The “Ding Zhen Effect” and the Reshaping of Tourism Markets in Marginal Regions from the Perspective of the Long Tail Theory —A Case Study of Litang County, Garzê Prefecture

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ABSTRACT

Activating the tourism demand of surrounding destinations is still a challenge for regional tourism economy. The Ding Zhen phenomenon in November 2020 provides an ideal and almost natural experimental framework to study the impact of IP grid impact on the reshaping of marginal markets. In this paper, the long tail theory is used as the theoretical framework, and the two-way fixed effect (TWFE) difference estimator (DID) is used to identify causal effects, using the monthly panel data from 2019 to 2022. The results showed that after controlling the related fixed effects and economic covariates, Ding Zhen phenomenon induced a statistically significant net increase of about 18.5% in Litang tourism search compared with the control group ($p < 0.01$). This definite treatment effect lasted for two years, indicating that the market structure was reshaped, rather than the flow fluctuated temporarily. It is worth noting that the net effect found is far greater than the observed total increase (9.8%), which shows that the rough IP has a very strong power when the mixed factors are eliminated. The mechanism analysis confirms the transmission path of three stages: the end of information barrier, the demand meeting driven by UGC, and the activation of the long tail market. This paper changes the application of the long tail theory from a simple description to a real causal conclusion, and provides theoretical basis and practical cases for poor counties to use IP to transform the tourism market.

Keywords: Long Tail Theory; Ding Zhen Effect; Peripheral Tourism Destinations; Difference-in-Differences Method; Tourism Demand Activation

1. INTRODUCTION

1.1 Research Background

Reviving marginal tourist destinations has long been a challenge for regional tourism economy. Limited by structural obstacles such as information asymmetry and inconvenient transportation, remote inland areas such as Litang County in Galzi County have been on the edge of the main tourism market for a long time, and it is difficult to effectively stimulate tourism demand, although they are rich in natural landscapes and ethnic cultural resources.

In November 2020, a short film depicting the daily life of Ding Zhen, a Tibetan teenager, unexpectedly spread on social media, which quickly attracted the attention of the whole country. In just a few weeks, the Baidu search index in Litang County has increased several times. “Ding Zhen effect” has become a classic case study, discussing how marginal tourist destinations redefine the market by using “rough IP”; Its spontaneous nature and the importance of its influence provide a rare opportunity for research to experience near nature.

1.2 Research Questions

Under this background, the main question that this paper tries to discuss is: To what extent has the Dingzhen phenomenon reversed the long-term trend of tourism demand in Litang? Is this change only a temporary traffic interruption, or does it represent a continuous structural transformation? In addition, can the potential transmission mechanism be systematically explained in the long tail theory?

The value of exploring this proposition goes beyond the simple evaluation of the Ding Zhen effect itself. Litang is not an isolated case-there are still many counties in remote areas with rich resources on the vast land of China, but they have been dormant for a long time due to information barriers. If the transferable logic of revitalization can be extracted from the “step-by-step” growth of vertical pond, it will provide concrete guidance for underdeveloped areas seeking sustainable and low-cost ways to develop tourism market.

1.3 Research Significance

This research has two great values, academic value and practical value. It is helpful to develop tourism economic theory and formulate regional tourism brand strategy.

Theoretically, this study broadens the conceptual boundaries of the long tail theory in the field of tourism. Other studies mainly use the long tail theory to discuss product distribution and consumer behavior on OTA platform. But there is still a lack of serious tests to determine whether external shocks (such as "rough IP") can change the demand for marginal destinations. Using quasi-natural experiments, this study goes beyond simple descriptions. It finds causality in the activation of regional tourism market. More specifically, this study shows how an amateur IP ("crude IP") can act as a catalyst for "garbage" and change the distribution of the long tail. This has changed the explanation: we are no longer just talking about discovering products, but completely revitalizing marginal destinations. In terms of methods, this paper gives a solid counterfactual framework by using TWFE model. This makes the long tail theory change from a simple qualitative observation to a statistically verifiable tool for causal inference in regional economy.

On the practical level, although Ding Zhen phenomenon may seem special, its potential mechanism provides an extensible model for the development of tourism in marginal areas. In the digital priority communication ecosystem, this study shows that the emergence of amateur IP can trigger a large number of lasting demand activation at negligible marginal cost. For the regions with limited resources and underdeveloped areas, these results provide an important reference for decision-making, and explain the ways to establish tourism brands with high influence and low cost. Bridging the information gap through scattered digital storytelling, this study provides specific insights on how to bypass the obstacles of traditional marketing in marginal areas and successfully integrate scattered and long-term consumer interests into sustainable competitive advantages.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Review of Research on the Long Tail Theory

The "Long Tail Theory" (The Long Tail) was first proposed by Anderson [1] in Wired magazine and systematically elaborated in his 2006 book of the same name [2]. The core of this theory is that in the digital economy, the Internet has greatly reduced the cost of saving, searching and disseminating information. This makes niche products-previously abandoned by the mainstream market because people who want them are scattered-reach a huge market scale through the aggregation effect of digital platforms. Using power-law distribution, Anderson divides the market into a "head" composed of several best-selling books and a "tail" composed of many minority products. He pointed out that when the research cost continues to decline, the total demand of the long tail may be greater than that of the head.

Early empirical research on this theory focused on the e-commerce sector. Brynjolfsson et al. [3] conducted an econometric analysis of Amazon's book sales data, confirming the existence of the aggregation effect of niche demand in the internet environment and demonstrating that the sales share of long-tail products is continuously expanding. Subsequently, related research extended to content industries such as music, film, and digital news, focusing on the diluting effect of improved distribution efficiency on market concentration.

In recent years, the Long Tail theory has gradually been introduced into the field of tourism economics. Traditional tourism markets have long been highly concentrated, and demand for niche destinations at the "tail end" of the market is extremely fragmented due to information asymmetry and transportation constraints [4]. With the proliferation of OTAs, the lowered barrier to information access has effectively stimulated the release of niche tourism demand [5]. However, existing research has largely been limited to descriptive analysis and discussions of static distributions; empirical tests of the causal mechanism—specifically, "what kind of exogenous shock can systematically activate long-tail demand for marginal destinations"—remain scarce. This paper uses the "Ding Zhen phenomenon" as a quasi-natural experiment to attempt to fill this research gap.

2.2 Research on the Activation of Peripheral Tourism Destinations

Peripheral tourism destinations refer to regions that are geographically remote, have limited transportation accessibility, and possess limited tourism visibility. Insufficient accessibility and information asymmetry are the two core obstacles to their development [6][4][7]. Existing research has identified various activation mechanisms, including government policy promotion, the hosting of festivals and events, and the film-location effect, among which research on film-induced tourism is the most extensive [8][9]. In recent years, the rise of short-video platforms has brought new forms of dissemination—such as influencer hotspots and live-streamed e-commerce—increasingly into the spotlight [10].

However, most of the aforementioned studies have focused on commercial influencers or organized marketing campaigns, with a marked lack of attention paid to the novel activation mechanism of "unplanned, accidental fame among ordinary individuals." The Ding Zhen phenomenon—which garnered nationwide attention solely through the natural presentation of an ordinary herding teenager, without any government-led marketing—offers a unique and research-worthy case that forms the core rationale for this study's topic selection [11].

2.3 Grassroots IP and the Activation of Tourism Demand

With the widespread adoption of short-video platforms, amateur content creators have gradually become key agents in the dissemination of tourism information. Unlike professional influencers or commercial kols, the content created by amateurs conveys a stronger sense of reality and closeness, which usually leads to greater emotional resonance among users [12]. Existing research shows that UGC on social media has a great influence on the choice of destinations [13] [14], and publishing travel-related content on platforms such as Douyin and Xiaohongshu can significantly increase the online visibility of destinations and turn them into real travel intentions [11]. However, most of the existing studies rely on questionnaires or content analysis methods, and lack causal identification of amateur IP communication effects. The exogenous nature of Ding Zhen phenomenon provides an opportunity to fill this methodological gap.

2.4 Theoretical Framework

On the basis of the above literature, this paper constructs the following theoretical framework (see Figure 1) to explain the basic logic of how amateur IP activates long-tail tourism demand in marginal areas, which can be summarized as three gradual steps.

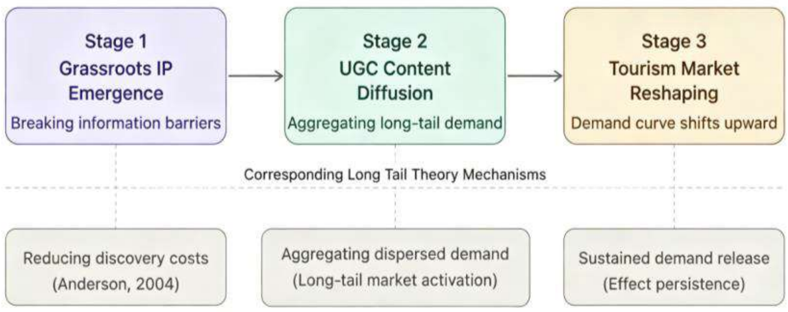
The first step: the appearance of rough IP broke the information barrier. The unexpected viral success of Ding Zhen's short film promoted the regional characteristics of Litang to a huge audience at a very low broadcast cost, and broke the long-standing information asymmetry between peripheral destinations and potential tourists-this development accords with the core condition of "reducing the discovery cost" in the long tail theory.

Step 2: UGC content diffusion, aggregating long-tail demand. The large-scale wave of derivative content creation and sharing triggered by Ding Zhen phenomenon has produced a continuous supply of UGC. This prompted users who had potential interest in the remote destination of western Sichuan before, but lacked the trigger to turn their potential preferences into observable search behavior, which reflected the market mechanism of "aggregate and disperse demand" in the long tail theory.

Stage three: Tourism Market Reshaping and Upward Shift of the Demand Curve. As search interest persisted, Litang transformed from an "unknown, marginal destination" into a tourism option with a certain level of recognition. The demand curve underwent a structural upward shift, indicating that the long-tail effect was being sustained rather than being a fleeting phenomenon.

Based on this, this paper proposes the core hypothesis: The Ding Zhen phenomenon significantly activated Litang County's long-tail tourism demand through the aforementioned three-stage mechanism, and the effect is both statistically significant and enduring.

Figure 1. Theoretical Framework of the Ding Zhen Effect



Source: Compiled and illustrated by the author based on Anderson's [1] Long Tail theory

3. RESEARCH DESIGN AND DATA

3.1 Identification Strategy and Model Specification

The challenge in identifying the causal effect of a grassroots IP on tourism demand lies in controlling for the interference of other contemporaneous factors. The unexpected nature of the Ding Zhen phenomenon provides an opportunity to address this issue—his rise to fame was not the result of government policy intervention or proactive marketing by Litang, but rather a spontaneous outbreak on social media, exhibiting the typical characteristics of an exogenous shock, thereby providing the conditions for constructing a quasi-natural experiment in this study.Accordingly, this study employs the Difference-in-Differences (DID) method for causal inference [15], constructing the following two-way fixed effects model:

$$Y_{it}=\alpha+\beta(Treat_i\times Post_t)+\gamma \ln(GDP_{it})+\mu_i+\lambda_t+\varepsilon_{it} \tag{1}$$

where Y_{it} is the logarithm of the Baidu search index for county i in month t, proxying the intensity of tourism demand;$Treat_i$ is the treatment group dummy variable (Litang = 1, control group = 0);$Post_t$ is the post-policy dummy variable (November 2020 and later = 1, earlier = 0);$Treat_i\times Post_t$ is the core explanatory variable in the DID, and its coefficient β serves as the estimator of the Ding Zhen effect;$\ln(GDP_{it})$ represents the logarithm of county GDP, controlling for the level of economic development;μ_i and λ_t are the county fixed effects and time fixed effects, respectively;ε_{it} is the random error term.

3.2 Sample Selection

Litang county was designated as the processing unit, and Baiyu, Luguo and Ganzi counties were used as the control units, and a monthly panel data set covering the period from 2019 to 2022 was constructed. The selection of these control units is based on three strict criteria: first, geographical and cultural homogeneity, because all counties are located in Galzi Province, sharing the same cultural heritage and the same natural landscape; Secondly, the comparability of development stages, in which the tourism infrastructure, economic indicators and research volume of the control group are very similar to those of the vertical pond before the impact; Third, verify the assumed parallel trend and ensure that the trajectory of the control unit of the pre-oscillation search index is the same processing unit.

In order to reduce the risk of bias, Daofu county-which experienced abnormal fluctuations related to pandemic-and Sertar county-which were affected by independent cultural and tourism events during the study period-were excluded from the sample. This strategic choice ensures that the final control group is highly consistent with Litang County in terms of external policies and market disturbances unrelated to “Ding Zhen phenomenon”. This rigorous sample reconstruction strictly abides by the requirements of DID model for homogeneity of unit and parallel trend, thus effectively solving the concern about estimation instability and improving the internal validity of empirical results. The final balance panel data set includes 48-month observations in four counties, with a total of 192 observations.

3.3 Variable Definitions and Data Sources

The dependent variable is the logarithm of the Baidu Search Index for each county (ln_baidu), serving as a proxy for the intensity of tourism demand. The data are sourced from the Baidu Index platform (index.baidu.com) and were extracted and organized into monthly time series through graphical analysis [16] [17]. The core explanatory variable is the Treat× Post interaction term. The control variable is the logarithm of county GDP (ln_gdp), sourced from the Ganzi Tibetan Autonomous Prefecture Statistical Yearbook (2019–2022), with the same value assigned to each month within the same year. The model also controls for county fixed effects (μ_i) to account for geographical and cultural heterogeneity, as well as time fixed effects (λ_t) to control for global seasonal fluctuations and macroeconomic shocks such as the COVID-19 pandemic. Descriptive statistics for each variable are presented in Table 1.

Table 1. Descriptive Statistics

County	Role	Mean	Standard Deviation	Minimum	Maximum
Litang County	Treatment group	299	118	204	900

Table 1. (continued) Descriptive Statistics

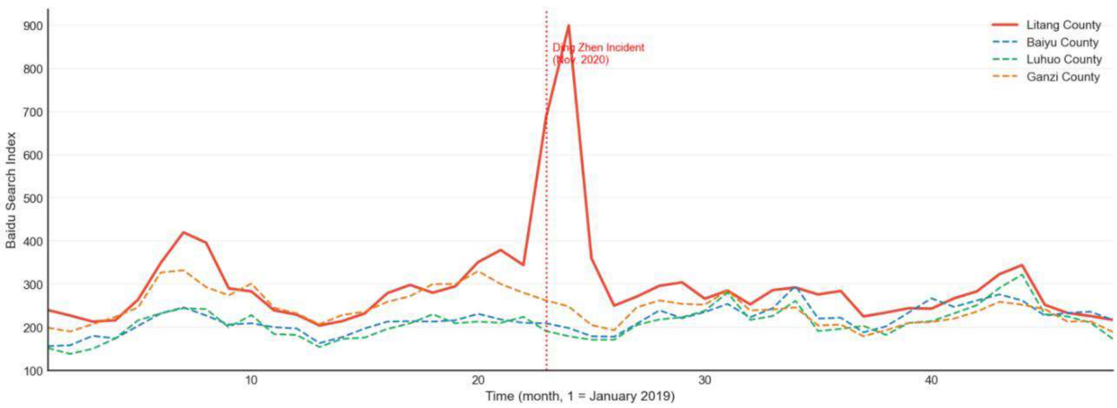
County	Role	Mean	Standard Deviation	Minimum	Maximum
Baiyu County	Control group	217	30	156	296
Luhuo County	Control group	209	36	138	322
Ganzi County	Control group	245	40	179	332
Comparison Before and After the Impact (Litang)					
Before the Impact (Jan 2019–Oct 2020)			284		
After the Impact (Nov 2020–Dec 2022)			312		
Increase			+9.8%		

Note: Baidu Index data are sourced from index.baidu.com and have been organized into monthly series; GDP data are sourced from the *Statistical Yearbook of Garzê Tibetan Autonomous Prefecture (2019–2022) *; the shock point is November 2020.

3.4 Descriptive Statistics

Table 1 shows that the average search indexes of the four counties are similar during the sampling period: Litang County has an average of 299, Baiyu County has 217, Luguo County has 209 and Ganzi County has 245. The tourism development level of the three control counties is similar to that of Litang, which makes them very comparable. The monthly average value of vertical pond search index rose from 284 points before the earthquake to 312 points after the earthquake, with an increase of 9.8%, which initially showed that the phenomenon of fixed earthquake had a positive impact. Figure 2 further illustrates the monthly trend of the four counties: the trend before the impact is roughly the same, but after the impact, the vertical pond shows obvious growth, while the counties in the control group do not show similar changes, which provides intuitive support for the effectiveness of the DID identification strategy.

Figure 2. Baidu Search Index Trends for the Four Counties (January 2019–December 2022)



Source: Compiled and plotted by the authors based on Baidu Index data

4. EMPIRICAL ANALYSIS

4.1 Baseline Regression Results

Table 2 shows the empirical results of DID estimation of two-way fixed effect (TWFE). Model (1) gives the basic estimation value without additional covariates, while model (2) includes ln (GDP) to reflect the economic fundamentals of counties that change with time.

The result of model (1) shows a coefficient of 0.0169 (p=0.6996), which is not statistically significant. This lack of significance shows that if the economic development is not adjusted, the potential growth trend shared by four counties (Litang and its three neighboring countries) masks the specific impact of the impact. However, if ln (GDP) is included in the model (2), the therapeutic effect coefficient (Treat× Post) becomes 0.1696, and the statistical t is 3.8450, which reaches 1% through the significance test (P < 0.01). This discovery emphasizes the necessity of controlling economic fundamentals to isolate the therapeutic effect and accurately identify the trajectory of reverse demand. R in model (2) is 0.2183, which further proves that the inclusion of regional economic variables greatly improves the explanatory ability of the model.

For the economic scale, the estimated coefficient is 0.1696, which shows that the “Ding Zhen” phenomenon has produced a net increase of about 18.5% (“E” “0.1696”-1). Compared with the control group, in the research related to tourism in Litang, Using comparable peripheral counties as control groups-rather than more mature destinations-this study provides a powerful and reliable estimate of how exogenous digital shocks systematically reshape the long-tail tourism market. The regression results were confirmed by descriptive data: Litang’s monthly average search index rose from 284 before the incident to 312 after the shock. Although the total growth of 9.8% is substantial, the net effect determined by the regression of 18.5% shows that the Deng Zhen effect is stronger after the filtered macroeconomic fluctuations, which confirms the role of amateur IP in promoting the structural changes of regional niche markets.

Table 2. Baseline Regression Results (Two-Way Fixed Effects DID)

Variables	Model 1 Coefficients	Model 1 Standard Error	Model 2 Coefficient	Standard Error of Model 2
Treat× Post (DID core term)	0.0169	(0.0438)	0.1696***	(0.0441)
Ln (GDP)	—	—	-1.7276***	(0.2376)
County fixed effects	Control		Control	
Time fixed effects	Control		Control	
Number of observations	192		192	
R^2	0.0008		0.2183	

Note: The dependent variable is ln (Baidu Search Index); the sample consists of monthly panel data from four counties for January 2019–December 2022; standard errors are shown in parentheses; ***p<0.01.

4.2 Parallel Trends Test

The core premise of the validity of the difference-in-differences method is the parallel trends assumption. This study compares the mean values of the treatment and control groups for each quarter prior to the shock (Q1 2019 to Q3 2020) (see Table 3). The results show that the difference between the two groups fluctuated between 30 and 120 in the pre-shock periods. The values are small and show no systematic trend of expansion or contraction, indicating that the trajectories of the two groups were essentially parallel prior to the shock, and that the DID identification strategy is valid.

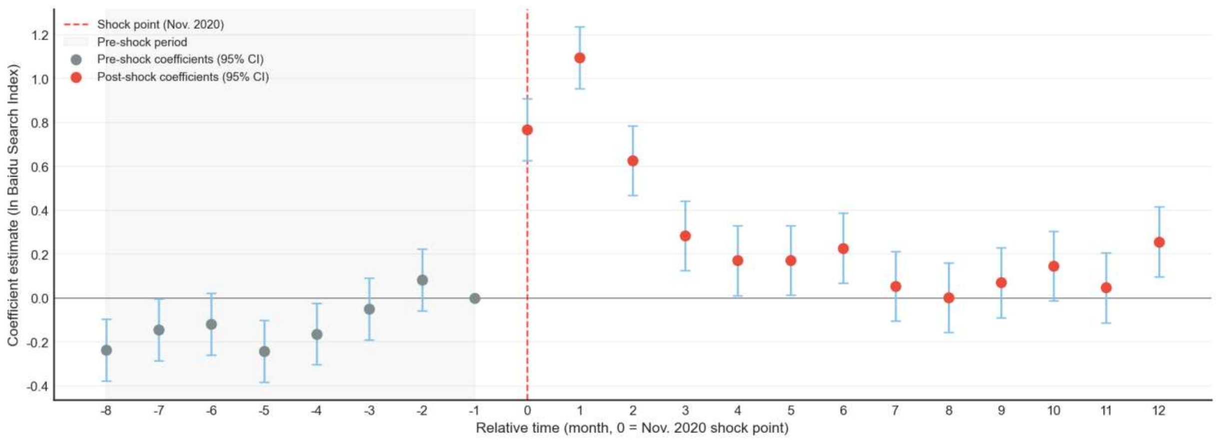
Table 3. Parallel Trends Test (Pre-shock Quarters)

Period	Litang Mean	Control Group Mean	Difference
Q1 2019	227	170	57
Q2 2019	276	225	51
Q3 2019	369	252	117
Q4 2019	250	220	31
Q1 2020	217	190	27
Q2 2020	286	234	52
Q3 2020	342	247	94

Note: Difference = Litang mean − control group mean; the sample period is Q1 2019–Q3 2020 prior to the shock; if the difference shows no systematic trend, the parallel trend assumption holds.

Figure 3 further presents the estimated coefficients for each period using event study methods. It can be observed that the coefficients for all periods prior to the shock (rel_t = −6 to −1) fluctuate around zero and the confidence intervals cover zero; after the shock, the coefficients surge and remain consistently and significantly positive, visually illustrating the parallel trend before the shock and the significant divergence after the shock.

Figure 3. Parallel Trend Test: Event Study Method



Note: Gray points represent coefficients for periods before the shock, red points represent coefficients for periods after the shock, and error bars indicate the 95% confidence interval; rel_t = −1 is taken as the base period (coefficient set to zero); coefficients for all periods before the shock are not significantly different from zero, and the parallel trend hypothesis holds.

4.3 Robustness Tests

To verify the reliability of the baseline regression results, this study conducts 500 placebo tests: treatment group assignments are randomly reassigned, the DID estimator is re-estimated, and the resulting coefficient distribution under random assignment is examined (see Table 4). The results show that the mean placebo β is 0.0049, close to zero, indicating that the expected value of the DID estimator is zero under random conditions, and there is no systematic bias. The true DID coefficient β = 0.1696 exceeds the majority of placebo coefficients; however, the placebo results provide limited supportive evidence but are not statistically decisive due to the small sample. It should be noted that, since the sample consists of only four counties, the statistical power of the placebo test is relatively limited; the parallel trends test serves as the primary basis for verifying the validity of this study's identification strategy.

Table 4. Placebo Test (500 randomizations of treatment group assignment)

Statistic	Value	Description
True DID coefficient β	0.1696	Estimated value in this paper (Model 2)
Mean placebo β	0.0049	Should be close to 0
Standard deviation of placebo β	0.1291	Range of random variation
|Placebo|≥|True β|Proportion	0.1480	Small sample size; for reference only

Note: The relatively high proportion of |Placebo| ≥ |True β| is due to the small sample size; conclusions should still be based primarily on the parallel trends test.

4.4 Mechanism Analysis

The previous results show that Ding Zhen phenomenon has greatly increased the concern of tourism research in Litang. This part explains how it happened, using the idea of long tail theory.

First of all, eliminate information barriers: Litang is located in the center of the western Sichuan Plateau. Before Ding Zhen became famous, his average monthly search index was about 284, almost the same as other counties around him. Ding Zhen's short film has achieved unexpected success, showing the Xizang scenery and culture of Litang to hundreds of millions of people at a very low cost. This greatly reduces the cost for the public to obtain information about the vertical pond, thus eliminating the information barrier between this remote destination and potential tourists [6][7].

Secondly, from the perspective of niche demand aggregation, many users created and shared UGC content after watching short videos, which formed a continuous content supply and further expanded the information scope. Users who used to be interested in this remote destination in western Sichuan but didn't have a trigger turned their potential preferences into observable search behavior under the impetus of this content wave, and realized the large-scale aggregation of niche tourism demand [1], which corresponds to the significant positive impact of DID estimation capture.

In addition, regarding the persistence of the effect, the data show that from 2021 to 2022, the average monthly search index of the vertical pond remained at around 312, which was higher than the pre-earthquake level (284), indicating that the demand activation effect has structural characteristics. This is in line with the logic described in the long tail theory that "once the cost is reduced, the marginal demand will continue to be released"-Ding Zhen phenomenon reshapes the public's view of the opposite pond, leading to the structural upward shift of the demand curve [10] [11].

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1 Main Conclusions

Ding Zhen phenomenon in November, 2020 is used as a quasi-natural experiment, and the difference-difference method is adopted in this paper. According to the monthly group data of four counties from January 2019 to December 2022, we tested the causal effect of "rough IP" phenomenon on tourism-related search concerns in marginal areas based on experience, and drew the following three conclusions.

First of all, the phenomenon of Ding Zhen greatly stimulated the concern of tourism-related search in Litang County. After controlling the county-level fixed effect, the fixed time limit effect and the level of economic development, Ding Zhen phenomenon led to an increase of about 18.5% in the attention of tourism-related search in Litang compared with the control group. The coefficient passed the significance level test of 1%, indicating that the conclusion is reliable and reliable.

Secondly, the tinkle effect lasts for a long time, and it is not just a short peak flow. From 2021 to 2022, the average monthly search index of Litang remained at around 312, which was higher than the level of 284 before the effect. This shows that the demand growth driven by amateur IP has structural characteristics, which is consistent with the logic of "continuous release of demand curve" predicted by the long tail theory.

Third, the long tail theory provides a powerful explanation for revitalizing the tourism market in the surrounding areas. Through the three-step mechanism of “breaking the down information barrier-driving UGC communication-aggregating the long tail demand”, grassroots IP redesigned the tourism market of surrounding destinations, which provided empirical evidence for the application of the long tail theory in the field of tourism economics.

5.2 Policy Recommendations

The above results provide us with insights into little-known tourist destinations. First of all, you must find and help local ordinary people, who can become IP. The core of “Ding Zhen effect” is the real emotion it creates. Local governments should first find these people who can represent their areas well. They must help them create stories and be seen by more people to attract potential tourists with real personal stories.

Next, you need to create an UGC content ecosystem for continuous attention. Visitors should be encouraged to create and share excellent UGC content. We can create a reward system to encourage them to “stay”. Therefore, the temporary popularity may turn into a constant influx of new content.

Finally, we must use this popularity peak to improve the travel quotation. Doing a lot of research on the Internet is only the first step. If a place doesn’t have enough hotels, transportation or all tourists’ activities, then this kind of attention won’t bring a lot of money. Counties like Litang should use the attention window created by intellectual property rights to improve facilities-such as transportation, accommodation and cultural experience. This will change the tourism industry from “passive exposure” to “active participation”.

5.3 Research Limitations and Outlook

This study has the following limitations. First, the dependent variable is a proxy. Baidu search index cannot directly measure the actual number of tourists or tourism income. Future research can obtain the data of visitors received every month, and can verify whether the activation of search queries has turned into tangible economic benefits. Secondly, the choice of control group is limited by the availability of Baidu index data; Lack of data for most counties around Garzê county. Therefore, this study finally took Baiyu County, Luguo County and Ganzi County as the control group, and Litang County as the only treatment unit. Therefore, the statistical strength of DID estimation needs to be improved. Future research can explore more extensive county panel data, or introduce composite control method (SCM) to enhance the robustness of the recognition strategy. Thirdly, mechanism analysis mainly depends on theoretical logic reasoning; Further research can integrate the content data from the short video platform, and use the text analysis method to conduct a more rigorous empirical inspection of the transmission chain.

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