Rural Tourism and Rural Economic Development

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Rural tourism is considered an essential tool to promote rural economic development through the integrated development of the primary, secondary, and tertiary industries. Based on a natural village-level panel data set of 39 villages in Lincang City, Yunnan, China from 2015 to 2021, this paper uses the difference-in-differences method with a propensity score matching approach (PSM-DID) to investigate the impact of rural tourism development on rural economic development in villages. The research results show that rural tourism positively affects gross income and poverty reduction in rural areas. However, the results do not show significant evidence of transforming the rural industrial structure. Based on the results, promoting policies for rural tourism should also be implemented in other regions in China, and additional policies should be considered to promote industrial structure transformation.

Keywords: rural tourism, rural economy, development, natural village

INTRODUCTION

China's rural landscape has undergone significant change since 1960, with the rural population dropping from 84% to 38% in 2021. Yet, despite this rapid urbanization, the rural population remains vast, at approximately 0.5 billion people. Moreover, while China declared the elimination of absolute poverty in 2021, more than half of rural residents still subsist below the World Bank's poverty line of $3.20 per day for lower-middle-income countries. These conditions underscore the necessity of ongoing rural development efforts for China’s broader economic growth. In response, the Chinese government introduced the Rural Revitalization Strategy to address rural development needs, with integrated industrial growth as a cornerstone for revitalization.

Key stakeholders in China, including government bodies and researchers, have highlighted the integration of primary, secondary, and tertiary industries as a pivotal approach for rural revitalization. This integrated industrial model encourages synergy between agriculture, manufacturing, and service-based industries, enhancing overall productivity and sustainability in rural areas. Zhou (2018) notes the shift from industrial isolation to integration, while Wan et al. (2018) argue that rural revitalization hinges on integrating agriculture with other industries. Various governmental directives further support this strategy, emphasizing the importance of industrial fusion as a pathway to revitalized rural economies.

Within this framework, rural tourism has emerged as a critical tool for fostering integrated development across industries. The National Development and Reform Commission's 2017 report highlights that rural tourism and leisure agriculture generated over 620 billion yuan RMB (about 85.7 billion US$) in operating income and attracted 2.2 billion tourists annually, employing over 9 million people. Furthermore, rural tourism contributed to poverty alleviation efforts, accounting for 30.4% of poverty reduction across 25 provinces in 2019. However, despite the observed economic contributions, questions remain about income distribution within rural tourism, with some studies highlighting the uneven economic benefits between regions and populations.

Existing research generally supports the positive economic impact of tourism. For instance, Sequeira and Nunes (2008) and Eugenio-Martín et al. (2004) show that tourism enhances economic growth across diverse international contexts. Studies specific to rural tourism, like those by Paresishvili et al. (2017) in Georgia and Fleischer and Pizam (1997) in Israel, reveal significant benefits for rural economies, including employment growth, income increase, and population retention. In China, Jiang et al. (2020) demonstrate that rural tourism cooperatives in Sichuan Province positively impacted county-level economic indicators, such as employment and per capita GDP, affirming the role of rural tourism in economic development. However, nuanced studies have shown that tourism's economic impacts vary based on factors like development level, tourism specialization, and regional economic structure (Adamou and Clerides 2010; Brau et al. 2007).

The relationship between tourism and income inequality further complicates tourism's impact. Alam and Paramati (2016) found that tourism generally increases income inequality in developing countries, while Fang et al. (2020) indicate that its effects vary significantly across economic contexts. In China, tourism has shown potential for reducing urban-rural income inequality, with Zhao and Xia (2019) identifying tourism as a catalyst for economic growth in less-developed western provinces. Similarly, Zeng and Wang (2021) found a negative association between tourism revenue and the urban-rural income ratio, suggesting that increased tourism revenue could narrow income disparities.

Tourism's effects on poverty reduction also reveal a complex picture. Although tourism is widely promoted as a pro-poor policy, its benefits can be unevenly distributed across income groups. For example, Blake et al. (2007) find that while tourism in Brazil positively impacted poverty alleviation across income groups, the lowest-income households benefited the least. Studies in China, such as those by Zhao and Xia (2019), indicate that tourism's poverty reduction effects are more pronounced in underdeveloped regions.

This paper contributes to the existing literature by focusing on rural tourism's specific effects on economic outcomes, income inequality, and poverty reduction at a granular, village level. Whereas most studies operate at a national scale, averaging effects across rural and urban settings, this study provides a detailed, localized analysis, eliminating the heterogeneity inherent in broader studies. Additionally, while many studies observe only linear trends in tourism's economic impacts, this paper applies a Propensity Score Matching with Difference-in-Differences (PSM-DID) approach to establish causality. This method examines the impacts of rural tourism on economic growth, poverty alleviation, and industrial transformation in Lincang City, a predominantly rural region in China with a newly expanding tourism sector.

Our findings reveal that rural tourism positively influences gross income and poverty reduction in Lincang City's rural areas. However, we find limited evidence for its impact on transforming the rural industrial structure. This nuanced view provides essential insights for policymakers and stakeholders on tailoring tourism development strategies to maximize socioeconomic benefits in rural regions.

EMPIRICAL STRATEGY

This paper examines the impact of rural tourism development using a Difference-in-Differences (DID) approach. The DID method is widely recognized in policy evaluation research for its ability to address endogeneity issues that arise from omitted variable bias in OLS estimation, thereby isolating the causal effect of policy interventions. In Lincang City, only a limited number of villages engaged in rural tourism before 2018. Most villages started tourism activities in either 2018 or 2019, providing a robust foundation for applying DID analysis to assess the outcomes of tourism development.

This paper regarded the implementation of policies to develop rural tourism as a quasi-natural experiment. 40 villages from a list in the *"Three years (2020-2022) action plan for the high-quality development of Lincang's cultural tourism industry"* document was randomly chosen as the treatment group. The document identifies all 102 villages in Lincang City that had developed rural tourism by 2020. To establish a control group, 30 villages not included in this list were randomly selected. 13 villages from the treatment group and 12 villages from the control group were excluded from the sample due to data credibility and availability.[1] Additionally, to ensure that the estimated results reflect the net effect of the 2018 promotion policies, six villages that had already established rural tourism prior to 2018 were excluded from the sample. Consequently, the treatment group comprises 21 villages that developed rural tourism post-2018, while the control group includes 18 villages that have not engaged in rural tourism.

By definition, rural tourism can theoretically be developed in any village exhibiting rural characteristics, suggesting that villages without tourism development may serve as counterfactuals to those that have developed tourism in causal inference studies. However, endogeneity issues due to self-selection bias may arise from each village's choice to engage in rural tourism. This paper addresses these concerns using the Propensity Score Matching with Difference-in-Differences (PSM-DID) approach, as advocated by Heckman (1997 1998b). This method integrates propensity score matching (PSM) within the DID framework to strengthen the common trend assumption. Rosenbaum and Rubin (1983) demonstrated that PSM effectively mitigates endogeneity resulting from sample selection bias.

Following these methods, this paper employs the following empirical strategy. First, the treatment and control groups are matched based on propensity scores derived from villages' baseline characteristics. A DID regression is then conducted using the matched treatment and control groups. The primary results reflect the DID estimation using kernel matching (Epanechnikov kernel), with additional robustness checks provided through nearest-neighbor matching, radius matching, and local linear matching.

The DID regression model is as follows:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \gamma Treat_i \times Post_t + \sum_{i=1}^{n} \delta_i X_{it} + \varepsilon_i + \sigma_t + \mu_{it} \quad (1)$$

In the above model, Y_{it} is the outcome variable of village i in time t, $i = 1, 2, \dots, n$. Outcome variables are: (1) the villages' gross income (taking the natural logarithm), (2) the villages' poverty rate, and (3) the villages' industrial structure index. $Treat_i$ is a dummy variable for policy intervention which takes 1 if village i has developed rural tourism and 0 otherwise. $Post_t$ is a dummy variable indicating pre- and post-treatment which takes 1 if the year is after 2018. $Treat_i \times Post_t$ is the cross term of $Treat_i$ and $Post_t$, therefore γ will be the coefficient of interest. X_{it} is a vector of villages' baseline characteristics. ε_i represents the villages' village fixed effect and σ_t represents the time fixed effect. μ_{it} is the error term. Table 1 summarizes the name, definitions, and calculations of each variable.

In line with Xiao (2016), this study measures the poverty rate as the ratio of the Dibao population—individuals receiving government allowances under the Rural Minimum Living Standard Security System—to the total population.

To evaluate industrial structure, this paper adopts an industrial structure index based on the approaches of Xu (2008) and Wang (2015), assigning weights to the value-added proportions of the primary, secondary, and tertiary industries. This method draws on Kuznets' (1957) research, which posits that as economies grow, the shares of income and consumption in services tend to increase, those in agriculture decrease, while manufacturing remains relatively stable. A higher index value indicates a more advanced level of industrial structure.

Migrant workers (nongminggong in Chinese) are rural residents who engage in nonagricultural work outside their hometowns, primarily in urban areas. In China and other developing countries, individuals from underdeveloped rural regions often migrate to urban areas in search of employment opportunities. The ratio of migrant workers thus serves as an indicator of local employment availability and the level of industrial vitality in a given area.

The primary target market for rural tourism consists of residents from nearby cities, making the distance to the nearest city a critical factor in assessing the impact of rural tourism. This variable is used to match treatment and control groups.

TABLE 1
VARIABLE DEFINITIONS

Variable Name	Definition and Calculation	Calculation
ginc	Gross income (in ten thousand CNY)	
pcinc	Per-capita gross income (in CNY)	
pop	Population	
pov	Poverty rate	$\frac{Number\ of\ Dibao\ Population}{Population}$
mig	The ratio of migrant workers	$\frac{Number\ of\ Migrant\ Workers}{Population}$
index	Industrial Structure Index	$\sum_{j=1}^{3} j * p_j,\ j = 1,2,3,\ p_j$ is the ratio of the value-added of the j-th industry to the gross income.
dist	Travel distance between the village and the nearest city (in kilometers) ※Only used for propensity score matching purpose	

Source: Created by the author

DATA AND SUMMARY STATISTICS

This paper compiles an original yearly panel dataset consisting of 39 natural villages in Lincang City, Yunnan, China, covering the period from 2015 to 2021. The data was sourced directly from local government records, primarily through government work reports and Statistical Yearbooks. The dataset includes 21 villages in the treatment group and 18 in the control group.

Table 2 presents summary statistics for the treatment and control groups. An essential prerequisite for applying the DID method is the common trend hypothesis, which requires that the economic development trends in the treatment and control groups exhibit no significant differences prior to the policy intervention. Additionally, the PSM method mitigates systematic differences between the groups by matching them based on similar propensity scores derived from observable covariates. Therefore, it is crucial to assess the balance of the data to ensure robustness in the analysis.

The treatment group shows a maximum population of 3,212, significantly higher than the 783 in the control group, resulting in an imbalance in gross income both before and after the intervention. Additionally, the standardized difference in per capita income exceeds 0.1, indicating another imbalance. The travel distance to the nearest city also displays imbalance, with a standardized difference of 0.252. Although villages closer to cities are theoretically better positioned for rural tourism development, the data shows that treatment group villages do not enjoy a locational advantage over those in the control group. All other variables exhibit a standardized difference below 0.1 before the intervention, indicating similarity in baseline characteristics across both groups. These summary statistics underscore the importance of employing PSM to align treatment and control groups before conducting the DID analysis.

TABLE 2
SUMMARY STATISTICS BETWEEN TREATMENT AND CONTROL GROUPS

		Control				Treatment				
Variables		**N**	**Mean**	**Min**	**Max**	**N**	**Mean**	**Min**	**Max**	**Std Diff**
ginp	Pre	72	269.944 (160.864)	97.943	670.800	84	690.573 (911.983)	102.720	4032.060	0.642
	After	54	322.960 (194.055)	105.463	924.128	63	942.544 (1217.780)	151.940	6198.120	0.681
pcinc	Pre	72	10576.280 (2419.032)	4957.000	15306.120	84	10993.640 (3114.308)	3000.051	17240.140	0.150
	After	54	12384.580 (1647.299)	8505.362	15225.930	63	14686.140 (3762.459)	151.940	6198.120	0.792
pop	Pre	72	263.569 (192.402)	94.000	783.000	84	603.881 (758.987)	107.000	3212.000	0.615
	After	54	267.130 (191.672)	94.000	780.000	63	630.603 (813.940)	107.000	3338.000	0.615
pov	Pre	72	0.071 (0.044)	0.014	0.225	84	0.067 (0.047)	0.003	0.272	-0.080
	After	54	0.073 (0.060)	0.008	0.318	63	0.045 (0.026)	0.003	0.116	-0.601
mig	Pre	72	0.127 (0.091)	0.023	0.425	84	0.132 (0.097)	0.022	0.394	0.047
	After	54	0.150 (0.099)	0.035	0.476	63	0.140 (0.102)	0.012	0.041	-0.099
index	Pre	72	1.395 (0.326)	0.605	1.740	84	1.417 (0.258)	0.786	2.032	0.076
	After	54	1.391 (0.327)	0.670	1.740	63	1.464 (0.261)	0.742	1.914	0.248
dist	Pre	72	30.861 (30.414)	6.300	120.200	84	38.481 (29.874)	3.1	94.9	0.252
	After	54	30.861 (30.414)	6.300	120.200	63	38.481 (29.874)	3.1	94.9	0.252

Standard errors in parentheses. *Source:* Calculated and created by author

The standardized differences in both gross income and per capita income increased after treatment, suggesting that rural tourism development may positively influence village income levels. The poverty rate also became unbalanced, with its standardized difference shifting from -0.080 to -0.061 after treatment, indicating that rural tourism may contribute to poverty reduction. Similarly, the industrial index showed increased imbalance, with the standardized difference rising from 0.076 to 0.248, suggesting potential for rural tourism to aid in transforming rural industrial structures. Lastly, although remaining unbalanced, the standardized difference in the ratio of migrant workers shifted from positive to negative, implying that rural tourism may create employment opportunities in rural areas.

RESULTS

Propensity Score Matching

Given the use of panel data for villages across multiple periods, this study follows Böckerman and Ilmakunnas (2009) and Heyman et al. (2007) by conducting kernel matching with the Epanechnikov kernel function on a year-by-year basis. This approach effectively controls time fixed effects.

In the PSM matching process, a logit regression is conducted on the treatment dummy variable with covariates to derive the propensity score. Individuals in the treatment and control groups with the closest propensity scores are then matched, minimizing systematic differences between the groups and thereby reducing estimation bias. A covariate balance test is subsequently performed to verify whether each variable achieves balance between the treatment and control groups post-matching. The absence of significant differences supports the reliability of further estimations.

TABLE 3
PSM BALANCE TEST

		Mean				
Variable	**Samples**	**Treated**	**Control**	**% Bias**	**t-value**	**P>|t|**
pop	Before Matching	615.33	265.1	61.6	4.91	0.000
	After Matching	298.45	269.76	5.9	1.44	0.151
mig	Before Matching	0.13526	0.13701	-1.8	-0.15	0.882
	After Matching	0.14296	0.13253	1.5	0.09	0.927
dist	Before Matching	38.481	30.861	25.3	2.09	0.038
	After Matching	36.812	39.007	-8.0	-0.53	0.599
index	Before Matching	1.4376	1.3933	15.1	1.25	0.212
	After Matching	1.4181	1.3981	3.5	0.24	0.811

Source: Calculated and created by author

A balance test for covariates was conducted to assess the effectiveness of the matching process, with results presented in Table 3. Post-matching, the bias for each variable was controlled within 10%. Additionally, t-test results indicate no significant differences in baseline characteristics between the treatment and control groups after matching. Figure 1 presents a histogram of the propensity score distribution and the region of common support, where the propensity scores of the treatment and control groups overlap. This common support assumption, as defined by Heckman et al. (1999), ensures that villages with similar characteristics have a positive probability of belonging to either group. The results are satisfactory, as most observations meet the common support assumption. Additionally, the distribution of propensity scores is relatively balanced between the two groups, indicating similarity among villages in both the treatment and control groups.

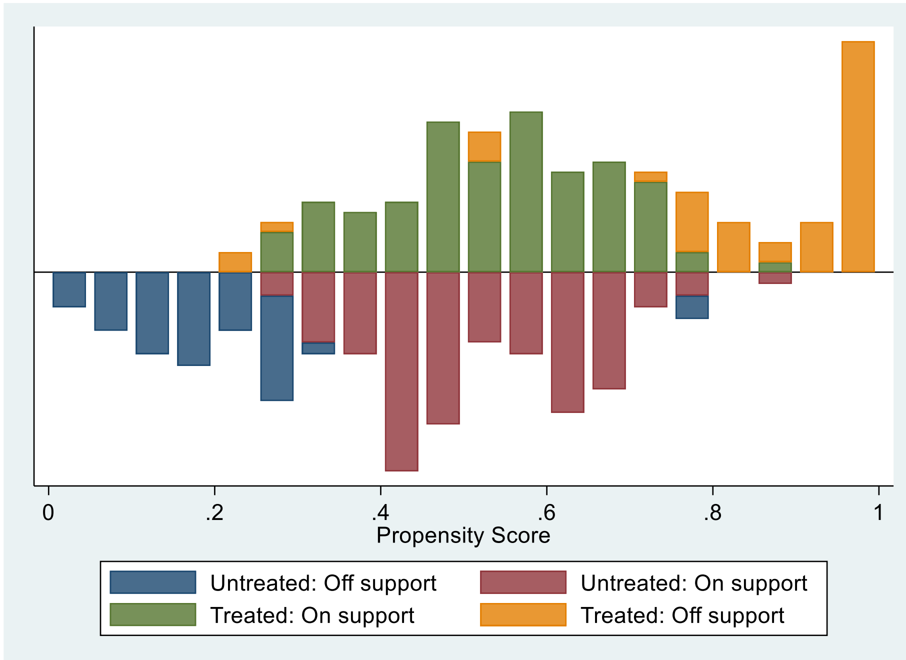

Figure 1: Common support and propensity scores. *Source:* Calculated and created by author

Figure 1 presents a histogram of the propensity score distribution and the region of common support, where the propensity scores of the treatment and control groups overlap. This common support assumption, as defined by Heckman et al. (1999), ensures that villages with similar characteristics have a positive probability of belonging to either group. The results are satisfactory, as most observations meet the common support assumption. Additionally, the distribution of propensity scores is relatively balanced between the two groups, indicating similarity among villages in both the treatment and control groups.

Figure 2 compares the kernel density distribution of propensity scores before and after matching. The kernel density plots for the treatment and control groups are notably more aligned post-matching, demonstrating the adequacy of the matching process.

The above results show that group comparability improved after applying propensity score matching and further prove the reliability of the difference-in-differences estimation.

Difference-In-Differences Estimation Results

Table 4 presents the main estimation results of this study. Columns (1), (2), and (3) display the regression outcomes from the DID estimation without applying the PSM method to match the treatment and control groups. Columns (4), (5), and (6) provide the regression results with matched treatment and control groups. The coefficients of $Treat_i \times Post_t$ represent the impact of rural tourism development on the rural economy, controlling for village-specific characteristics, village fixed effects, and time fixed effects.

As shown in Table 4, the number of observations decreases after matching due to the exclusion of off-support observations in the matching process. However, the cross-term coefficients remain consistent in both sign and statistical significance between the DID and PSM-DID estimations, with values closely aligned. This consistency suggests minimal endogeneity concerns related to self-selection bias in each village's decision to participate in rural tourism development.

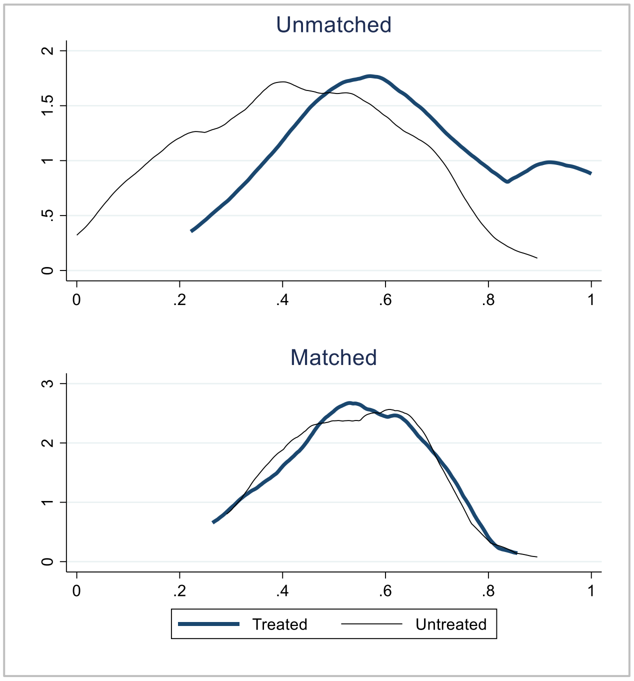

Figure 2: Kernel density distribution.
Source: Calculated and created by author.

TABLE 4
ESTIMATION RESULTS

	Before matching			After matching		
	DID			PSM-DID		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	lnginc	pov	index	lnginc	pov	Index
$Treat_i \times Post_t$	0.128**	-0.018**	0.065	0.127**	-0.016***	0.059
	(0.058)	(0.007)	(0.050)	(0.072)	(0.006)	(0.073)
Control Variables	YES	YES	YES	YES	YES	YES
Village Fixed Effect	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES	YES
N	273	273	273	184	184	184

Village cluster-robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Calculated and created by author.

The coefficient of the cross-term for gross income (log-transformed) is positive and significant, indicating that rural tourism development positively impacts villages' gross income and promotes economic development in rural areas.

The coefficient of the cross-term for the poverty rate is negative and significant, indicating that rural tourism development contributes positively to poverty alleviation. However, the coefficient's relatively low magnitude may reflect the already low poverty rates in the sample villages, likely due to China's longstanding and successful poverty reduction initiatives. Since 1978, China has reduced the number of people in poverty from 770 million to 30.46 million by the end of 2017, lowering the poverty rate from

97.5% to 3.1%. This suggests that those remaining in poverty might be harder to lift out of it. Thus, the results imply that rural tourism development may provide additional support for those still in poverty.

The coefficient of the cross-term for the industrial structure index is positive but not statistically significant, indicating no clear evidence that rural tourism development transforms the industrial structure in rural areas. One potential reason for this is that structural transformation may require a longer period to materialize. Another consideration is the challenge of distinguishing income sources between agriculture and rural tourism. For instance, agricultural products purchased by tourists, such as fruits or tea—key income sources from rural tourism in Lincang City—are often categorized as agricultural revenue. However, it may be more accurate to include these in tourism revenues. This categorization may undervalue the contribution of the tertiary industry, resulting in a lower industrial structure index.

ROBUSTNESS CHECK

Matching Methods

To test the robustness of the main results, this paper also conducted PSM-DID analyses using nearest-neighbor matching, radius matching, and local linear matching. Table 5 presents these PSM-DID estimations alongside the DID estimations before matching. While the magnitude and significance levels of the coefficients varied slightly across matching methods, the signs and statistical significance of the coefficients remained consistent with the main results. This consistency indicates that the primary conclusions are robust and unaffected by the choice of PSM matching method.

TABLE 5
ROBUSTNESS TEST

		(1)	**(2)**	**(3)**
	Variables	lnginc	pov	Index
DID	$Treat_i \times Post_t$	0.128**	-0.018**	0.065
		(0.058)	(0.007)	(0.050)
	N	273	273	273
Kernel Matching	$Treat_i \times Post_t$	0.127**	-0.016***	0.059
		(0.072)	(0.006)	(0.073)
	N	184	184	184
Nearest Neighbor Matching	$Treat_i \times Post_t$	0.162**	-0.024**	0.034
		(0.088)	(0.012)	(0.067)
	N	175	175	175
Radius Matching	$Treat_i \times Post_t$	0.117**	-0.016**	0.053
		(0.046)	(0.007)	(0.075)
	N	180	180	180
Local Linear Matching	$Treat_i \times Post_t$	0.151*	-0.022*	0.033
		(0.086)	(0.012)	(0.065)
	N	103	103	103
	Control Variables	YES	YES	YES
	Village Fixed Effect	YES	YES	YES
	Time Fixed Effect	YES	YES	YES

Village cluster-robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Calculated and created by author

Placebo Test

Following Li et al. (2016), this paper conducts a placebo test to determine whether the observed effects result from unobservable factors other than the policy intervention of interest. The concept behind the placebo test is to create a fictitious treatment group; if the coefficient of the pseudo-treatment dummy variable remains significant under this simulated condition, the original estimation may be biased, suggesting that other policies or random factors could have influenced the dependent variables.

In the placebo test, 21 villages are randomly selected from the sample of 39 and designated as the pseudo-treatment group, with the remaining 18 villages as the pseudo-control group. Pseudo-dummy variables are then constructed, and a DID estimation is performed using model (1). This procedure is repeated 500 times.

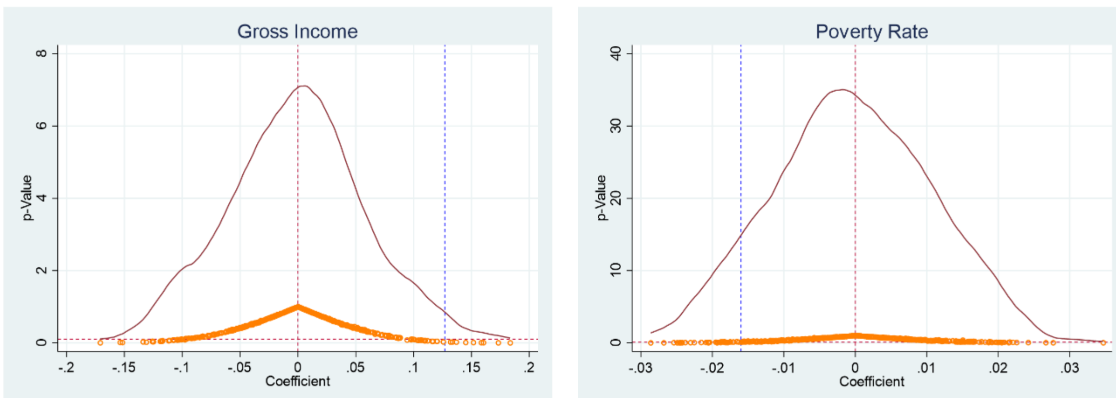

Figure 3: Placebo test. *Source:* Calculated and created by author.

Figure 3 displays the magnitude, p-values, and distribution of the pseudo-cross-term coefficients for gross income and poverty rate across 500 random simulations. The estimated coefficients are plotted on the horizontal axis, with p-values on the vertical axis, represented by orange dots. Red smooth curves depict the kernel density of the coefficients, while horizontal red dashed lines mark the 10% significance level. Blue vertical dashed lines are positioned at 0.127 and -0.016, which represent the estimated coefficients of the cross terms in the PSM-DID estimation using the kernel matching method. The figure shows that the coefficients from the 500 random simulations are centered around zero and are statistically insignificant, indicating that the results in this paper are unlikely to be random and are thus robust.

CONCLUSION

By treating the implementation of rural tourism development policies as a quasi-natural experiment, this paper employs a panel dataset of 39 natural villages in Lincang City, Yunnan Province, and applies the PSM-DID method to investigate the effects of rural tourism on rural economic development. The empirical findings provide evidence that rural tourism development promotes economic growth in rural areas, specifically showing a significant positive impact on gross income and poverty reduction. However, no evidence was found to suggest that rural tourism development contributes to transforming the industrial structure in rural areas.

The robustness of the estimation results is investigated by comparing the results of the DID estimation and the PSM-DID estimation with various matching methods. This paper also conducts a placebo test to further check for robustness. The results show that the conclusion does not depend on a typical matching method and remains robust after dealing with endogeneity issues.

DISCUSSION

This result aligns with the hypothesis that rural tourism can enhance rural economic development but contrasts with the expectation that this development would occur through integrating the three industries. Potential explanations include the following. First, unlike traditional tourism, rural tourism primarily targets residents from nearby cities, enabling income increases over a relatively short period. However, structural transformation may require a longer time frame, and its effects may not yet be evident. Second, income growth in villages with rural tourism may stem from increased sales of agricultural products to tourists. This overlap in revenue sources between the primary and tertiary industries likely leads to an underestimation of tourism's value-added contribution. Lastly, the COVID-19 pandemic may have dampened local residents' confidence in investing in new businesses, thereby slowing the growth of the tertiary industry.

This paper makes two primary contributions to the existing literature. First, it conducts an empirical analysis at the natural village level, the smallest administrative unit in China, thereby isolating rural areas and eliminating heterogeneities between rural and urban contexts to capture a net effect specific to rural settings. Second, by employing the PSM-DID method, this study estimates the causal effect of tourism development on rural economic growth.

This paper offers two key policy implications based on the empirical findings. First, promoting rural tourism can effectively increase gross income in rural areas. Since rural tourism development is less dependent on traditional tourism resources and substantial investment, its benefits are replicable and can materialize relatively quickly. This is critical for poverty alleviation and rural revitalization, suggesting that similar promotion policies could be beneficial if implemented in other regions of China. Second, the results indicate limited change in the industrial structure following rural tourism development. Therefore, policymakers should encourage a broader range of business activities in rural tourism destinations, such as handicrafts, processing, manufacturing, and service industries, to foster a more diversified economic base.

This research has several limitations that future studies could address. First, due to constraints in data collection, the sample size is relatively small, and the dataset contains limited information, particularly on villages' baseline characteristics. Future research should aim to include a larger sample size and more comprehensive data. Additionally, this study does not explore the potential channels through which rural tourism impacts rural economic development. Further research with more detailed data and suitable methodologies would be beneficial for investigating the underlying mechanisms.

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ENDNOTE

1. Some villages do not report statistical data at the natural village level. Some villages' data lack the value-added for each industry separately. Some villages report income data which is unreasonably greater than the average.

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