth" development model.

Importantly, although the results show that rural tourism development can achieve an effective "conversion rate" by exchanging a certain level of environmental pollution for economic benefits during the sample period, it must be noted that this trade-off between economy and environment must be treated with caution. If these environmental costs are not effectively managed and mitigated, pollution will gradually accumulate, potentially reaching irreversible levels, severely impacting environmental quality and the sustainable use of tourism resources.

To achieve the sustainable development of rural tourism and, more broadly, the tourism industry, the key lies in whether policies, technologies, and institutional frameworks can be put in place to effectively control and restore these environmental issues promptly [22,66]. Specifically, for policymakers, the following aspects deserve attention to better harness the government's role in promoting green development in rural tourism and achieving sustainable economic development.

Firstly, from the perspective of administrative approval, the government should integrate the concept of sustainable development into the decision-making and actions related to the development of the rural tourism industry, reflecting this in the administrative approval process. Before new rural tourism projects are approved, an environmental impact assessment should be undergone to ensure they align with long-term ecological protection standards. In particular, during the project planning and approval stages, priority should be given to these tourism projects that reduce environmental burdens, adopt green technologies, and have lower pollution emissions, thus promoting the development of green rural tourism.

Additionally, from the perspective of fiscal expenditure, a specific portion of the economic benefits and fiscal revenue from rural tourism should be earmarked to support local sustainable development. Fiscal subsidies can be prioritized for constructing environmental protection infrastructure, such as wastewater treatment, waste classification and recycling, and the use of green energy. Tax reductions and interest subsidies can encourage enterprises to adopt environmental protection measures, support the use of renewable energy, green building materials, and form green business models. In technology and management, the government can invest more in introducing advanced environmental technologies and green management practices and increasing the technical assistance for ecological restoration and rural environmental protection projects, further promoting the sustainable development of the rural tourism industry.

Last but not least, from an institutional design perspective, the government should establish a decision-making framework that aligns long-term economic growth with environmental protection to ensure the sustainability of rural tourism policies. This framework should prevent policymakers from focusing solely on short-term economic benefits while neglecting long-term environmental impacts. Moreover, the government should establish a long-term accountability mechanism, holding policymakers accountable for extended periods. If necessary, accountability should extend to as far back as twenty years or more to ensure that even after policymakers have left the regions where they implemented their decisions, they can still be held responsible for short-sighted decisions. By constructing such an institution, short-term decision-making can be effectively prevented, and sustainable development goals can be more easily realized.

8. Conclusions

The findings show that rural tourism policies significantly increase Per Capita GDP at the county level, with this result remaining robust across several tests, including parallel trend, placebo, Bacon decomposition, PSM-DID, SDID, double machine learning, and exclusion of other policy interferences. Mechanism analysis reveals that the policies promote economic growth through household income, consumption, infrastructure investment, newly registered enterprises, and land transfer. Heterogeneity analysis shows a more significant promoting effect in non-poor counties, those closer to city centers, and those with better transportation infrastructure. Further analysis shows that the environmental costs of rural tourism policies are much lower than the economic benefits, revealing the important role of rural tourism in fostering a sustainable development pattern that balances economic growth and environmental protection.

The potential theoretical contributions of this study can be summarized in the following ways: First, from the research framework perspective, this study integrates rural tourism, economic development, and environmental quality into a unified theoretical framework, enhancing the understanding of both the economic and environmental effects of rural tourism policies. Second, from the research paradigm perspective, this study employs a DID approach combined with a quasi-natural experiment design, supported by robustness tests and statistical methods, to provide solid empirical evidence and ensure accurate policy effect evaluation, offering a reference for future research. Third, from a research approach perspective, compared to previous studies that focus on a single aspect of policy effects, this study simultaneously addresses both the economic and environmental impacts of rural tourism policies and links them up to provide a more comprehensive analysis. Furthermore, this study quantifies the potential adverse environmental impacts of rural tourism policies and compares them with the economic effects to assess the role of rural tourism in fostering sustainable development.

The potential policy implications of this study can be summarized in the following ways: First, compared to previous literature, the empirical results of this study emphasize the role of newly registered enterprises and land transfers in facilitating regional economic growth under rural tourism policies. The heterogeneity analysis highlights the importance of factors such as accessibility to the resource endowments of rural tourism and the development of transportation infrastructure in determining policy effectiveness. Governments seeking to promote rural revitalization through rural tourism should consider these factors for more efficient policy implementation. Second, while rural tourism has achieved a sustainable development pattern in the observed period, policymakers must avoid short-sighted decisions to maintain a long-term balance between economic growth and environmental protection. Efforts in value guidance, administrative approvals, fiscal expenditures, and institutional construction are crucial for embedding sustainable principles in rural tourism.

One limitation of this paper is that data availability for some dimensions did not permit updating the sample period to 2024 due to the multidimensional nature of the study. Future research can incorporate more recent data as it becomes available. In addition, future research can build upon the existing framework by incorporating more dimensions, such as rural cultural heritage preservation and the protection of local heritage, and a sustainable development pattern that integrates rural tourism development with environmental protection and cultural heritage preservation can be explored.

Author Contributions: Conceptualization, J.L. and Y.Y. (Yuqi Ye); methodology, J.L. and Y.Y. (Yuqi Ye); software, Y.Y. (Yuqi Ye); validation, Y.Y. (Yu Yang)., Y.Y. (Yuqi Ye) and J.L.; formal analysis, Y.Y. (Yuqi Ye) and J.L.; investigation, Y.Y. (Yu Yang).; data curation, J.L.; writing—original draft preparation, J.L. and Y.Y. (Yuqi Ye); writing—review and editing, J.L., Y.Y. (Yu Yang)., and Y.Y. (Yuqi Ye); visualization, J.L. and Y.Y. (Yuqi Ye); supervision, J.L.; project administration, J.L., Y.Y. (Yu Yang) and Y.Y. (Yuqi Ye). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SDGs	Sustainable Development Goals
EKC	Environmental Kuznets Curve
AI	Artificial Intelligence
LLMs	Large Language Models
GDP	Gross Domestic Product
DID	Difference-in-Differences
PSM-DID	Propensity Score Matching Difference-in-Differences
SDID	Synthetic Difference-in-Differences
EER	Environmental Efficiency Ratio
NDVI	Landsat Normalized Difference Vegetation Index

References

1. Mensah, J. Sustainable Development: Meaning, History, Principles, Pillars, and Implications for Human Action: Literature Review. *Cogent Soc. Sci.* **2019**, *5*, 1653531. [CrossRef]
2. Basheer, M.; Nechifor, V.; Calzadilla, A.; Ringler, C.; Hulme, D.; Harou, J.J. Balancing National Economic Policy Outcomes for Sustainable Development. *Nat. Commun.* **2022**, *13*, 5041. [CrossRef] [PubMed]
3. Teixeira, N.; Rodrigues, R.; Rodrigues, A. Economic Growth and Environmental Sustainability in More and Less Sustainable Countries. *Discov. Sustain.* **2025**, *6*, 618. [CrossRef]
4. Antoci, A.; Galeotti, M.; Sordi, S. Environmental Pollution as Engine of Industrialization. *Commun. Nonlinear Sci. Numer. Simul.* **2018**, *58*, 262–273. [CrossRef]
5. Geçikli, R.M.; Turan, O.; Lachytová, L.; Dağlı, E.; Kasalak, M.A.; Uğur, S.B.; Guven, Y. Cultural Heritage Tourism and Sustainability: A Bibliometric Analysis. *Sustainability* **2024**, *16*, 6424. [CrossRef]
6. Ottaviani, D.; De Luca, C.; Åberg, H.E. Achieving the SDGs through Cultural Tourism: Evidence from Practice in the TExTOUR Project. *Eur. J. Cult. Manag. Policy* **2024**, *14*, 12238. [CrossRef]

7. López-Naranjo, A.L.; Puente-Riofrio, M.I.; Carrasco-Salazar, V.A.; Erazo-Rodríguez, J.D.; Buñay-Guisñan, P.A. Artificial Intelligence in the Tourism Business: A Systematic Review. *Front. Artif. Intell.* **2025**, *8*, 1599391. [CrossRef]
8. Huang, A.; Chao, Y.; De La Mora Velasco, E.; Bilgihan, A.; Wei, W. When Artificial Intelligence Meets the Hospitality and Tourism Industry: An Assessment Framework to Inform Theory and Management. *J. Hosp. Tour. Insights* **2022**, *5*, 1080–1100. [CrossRef]
9. Gursoy, D.; Li, Y.; Song, H. ChatGPT and the Hospitality and Tourism Industry: An Overview of Current Trends and Future Research Directions. *J. Hosp. Mark. Manag.* **2023**, *32*, 579–592. [CrossRef]
10. El Hajal, G.; Yeoman, I. AI and the Future of Talent Management in Tourism and Hospitality. *Curr. Issues Tour.* **2024**, 1–18. [CrossRef]
11. Liu, Y.-L.; Chiang, J.-T.; Ko, P.-F. The Benefits of Tourism for Rural Community Development. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 137. [CrossRef] [PubMed]
12. Wang, J.; Xia, L.; Zhou, F.; Chen, C.; Zhu, Q. Impacts of the Integrated Development of Agriculture and Tourism on Sustainable Development of Agriculture–Based on Provincial Data of China from 2008 to 2019. *Pol. J. Environ. Stud.* **2023**, *32*, 3825–3843. [CrossRef] [PubMed]
13. Li, S.; Shen, S.; Hu, Y.; Sun, R. The Impact of Government Intervention in Rural Tourism Development on Residents' Income: A Quasi-Natural Experiment from China. *Agriculture* **2025**, *15*, 1269. [CrossRef]
14. Karali, A.; Das, S.; Roy, H. Forty Years of the Rural Tourism Research: Reviewing the Trend, Pattern and Future Agenda. *Tour. Recreat. Res.* **2024**, *49*, 173–200. [CrossRef]
15. Wanner, A.; Seier, G.; Pröbstl-Haider, U. Policies Related to Sustainable Tourism—An Assessment and Comparison of European Policies, Frameworks and Plans. *J. Outdoor Recreat. Tour.* **2020**, *29*, 100275. [CrossRef]
16. Liu, C.; Dou, X.; Li, J.; Cai, L.A. Analyzing Government Role in Rural Tourism Development: An Empirical Investigation from China. *J. Rural Stud.* **2020**, *79*, 177–188. [CrossRef]
17. Zhu, Y.; Chai, S.; Chen, J.; Phau, I. How Was Rural Tourism Developed in China? Examining the Impact of China's Evolving Rural Tourism Policies. *Environ. Dev. Sustain.* **2023**, *26*, 28945–28969. [CrossRef]
18. Ngo, T.H.; Creutz, S. Assessing the Sustainability of Community-Based Tourism: A Case Study in Rural Areas of Hoi An, Vietnam. *Cogent Soc. Sci.* **2022**, *8*, 2116812. [CrossRef]
19. Tang, M.; Xu, H. Cultural Integration and Rural Tourism Development: A Scoping Literature Review. *Tour. Hosp.* **2023**, *4*, 75–90. [CrossRef]
20. Gocer, O.; Boyacioglu, D.; Karahan, E.E.; Shrestha, P. Cultural Tourism and Rural Community Resilience: A Framework and Its Application. *J. Rural Stud.* **2024**, *107*, 103238. [CrossRef]
21. Navarro-Chávez, C.L.; Ayvar-Campos, F.J.; Camacho-Cortez, C. Tourism, Economic Growth, and Environmental Pollution in APEC Economies, 1995–2020: An Econometric Analysis of the Kuznets Hypothesis. *Economies* **2023**, *11*, 264. [CrossRef]
22. Baloch, Q.B.; Shah, S.N.; Iqbal, N.; Sheeraz, M.; Asadullah, M.; Mahar, S.; Khan, A.U. Impact of Tourism Development upon Environmental Sustainability: A Suggested Framework for Sustainable Ecotourism. *Environ. Sci. Pollut. Res.* **2023**, *30*, 5917–5930. [CrossRef]
23. Zhao, X.; Li, T.; Duan, X. Studying Tourism Development and Its Impact on Carbon Emissions. *Sci. Rep.* **2024**, *14*, 7463. [CrossRef]
24. Kuznets, S. Economic Growth and Income Inequality. *Am. Econ. Rev.* **1955**, *45*, 1–28. Available online: http://www.jstor.org/stable/181158 (accessed on 14 October 2025).
25. Stern, D.I. Environmental Kuznets Curve. In *Encyclopedia of Energy*; Elsevier: Amsterdam, The Netherlands, 2004; pp. 517–525, ISBN 978-0-12-176480-7. Available online: https://linkinghub.elsevier.com/retrieve/pii/B012176480X00454X (accessed on 14 October 2025).
26. Khan, A.; Bibi, S.; Li, H.; Fubing, X.; Jiang, S.; Hussain, S. Does the Tourism and Travel Industry Really Matter to Economic Growth and Environmental Degradation in the US: A Sustainable Policy Development Approach. *Front. Environ. Sci.* **2023**, *11*, 1147504. [CrossRef]
27. Wang, S.; Cheablam, O. Sustainable Tourism and Its Environmental and Economic Impacts: Fresh Evidence from Major Tourism Hubs. *Sustainability* **2025**, *17*, 5058. [CrossRef]
28. Wang, L.; Li, T.; Peng, X.; Liu, R. Can the Integration of Cultural and Tourism Development Narrow the Regional Income Gap? The Role of Foreign Direct Investment. *Int. Rev. Econ. Financ.* **2025**, *102*, 104294. [CrossRef]
29. Mwakalobo, A.; Kaswamila, A.; Kira, A.; Chawala, O.; Tear, T. Tourism Regional Multiplier Effects in Tanzania: Analysis of Singita Grumeti Reserves Tourism in the Mara Region. *J. Sustain. Dev.* **2016**, *9*, 44. [CrossRef]
30. Twining-Ward, L.D.; Aguerrevere Yanes, G.; Bakker, M.H.E.; Bartlett, J.L.; Chappell, R.L., Jr.; Harman, P.A.; Li, W.; Mann, S.; Miguel, J.; Villascusa Cerezo, J.M.; et al. *Twenty Reasons Sustainable Tourism Counts for Development*; Tourism for Development knowledge series; World Bank Group: Washington, DC, USA, 2017. Available online: http://documents.worldbank.org/curated/en/558121506324624240 (accessed on 14 October 2025).
31. Guo, Y.; Li, S. A Policy Analysis of China's Sustainable Rural Revitalization: Integrating Environmental, Social and Economic Dimensions. *Front. Environ. Sci.* **2024**, *12*, 1436869. [CrossRef]

32. Crouch, G.I. Destination Competitiveness: An Analysis of Determinant Attributes. *J. Travel Res.* **2011**, *50*, 27–45. [CrossRef]
33. Székely, V. From Enthusiasm to Scepticism: Tourism Cluster Initiatives and Rural Development in Slovakia. *Stud. Agric. Econ.* **2014**, *116*, 74–81. [CrossRef]
34. Baggio, R.; Cooper, C. Knowledge Transfer in a Tourism Destination: The Effects of a Network Structure. *Serv. Ind. J.* **2010**, *30*, 1757–1771. [CrossRef]
35. Morrison, A.M. Editorial: Land Issues and Their Impact on Tourism Development. *Land* **2022**, *11*, 658. [CrossRef]
36. Chen, P.; Zhao, Y.; Zuo, D.; Kong, X. Tourism, Water Pollution, and Waterway Landscape Changes in a Traditional Village in the Huizhou Region, China. *Land* **2021**, *10*, 795. [CrossRef]
37. Li, J.; Bai, Y.; Alatalo, J.M. Impacts of Rural Tourism-Driven Land Use Change on Ecosystems Services Provision in Erhai Lake Basin, China. *Ecosyst. Serv.* **2020**, *42*, 101081. [CrossRef]
38. Hassan, T.H.; Salem, A.E.; Abdelmoaty, M.A. Impact of Rural Tourism Development on Residents' Satisfaction with the Local Environment, Socio-Economy and Quality of Life in Al-Ahsa Region, Saudi Arabia. *Int. J. Environ. Res. Public Health* **2022**, *19*, 4410. [CrossRef] [PubMed]
39. Lin, J.Y.; Krueger, A.; Rodrik, D. New Structural Economics: A Framework for Rethinking Development [with Comments]. *World Bank Res. Obs.* **2011**, *26*, 193–229. Available online: http://www.jstor.org/stable/41261429 (accessed on 14 October 2025). [CrossRef]
40. Wijijayanti, T.; Agustina, Y.; Winarno, A.; Istanti, L.; Dharma, B. Rural Tourism: A Local Economic Development. *Australas. Account. Bus. Financ. J.* **2020**, *14*, 5–13. [CrossRef]
41. Tong, Y.; Pang, L.; Li, H. The Air Pollution Mitigation Effect of Tourism Development and Its Formation Mechanism: New Insights from BMA and SEM Approaches. *Air Qual. Atmos. Health* **2023**, *16*, 2095–2113. [CrossRef]
42. Wei, J.; Li, Z. ChinaHighPM2.5: Daily Seamless 1 Km Ground-Level PM2.5 Dataset for China (2000–Present). Available online: https://zenodo.org/doi/10.5281/zenodo.3539349 (accessed on 14 October 2025).
43. Gao, J.; Shi, Y.; Zhang, H.; Chen, X.; Zhang, W.; Shen, W.; Xiao, T.; Zhang, Y. *China Regional 250 m Fractional Vegetation Cover Data Set (2000–2024)*; National Tibetan Plateau Data Center: Beijing, China, 2025. [CrossRef]
44. Yang, J.; Huang, X. The 30 m Annual Land Cover Datasets and Its Dynamics in China from 1990 to 2019. *Earth Syst. Sci.* **2021**, *13*, 3907–3925. Available online: https://essd.copernicus.org/articles/13/3907/2021/ (accessed on 14 October 2025). [CrossRef]
45. Brueckner, M.; Lederman, D. Inequality and Economic Growth: The Role of Initial Income. *J. Econ. Growth* **2018**, *23*, 341–366. [CrossRef]
46. Ebenstein, A.; Fan, M.; Greenstone, M.; He, G.; Yin, P.; Zhou, M. Growth, Pollution, and Life Expectancy: China from 1991–2012. *Am. Econ. Rev.* **2015**, *105*, 226–231. [CrossRef]
47. Gong, Y.; Li, S.; Sanders, N.J.; Shi, G. The Mortality Impact of Fine Particulate Matter in China: Evidence from Trade Shocks. *J. Environ. Econ. Manag.* **2023**, *117*, 102759. [CrossRef]
48. Mohan, A.; Muller, N.Z.; Thyagarajan, A.; Martin, R.V.; Hammer, M.S.; Donkelaar, A.V. Measuring Global Monetary Damages from Particulate Matter and Carbon Dioxide Emissions to Track Sustainable Growth. *Commun. Earth Environ.* **2024**, *5*, 264. [CrossRef]
49. Chen, F.; Zhu, L.; Zhang, H.; Li, Y. Innovation-Driven Cities: Reconciling Economic Growth and Ecological Sustainability. *Sustain. Cities Soc.* **2025**, *121*, 106230. [CrossRef]
50. Beck, T.; Levine, R.; Levkov, A. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *J. Financ.* **2010**, *65*, 1637–1667. [CrossRef]
51. Ohrn, E. The Effect of Corporate Taxation on Investment and Financial Policy: Evidence from the DPAD. *Am. Econ. J. Econ. Policy* **2018**, *10*, 272–301. [CrossRef]
52. Cao, Y.; Chen, S. Rebel on the Canal: Disrupted Trade Access and Social Conflict in China, 1650–1911. *Am. Econ. Rev.* **2022**, *112*, 1555–1590. [CrossRef]
53. De Chaisemartin, C.; D'Haultfœuille, X. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *Am. Econ. Rev.* **2020**, *110*, 2964–2996. [CrossRef]
54. Goodman-Bacon, A. Difference-in-Differences with Variation in Treatment Timing. *J. Econom.* **2021**, *225*, 254–277. [CrossRef]
55. Zhang, Y.-J.; Wang, W. How Does China's Carbon Emissions Trading (CET) Policy Affect the Investment of CET-Covered Enterprises? *Energy Econ.* **2021**, *98*, 105224. [CrossRef]
56. Tian, J.; Sun, S.; Cao, W.; Bu, D.; Xue, R. Make Every Dollar Count: The Impact of Green Credit Regulation on Corporate Green Investment Efficiency. *Energy Econ.* **2024**, *130*, 107307. [CrossRef]
57. Arkhangelsky, D.; Athey, S.; Hirshberg, D.A.; Imbens, G.W.; Wager, S. Synthetic Difference-in-Differences. *Am. Econ. Rev.* **2021**, *111*, 4088–4118. [CrossRef]
58. Chernozhukov, V.; Chetverikov, D.; Demirer, M.; Duflo, E.; Hansen, C.; Newey, W.; Robins, J. Double/Debiased Machine Learning for Treatment and Structural Parameters. *Econom. J.* **2018**, *21*, C1–C68. [CrossRef]

59. Farbmacher, H.; Huber, M.; Laffers, L.; Langen, H.; Spindler, M. Causal Mediation Analysis with Double Machine Learning. *Econom. J.* **2022**, *25*, 277–300. [CrossRef]
60. Callaway, B.; Goodman-Bacon, A.; Sant'Anna, P.H.C. *Difference-in-Differences with a Continuous Treatment 2021*; National Bureau of Economic Research: Cambridge, MA, USA, 2024. Available online: http://www.nber.org/papers/w32117.pdf (accessed on 14 October 2025).
61. Li, B.; Gasser, T.; Ciais, P.; Piao, S.; Tao, S.; Balkanski, Y.; Hauglustaine, D.; Boisier, J.-P.; Chen, Z.; Huang, M.; et al. The Contribution of China's Emissions to Global Climate Forcing. *Nature* **2016**, *531*, 357–361. [CrossRef]
62. Chen, Y.; Fan, Z.; Gu, X.; Zhou, L.-A. Arrival of Young Talent: The Send-Down Movement and Rural Education in China. *Am. Econ. Rev.* **2020**, *110*, 3393–3430. [CrossRef]
63. Kong, D.; Qin, N.; Xiang, J. Minimum Wage and Entrepreneurship: Evidence from China. *J. Econ. Behav. Organ.* **2021**, *189*, 320–336. [CrossRef]
64. Sun, P.; Cao, H. Tourism Development and Rural Land Transfer-Out: Evidence from China Family Panel Studies. *Land* **2024**, *13*, 426. [CrossRef]
65. Horowitz, J.L. Bootstrap Methods in Econometrics. *Annu. Rev. Econ.* **2019**, *11*, 193–224. [CrossRef]
66. Kuščer, K.; Peters, M.; Schönherr, S. Tourism Policymaking in Troubling Times: Sustainability-Driven Challenges, Implemented Policies, and Goals for Sustainable Development. *Sustainability* **2024**, *16*, 10599. [CrossRef]