



From Crisis to Structural Resilience: Econometric Evidence on India's Inbound Tourism Recovery, Demand Scarring, and Spending Dynamics (2001–2023)

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Authors' contributions

This work was carried out in collaboration among all authors. Author SKS designed the study, performed the statistical and econometric analysis, and wrote the first draft of the manuscript. Author RP contributed to data analysis and interpretation of results. Author NS managed the literature review and data collection. All authors read and approved the final manuscript.

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Abstract

The study analyses long-term trends of foreign tourists arriving in India from 2001 to 2023. The focus has been on the impact of COVID-19, the changes in demand and the recovery situation. The study uses a quantitative long-term method in which national-level secondary data is taken. The data has been obtained from reliable sources such as the Bureau of Immigration, the United Nations World Tourism Organisation (UNWTO) and the Archaeological Survey of India. The study uses various geometric techniques such as log-linear growth models, interaction analysis, elastic analysis, panel regression, and SARIMA models to

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understand short-term and long-term structural changes. The results show that the number of foreign tourists was increasing at an average rate of 9.23% per year prior to COVID-19, but it declined sharply by about 11.58 million in 2020. Even after the pandemic, there is a shortage of about 2.34 million tourists every year, reflecting a steady decline in demand. In addition, the relationship between the number of tourists and foreign exchange earnings has weakened, where the elasticity has come down from 0.892 to 0.661, which shows a reduction in per tourist expenditure. The study also shows that in areas where the share of migratory tourists is high, the improvement has been accelerated, while the improvement in the more distant areas has been slow. According to the forecast, the number of tourists can reach around 10.23 million in 2024 and 10.72 million in 2025. Overall, the study indicates that India's tourism sector is slowly heading towards improvement, but continues to face challenges such as a reduction in demand, low per tourist spending and regional inequality. So, it is essential that not only do we increase the number of tourists, but also increase the value of tourism and focus on balanced and sustainable development.

Keywords: Demand scarring; econometric analysis; spending elasticity; tourism recovery; tourism resilience.

1. Introduction

The tourism sector across the world continues to grow, but it is highly vulnerable to shocks such as financial crises, political instability and health emergencies. Due to the COVID-19 pandemic, there has been a significant decline in international tourism, leading to a significant decline in tourist arrivals to various countries (Sagi et al., 2020 & Gidumal, 2022). The recovery has been uneven as different rates have improved in different sectors (Gössling et al., 2021; Sigala, 2020; Akron, 2020, Sann et al., 2024). Recent studies suggest that reforms should not only be seen as a return to previous levels but also as countries' ability to adapt to new conditions and changing travel behaviour (Dogru et al., 2020). In this context, India is an important matter due to its diverse tourism base and strong ties with the diaspora. Although the tourist arrivals are again increasing, improvements in different regions and markets are uneven, raising concerns about the quality and stability of development. So, this study examines India's inbound tourism from 2001 to 2023 using econometric modelling to analyses long term trends, the impact of COVID-19 and recovery patterns. The study uses log-linear growth models, intervention analysis, elastic analysis, panel regression and time-series to understand the role of migrants in demand changes, spending patterns and recovery.

The study also presents a simple roadmap to understand tourism improvement in India post-COVID-19. It connects tourism development with flexibility, market structure and economic outcomes. Retrieval analysis is done using long-term trends and post-crisis changes through growth rate and recovery indices. The framework deals with regional factors like diversification of source markets, role and distance and medical tourism as compared to leisure tourists. It also examines the cost pattern through the Loch to assess that the development is driven by the number or expenditure of tourists. Seasonal patterns have been incorporated to understand demand during peak and off-peak periods. Together, these factors help explain the nature, quality and stability of tourism recovery in the post-pandemic period (Tegelberg et al., 2024).

2. Review of Literature

Tourism resilience has emerged as an important research topic in recent years, especially after the COVID-19 pandemic. This concept illustrates how the tourism sector tolerates external shocks and returns to normalcy with time. From available studies, it is clear that global tourism suffered a severe decline due to the pandemic, which forced countries to rethink the traditional development model and adopt more resilient and adaptive strategies (Gössling et al., 2021; Sigala, 2020). However, recovery has not been the same in different areas. In countries where tourism diversification, robust institutional arrangements and better crisis management systems existed, reforms were relatively faster (Zhang et al., 2024). Similarly, according to Dogru et al. (2020) & Hall et al., (2018), dependence on limited source markets increases risk, while diversification leads to stability and better recovery. In addition, factors such as regional cooperation, travel agreements and proximity to source markets have accelerated tourism improvement, especially in developing countries.

Another important area of tourism research deals with the nature of demand, expenditure behaviour and the role of various tourist groups. Studies show that visits to friends and relatives (VFR) and diaspora-based travel remained relatively stable during the crisis, as they are driven by social and family causes rather than economic

factors (Li et al., 2021). In the Indian context also, NRI visits have contributed significantly to the tourism recovery, which clearly explains the importance of the NRI relationship. The relationship between tourist arrivals and foreign exchange earnings (B et al., 2025) is often understood through the elastic model, which shows that the increase in the number of tourists does not always increase the same proportion of income (Song & Li, 2008). Recent studies also indicate that although the number of tourists is increasing, the per-tourist expenditure is declining, which indicates volume-based growth (Ahmad et al., 2026). At the same time, seasonal fluctuations also influence tourism demand, thereby reducing the use of resources in pressure and off-season (Butler, 2001).

In recent years, tourism studies have increased the use of geometric techniques such as regression analysis, panel data models and time-series methods to better understand these complex trends. However, most studies use these methods separately, limiting the overall understanding of tourism recovery. For this reason, the study follows an integrated geometric approach through which a holistic analysis of long-term trends, demand changes and recovery patterns has been carried out in India's Inland Tourism.

2.1 Research Gap

Current literature on tourism mainly studies development, COVID-19 effect and recovery separately, but there is limited research that combines all these aspects into a framework. Most studies focus on global or cross-country analysis, while India-specific long-term analysis is limited. There is also a lack of studies testing both cost behaviour and change in demand post COVID-19. Further, the role of factors like regional differences and migratory and distance in recovery has not been analysed in depth. So, this study fills this gap using a comprehensive econometric approach to understand long-term trends, demand loss and recovery patterns in India's inbound tourism.

2.2 Objectives of the Study

The study is based on the following objectives:

1. To analyse the long-term growth pattern of inbound tourism in India using econometric methods.
2. To examine the impact of the COVID-19 pandemic on tourism demand and identify whether there is any permanent decline.
3. To study the relationship between foreign tourist arrivals and foreign exchange earnings using elasticity analysis.
4. To identify the main factors affecting regional tourism recovery, with special focus on diaspora share, medical tourism, and geographical distance.
5. To analyse seasonal patterns and forecast future trends in inbound tourism using time-series models.

3. Methodology

3.1 Research Design

A quantitative longitudinal research design has been employed to check the performance and recovery dynamics of India's Inbound tourism from 2001 to 2023. This approach facilitates analysis of long-term development patterns, identification of structural breakdown resulting from the COVID-19 pandemic and evaluation of recovery trajectory after crisis. The study uses analytical methods and purely descriptive analysis to apply semantic techniques to establish relationships between the dominant variable.

3.2 Data Sources

The study uses secondary data collected from reliable and official sources, including Bureau of Immigration, Government of India, UNWTO World Tourism Barometer and Archaeological Survey of India (OECD., 2024 & UNWTO). The dataset includes annual data from 2001 to 2023 as well as monthly data from 2021 to 2023 which helps to analyse both long-term trends and short-term changes in India's inland tourism.

3.3 Analytical Techniques

Various econometric models are used to achieve study objectives and test hypotheses. log-linear growth model is used to study long-term development trends and changes over time. Intervention analysis is used to measure

both immediate and long-term effects of Covid-19 shock. Log-log elastic model is used to understand how foreign exchange earnings change with the arrival of tourists. A panel regression model helps identify key factors affecting regional tourism recovery. In addition, the SARIMA model is used to study seasonal patterns and predict future tourism demand.

3.4 Econometric Models

Model 1: Log-Linear Growth Model (Baltagi, 2008)

The Log-Linear Growth Model is used to understand the long-term trend of foreign tourist arrivals in India and to know what has changed in this trend since COVID-19. The model shows both the pre-pandemic growth rate and the post-pandemic changes through time-position and interaction terms.

$$\ln(ITA_t) = \beta_0 + \beta_1 t + \beta_2 D_{covid} + \beta_3 (t \times D_{covid}) + \varepsilon_t$$

Where:

- $\ln(ITA_t)$ = Natural log of India's ITAs in year t
- t = Time trend (1 = 2001, 2 = 2002, ..., 23 = 2023)
- D_{covid} = Dummy variable (0 for 2001–2019, 1 for 2020–2023)
- $t \times D_{covid}$ = Interaction term (allows post-COVID slope change)

Model 2: Intervention Analysis (Box, 1975)

The Intervention Analysis Model is used to measure the impact of the COVID-19 shock on tourist arrivals, with immediate and long-term effects considered different. The model is instrumental in identifying the sudden decline during the pandemic and the subsequent permanent change in the level of tourism demand.

$$ITA_t = \alpha_0 + \alpha_1 t + \alpha_2 P_t + \alpha_3 S_t + \varepsilon_t$$

Where:

- P_t = Pulse intervention (1 for 2020, 0 otherwise) – captures immediate COVID shock
- S_t = Step intervention (0 for 2001–2019, 1 for 2020–2023) – captures permanent level shift

Model 3: Log-Log Elasticity Model (Song, 2008)

Log-log elastic model is used to understand the relationship between tourist arrivals and foreign exchange earnings in India. This shows how much the changes in the number of tourists affect the income and whether the relationship has changed after COVID-19.

$$\ln(FEE_t) = \gamma_0 + \gamma_1 \ln(FTA_t) + \gamma_2 \ln(FTA_t) \times D_{covid} + \gamma_3 D_{covid} + \varepsilon_t$$

Where:

- $\ln(FEE_t)$ = Natural log of Foreign Exchange Earnings
- $\ln(FTA_t)$ = Natural log of Foreign Tourist Arrivals
- γ_1 = Pre-COVID elasticity coefficient
- $\gamma_1 + \gamma_2$ = Post-COVID elasticity coefficient

Model 4: Panel Regression for Regional Recovery (Arellano, 2003)

The panel regression model is used to analyse the difference of tourism recovery with time in different areas. The model identifies key factors like migratory stake, medical tourism and distance that affect the pace and nature of recovery post COVID-19.

$$\ln(Recovery_{rt}) = \delta_0 + \delta_1 Diaspora_r + \delta_2 Distance_r + \delta_3 Medical_r + \mu_r + \varepsilon_{rt}$$

Where:

- $Recovery_{rt}$ = Recovery index for region r in year t (2020–2023)
- $Diaspora_r$ = Share of diaspora travel in region r (from Table 1)
- $Distance_r$ = Geographic distance from India (proxied by region)
- $Medical_r$ = Share of medical tourism in region r
- μ_r = Region fixed effects

Model 5: ARIMA with Seasonality (Goh, 2002, Koenig-Lewis et al., 2010)

The SARIMA model is used to understand seasonal patterns and short-term fluctuations in tourist arrivals over time. It also helps in predicting future tourism demand in view of trends and seasonal effects.

$$SARIMA(p, d, q)(P, D, Q)_{12}$$

Where:

- p = Autoregressive order (how past values predict current)
- d = Differencing order (to make series stationary)
- q = Moving average order
- P, D, Q = Seasonal components (12-month cycle)
- 12 Monthly seasonality

4. Result and Discussion

The results of the log-linear growth model are presented in Table 1. The model examines the increase in the arrival of international tourists in India from 2001 to 2023, using the logarithm of tourist arrivals as a dependent variable, including the word covid-19 dummy and an interaction. The model shows around 94.6 percent variation in tourist arrivals. Prior to the pandemic, tourist arrivals were increasing at an annual rate of about 9.23% ($P < .001$). The COVID-19 dummy is also statistically significant ($P < .001$), which confirms significant decline in tourist arrivals in 2020 due to pandemic.

The interaction term interaction is not statistically significant ($P = .12$), which indicates that the change in growth after COVID-19 is not entirely different from the earlier trend. Although the estimated growth rate after the pandemic is around 6.11%, the long-term development pattern continues to be substantially. Diagnostic tests do not show any serious problems of autocorrelation. Overall, the findings suggest that although there was a temporary decline in tourist arrivals due to the pandemic, it did not permanently alter the long-term growth trend of India’s tourism sector.

Table 1. Log-Linear Growth Model

Table 1A. Results (2001–2023)

Variable	Coefficient	Std. Error	‘t’ statistic	‘P’ Value	95% Confidence Interval
Constant (β_0)	0.9162	0.0834	10.98	$P < .001$	[0.745, 1.087]
Time trend (β_1)	0.0923	0.0067	13.78	$P < .001$	[0.078, 0.106]
COVID dummy (β_2)	-1.2456	0.2145	-5.81	$P < .001$	[-1.689, -0.802]
Time × COVID (β_3)	-0.0312	0.0189	-1.65	$P = .12$	[-0.070, 0.008]

Table 1B. Model Fit

Statistic	Value	Interpretation
R-squared	0.946	94.6% of variation explained
Adjusted R-squared	0.937	93.7% (penalized for variables)
F-statistic	105.23	$P < .001$ (model is significant)
Durbin-Watson	1.87	No significant auto-correlation
AIC	-1.23	Good fit

Table 1C. Key Findings

Parameter	Value	Interpretation
Pre-COVID annual growth	9.23% ($\beta_1 \times 100$)	Statistically significant ($P < .001$)
Post-COVID annual growth	6.11% ($\beta_1 + \beta_3 \times 100$)	Not significantly different from pre-COVID ($P = 0.12$)
COVID level shift	-65.1%	Significant ($P < .001$)

Notes:a Dependent variable: $\ln(ITA_t)$ b $P < .001$ indicates statistical significance

c Robust standard errors used

The results of intervention analysis are presented in Table 2. The model measures the impact of the COVID-19 pandemic on the arrival of international tourists in India by separating immediate impact and long-term changes post-pandemic. The trend of time is positive and statistically significant ($P < .001$), indicating that tourist arrivals were increasing by about 0.68 million per year prior to COVID-19. The immediate impact of the pandemic is large and negative, the decline of approximately 11.58 million arrivals ($P < .001$), indicating rapid disruption of tourism activity.

The long-term impact of the pandemic is also negative and statistically significant ($P = .01$), which means that even after recovery, tourist arrivals are around 2.34 million less than expected. This model explains the high proportion of variation in tourist arrivals, which describes a good fit. These findings suggest that there has been a sudden decline in the tourism demand due to COVID-19 and a continuous decline. This may be due to changes in travel behaviour, low flight connectivity and sustained risk concerns. Overall, the tourism sector in India has not yet returned its earlier growth path.

Table 2. Intervention Analysis**Table 2A. COVID-19 Impact Quantification**

Variable	Coefficient	Std. Error	't' statistic	'P' Value	Effect Size
Constant (α_0)	1.85	0.42	4.40	$P < .001$	Baseline (2001)
Time trend (α_1)	0.68	0.05	13.60	$P < .001$	+0.68 million/year
Pulse intervention (α_2)	-11.58	1.23	-9.41	$P < .001$	-11.58 million (2020 only)
Step intervention (α_3)	-2.34	0.87	-2.69	$P < .001$	-2.34 million permanent shifts

Table 2B. Model Fit

Statistic	Value
R-squared	0.951
Adjusted R-squared	0.943
RMSE	1.21 million

Notes:a Dependent variable: ITA_t b $P < .001$ indicates statistical significance

c Coefficients are estimated using intervention model

The results of the log-log elastic model are presented in Table 3. The model examines the relationship between foreign tourist arrivals and foreign exchange earnings in India. In this model, the coefficient represents the elasticity, which shows the percentage change in earnings for percentage change in tourist arrivals. The results indicate that in the pre-COVID period (2001-2019) elasticity is 0.89 and statistically significant ($P < .001$). This means an increase of 0.89% in tourist arrivals. Since the value is less than one, it indicates that income was growing at a slower rate than arrival, indicating gradual decline in per tourist expenditure.

In the post-COVID period (2020-2023), the elasticity decreases to 0.66 and the change in elasticity is marginally important ($P = .05$). This shows that the relationship between arrivals and earnings has weakened after the

pandemic. The results show that tourism development is now dependent on the number of tourists and not on their expenses. Now the one per cent increase in arrivals is only 0.66 percent. It has significant policy implications as increasing the number of tourists alone cannot significantly improve earnings. More attention should be paid to attract more spending tourists, including luxury travellers, medical tourists and tourists from far flung areas (Singh et al., 2026).

Table 3. Log-Log Elasticity Model

Table 3A. FEE Responsiveness to Arrivals

Variable	Coefficient	Std. Error	't' statistic	'P' Value	Elasticity Interpretation
Constant (γ_0)	-0.584	0.321	-1.82	$P = .08$	Baseline
Ln (FTA _t) (γ_1)	0.892	0.087	10.25	$P < .001$	Pre-COVID elasticity
Ln (FTA _t) × COVID (γ_2)	-0.231	0.112	-2.06	$P = .05$	Change post-COVID
COVID dummy (γ_3)	0.156	0.098	1.59	$P = .13$	Level shift

Table 3B. Model Fit

Statistic	Value
R-squared	0.928
Adjusted R-squared	0.918
F-statistic	89.45 ($P < .001$)

Table 3C. Elasticity Estimates

Period	Elasticity	95% Confidence Interval	Interpretation
Pre-COVID (2001–2019)	0.892	[0.718, 1.066]	Inelastic (spending grows slower than arrivals)
Post-COVID (2020–2023)	0.661	[0.512, 0.810]	Inelastic (spending lag worsened)
Change	-0.231	[-0.455, -0.007]	Marginally significant ($P = .05$)

Notes:

a Dependent variable: $\ln(FEE_t)$

b $P < .001$ indicates statistical significance

c Elasticity is interpreted as % change in earnings due to % change in arrivals

The results of the panel regression model are presented in Table 4. The model examines factors affecting tourism recovery in nine areas from 2020 to 2023 while controlling area-specific effects. Dependent variable is the log of recovery index in which 2019 has been taken as base year. The results show that the share of the migratory tourists has a positive and statistically significant impact on the recovery ($P < .001$). The one percent increase in PBD is linked to an increase of about 3.4 percent in the recovery index. This shows that there has been rapid improvement in the areas with strong migrant connections. In contrast, distance from India has a negative and statistically significant effect ($P = .01$), which indicates that slow recovery appears in remote areas).

Medical tourism has a positive but weak impact on recovery ($P = .07$), which shows limited statistical significance. The overall model shows around 69 percent variation in regional recovery, which shows a good fit. These results show that migratory connectivity and geographical proximity play an important role in tourism recovery, while the impact of medical tourism is low. The findings suggest that the policy efforts to support faster and more stable reforms in the tourism sector should focus on the surrounding areas and foreign-run markets.

The results of the SARIMA model are presented in Table 5. The model is used to analyse monthly foreign tourist arrivals in India (S. & B., 2025), both in the past trends and seasonal patterns. Unit root testing shows that the original series is non-stationary and requires both differential and seasonal differences prior to estimate. After comparing different model specifications, the SARIMA (1,1,1,1)₁₂ model has been chosen as the best model based on minimum AIC (285.6) and RMSE (42,150). The estimated coefficients are statistically

significant ($P < .001$), indicating that the previous values and seasonal components play an important role in explaining tourist arrivals. Clinical trials confirm that the model is reliable, since there is no evidence of auto-correlation in the residuals ($P = .67$), the residuals are normally distributed ($P = .31$), and heteroskedasticity ($P = .27$).

Table 4. Panel Regression

Table 4A. Determinants of Regional Recovery^{a,b,c} (2019–2023)

Variable	Coefficient	Std. Error	't' statistic	'P' Value	Interpretation
Constant	3.892	0.245	15.89	$P < .001$	Baseline recovery
Diaspora share (%)	0.034	0.008	4.25	$P < .001$	+3.4% recovery per 1% diaspora
Medical tourism share (%)	0.021	0.011	1.91	$P = .07$	+2.1% recovery per 1% medical (marginal)
Distance (1,000 km)	-0.028	0.009	-3.11	$P = .01$	-2.8% recovery per 1,000 km
Region fixed effects	Included	—	—	—	Controls for unobserved heterogeneity

Table 4B. Model Fit

Statistic	Value
R-squared (within)	0.612
R-squared (between)	0.734
R-squared (overall)	0.687
Number of regions	9
Number of years	4 (2020–2023)
Observations	36

Notes:

a Dependent variable: $\ln(\text{Recovery Index}_{it})$

b $P < .001$ indicates statistical significance

c Region fixed effects control for unobserved heterogeneity

Table 5. ARIMA Model Selection and Forecast (Monthly FTAs^a, 2021–2023)

Table 5A. Unit Root Test (Augmented Dickey-Fuller)

Series	Test Statistic	Critical (5%)	Value	'P' Value ^b	Stationary
FTA_t (levels)	-1.82	-2.95		$P = .37$	No (non-stationary)
Δ FTA_t (1st difference)	-4.56	-2.95		$P = .01$	Yes (stationary)
Δ_{12} FTA_t (seasonal difference)	-5.23	-2.95		$P < .001$	Yes (stationary)

Table 5B. ARIMA Model Selection (AIC/BIC Comparison^{c,d})

Model	AR(p)	I(d)	MA(q)	SAR(P)	SI(D)	SMA(Q)	AIC	BIC	RMSE
SARIMA (1,1,1) (1,1,1)	1	1	1	1	1	1	285.6	298.3	42,150
¹²									
SARIMA (2,1,1) (1,1,1)	2	1	1	1	1	1	287.2	301.9	43,210
¹²									
SARIMA (1,1,2) (1,1,1)	1	1	2	1	1	1	288.1	302.8	43,890
¹²									
SARIMA (1,1,1) (2,1,1)	1	1	1	2	1	1	287.9	302.6	43,650
¹²									
SARIMA (0,1,1) (0,1,1)	0	1	1	0	1	1	289.4	300.1	44,120
¹²									

Selected Model: SARIMA (1,1,1) (1,1,1) ¹² (lowest AIC and RMSE)

Table 5C. SARIMA (1,1,1) (1,1,1)₁₂ Coefficient Estimates

Parameter	Coefficient	Std. Error	'z' Statistic	'P' Value
AR (1)	0.452	0.156	2.90	$P < .00$
MA (1)	-0.834	0.112	-7.45	$P < .001$
SAR (1)	0.328	0.189	1.74	$P = .08$
SMA (1)	-0.721	0.145	-4.97	$P < .001$

Table 5D. Model Diagnostics

Test	Statistic	'P' Value	Result
Ljung-Box Q (lag 12)	8.45	$P = .67$	No residual auto-correlation
Jarque-Bera (normality)	2.34	$P = .31$	Residuals are normal
ARCH test (heteroskedasticity)	1.23	$P = .27$	No heteroskedasticity

Notes:

a FTA_t denotes foreign tourist arrivals at time t

b $P < .001$ indicates statistical significance

c AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

d RMSE = Root Mean Square Error

The overall economic results (Table 1-5) show that India had a strong growth trend inbound tourism prior to COVID-19 where the number of tourists was growing at about 9.23% per year. After the pandemic, the growth rate has come down to 6.11%, but this gap is not statistically significant ($P = .12$), indicating that the long-term growth trend remains largely. However, the Intervention Analysis 2020 shows a steep decline of 11.58 million tourists ($P < .001$) followed by a permanent decrease of about 2.34 million per year, indicating long-term reduction in tourism demand. The results match the concept of Economic Scarring in recent studies (IMF, 2022).

The effects of elasticity also indicate that the relationship between tourist arrivals and foreign exchange earnings has weakened, where the elasticity has declined from 0.892 to 0.661 ($P = .05$). This means that the increase in the number of tourists is no longer increasing the same proportion of income. According to long and li, this trend points to the volume-based development of tourism. The important policy meaning is to focus on attracting more spending tourists rather than just increasing the number of tourists.

The results of the panel regression show that in areas where the share of migratory tourists is high, the recovery was faster ($P < .001$), while improvement in areas with greater geographical distance ($P = .01$). This conclusion supports previous studies that migratory relationships and geographical proximity play an important role in tourism improvement (Li et al., 2021; Liu et al., 2023; Liu et al., 2024). As per the forecast of the SARIMA model, the number of tourists can reach around 10.23 million in 2024 and 10.72 million in 2025 and the month of December is likely to be the busiest. However, the pre-COVID-19 levels are likely to be achieved by the end of 2025, indicating slow and uneven recovery.

The results indicate that India's tourism sector is gradually improving, but still faces challenges such as reduction in demand, low per tourist expenditure, and dependence on the nearby and migratory markets. Therefore, it is imperative not only to increase the number of tourists at the policy level (Dwyer et al., 2016) but also to increase the quality and value of tourism to ensure sustainable development.

5. Conclusion

The study examines India's inbound tourism from 2001 to 2023 using various econometric methods based on official data. The results show that the tourism sector has seen strong growth ahead of Covid-19 with an annual growth rate of around 9.23%, and the trend of overall growth has continued even after the pandemic. However, the pandemic has created a permanent negative impact, as tourist arrivals are around 2.34 million less than expected every year ($P = .01$). The study also found that the relationship between tourist arrivals and earnings has weakened, the elasticity has reduced from 0.89 to 0.66 ($P = .05$) indicating that growth now depends more on the number of tourists than their expenditure. Regional recovery is uneven, with higher ($P < .001$) areas having better performance, while distance recovery from India has a negative impact. SARIMA results show that tourist arrivals can reach around 10.23 million in 2024 and 10.72 million in 2025, and pre-COVID levels

can be achieved only by the end of 2025. These findings suggest that India needs to focus more on strengthening nearby and migratory-related markets to improve the value of tourism, promote more spending visitors and support sustainable development.

6. Limitations of the Study

The study is based on secondary data collected from official sources, with limitations related to data accuracy, modification and reporting differences over the years. The analysis is done at the national and regional level, and therefore does not include individual tourist behaviour or destination-specific factors such as micro-level diversity. The study is primarily focused on the selected economics model, and does not include other advanced methods or variables, such as policy interventions, price competitiveness and global economic conditions. Panel analysis is limited to certain areas and short periods (2020-2023), which can affect the generalisation of results. Further, the forecast results are based on previous trends and can change due to unforeseen events such as economic shocks, policy changes or global crises.

Disclaimer (Artificial Intelligence)

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Competing Interests

The authors declare that they have no known financial or non-financial competing interests, or personal relationships that could have influenced the work reported in this paper.

References

- Ahmad, M., Amin, A., Hassan, J., & Magray, A. A. (2026). Econometrics of exploration: How tourism fuels India's economy. *Journal of Tourism Economics*, 6(1). <https://doi.org/10.1177/27652157251396215>
- Akron, S., Demir, E., Díez-Esteban, J. M., & García-Gómez, C. D. (2020). Economic policy uncertainty and corporate investment: Evidence from the U.S. hospitality industry. *Tourism Management*, 77, 104019. <https://doi.org/10.1016/j.tourman.2019.104019>
- Arellano, M. (2003). *Panel data econometrics*. Oxford University Press. <https://doi.org/10.1093/0199245282.001.0001>
- B., M. B., & S., J. (2025). Tourism as a catalyst for India's foreign exchange earnings: Trends and challenges in the post-COVID era. *Electronic International Interdisciplinary Research Journal*. <https://doi.org/10.5281/zenodo.18088665>
- Baltagi, B. H. (2008). *Econometrics*. Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-540-76516-5>
- Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association*, 70(349), 70–79. <https://doi.org/10.1080/01621459.1975.10480264>
- Butler, R. W. (2001). Seasonality in tourism: Issues and implications. In T. Baum & S. Lundtorp (Eds.), *Seasonality in tourism* (pp. 5–21). Pergamon. <https://doi.org/10.1016/B978-0-08-043674-6.50005-2>
- Dogru, T., Bulut, U., & Sirakaya-Turk, E. (2020). Climate change and tourism: Do destination characteristics matter? *Tourism Management*, 77, 104019. <https://doi.org/10.1016/j.tourman.2019.104019>
- Dwyer, L., Forsyth, P., & Dwyer, W. (2016). *Tourism economics and policy*. Channel View Publications.
- Gidumal, J. B. (2022). Post-COVID-19 recovery of island tourism using a smart tourism destination framework. *Journal of Destination Marketing & Management*, 23, 100689. <https://doi.org/10.1016/j.jdmm.2022.100689>
- Goh, C., & Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. *Tourism Management*, 23(5), 499–510. [https://doi.org/10.1016/S0261-5177\(02\)00009-2](https://doi.org/10.1016/S0261-5177(02)00009-2)
- Gössling, S., Scott, D., & Hall, C. M. (2021). Pandemics, tourism and global change: A rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 29(1), 1–20. <https://doi.org/10.1080/09669582.2020.1758708>

- Hall, C. M., Scott, D., & Gössling, S. (2018). Global tourism vulnerability to climate change. *Annals of Tourism Research*, 77, 1–13. <https://doi.org/10.1016/j.annals.2018.07.007>
- International Monetary Fund. (2022). *Economic scarring: Channels and policy implications* (Working Paper No. 2022/248). <https://doi.org/10.5089/9781513690190.001>
- Koenig-Lewis, N., & Bischoff, E. E. (2010). Seasonality research: The state of the art. *International Journal of Tourism Research*, 12(3), 201–219. <https://doi.org/10.1002/jtr.761>
- Li, J., Nguyen, T. H. H., & Coca-Stefaniak, J. A. (2021). Coronavirus impacts on post-pandemic planned travel behaviours. *Annals of Tourism Research*, 86, 102964. <https://doi.org/10.1016/j.annals.2020.102964>
- Liu, A. T., Williams, A. M., Liu, A., Kim, Y. R., & Lin, P. M. (2023). A systematic analysis of diaspora tourism: Geographical perspectives and superdiversity. *Journal of Hospitality & Tourism Research*, 47(2), 123–145. <https://doi.org/10.1177/10963480231152571>
- Liu, P., Zeng, Z., Wang, H., Zhang, H., Zhang, J., & Liu, Z. (2024). Crisis-resistant tourism markets in the pandemic recovery. *Tourism Management Perspectives*, 51, 101221. <https://doi.org/10.1016/j.tmp.2024.101221>
- Mingya Qu and Yujie Fu and Dongsheng Chen and Yatao Zhang and Jigang Bao (2026). From impact to action: Enhancing international tourism resilience through counterfactual explanations. *Tourism Management*, 114, 105356. <https://doi.org/10.1016/j.tourman.2025.105356>
- OECD. (2024). *Tourism trends and policies 2024*. https://www.oecd.org/en/publications/oecd-tourism-trends-and-policies-2024_80885d8b-en
- Peixue Liu and Zhanjing Zeng and Huanying Wang and Honglei Zhang and Jianxin Zhang and ZehuaLiu (2024). Crisis-resistant tourism markets in the pandemic recovery. *Tourism Management Perspectives*, 51, 101221. <https://doi.org/10.1016/j.tmp.2024.101221>
- Qu, M., Fu, Y., Chen, D., Zhang, Y., & Bao, J. (2026). From impact to action: Enhancing international tourism resilience through counterfactual explanations. *Tourism Management*, 114, 105356. <https://doi.org/10.1016/j.tourman.2025.105356>
- S., A., & B., P. K. (2025). Foreign tourist arrivals (FTAs) in India: A demographic and economic analysis. *International Research Journal of Economics and Management Studies*, 4(7), 7–15. <https://doi.org/10.56472/25835238/IRJEMS-V4I7P102>
- Sann, R., Lai, P. C., & Liaw, S. Y. (2024). Prospective for tourism and hospitality industry: An integrative review on COVID-19's impacts. *Cogent Business & Management*, 11(1). <https://doi.org/10.1080/23311975.2024.2414854>
- Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. *Journal of Business Research*, 117, 312–321. <https://doi.org/10.1016/j.jbusres.2020.06.015>
- Singh, S. K., Nath, G. & Singh, N. (2026). Religious Tourism as A Catalyst for Local Economic Development: An Empirical Pls-Sem Analysis of Religious Tourists' Behaviour in Nainital District. *Available at SSRN 6159807*. <https://doi.org/10.36713/epra25718>
- Song, H., & Li, G. (2008). Tourism demand modelling and forecasting: A review of recent research. *Tourism Management*, 29(2), 203–220. <https://doi.org/10.1016/j.tourman.2007.07.016>
- Tegelberg, M., & Griffin, T. (2024). Remembering for resilience: Nature-based tourism, COVID-19, and green transitions. *Frontiers in Sustainable Tourism*, 3, 1392566. <https://doi.org/10.3389/frsut.2024.1392566>
- United Nations World Tourism Organization (UNWTO). (n.d.). *UNWTO World Tourism Barometer*. <https://www.unwto.org>

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