

Article

Post-Pandemic Tourism Recovery in Kazakhstan: Travel Expenditure, Long-Run Associations, and Regional Disparities

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Abstract

The COVID-19 pandemic caused an unprecedented disruption to global tourism, exposing the structural vulnerability of tourism-dependent economies and leading to a sharp decline in international mobility. This study examines post-pandemic tourism recovery in Kazakhstan, focusing on the association between travel expenditure and tourism demand, and on regional disparities in recovery patterns. The empirical strategy combines time-series econometric modelling, infrastructure index construction, and regional cluster analysis. Using annual data for 2000–2023, a parsimonious autoregressive distributed lag (ARDL) model is applied to estimate both short-run dynamics and long-run relationships. The results show a positive and statistically significant association between tourism demand and travel expenditure, supporting the interpretation of expenditure-related recovery dynamics. They also indicate persistence in demand and a significant negative association with the coronavirus disease 2019 (COVID-19) shock. The error correction mechanism indicates rapid adjustment toward long-run equilibrium. Infrastructure and regional analyses highlight substantial post-pandemic capacity expansion alongside pronounced spatial disparities, with activity concentrated in major urban centres. The findings suggest that recovery is closely associated with demand-side dynamics and accompanied by persistent structural and regional constraints, highlighting the need for coordinated policies that combine demand stimulation, infrastructure development, and balanced regional growth.

Keywords: tourism recovery; post-pandemic tourism; tourism demand; travel expenditure; long-run associations; regional disparities; Kazakhstan; ARDL model



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1. Introduction

The COVID-19 pandemic caused an unprecedented disruption to global tourism, leading to a sharp decline in international mobility and tourism activity. International tourist arrivals fell by more than 70% in 2020, making tourism one of the most affected sectors of the global economy. Although global tourism indicators have gradually improved in recent years, recovery trajectories remain uneven across countries, reflecting differences in infrastructure capacity, government policy responses, and the resilience of tourism-related investments. In this context, identifying the factors associated with tourism recovery has become a central issue in tourism economics.

Kazakhstan provides a relevant case for analysing post-pandemic tourism recovery. As the largest economy in Central Asia, the country possesses substantial tourism potential based on its natural resources, cultural heritage, and geographical diversity. At the same time, tourism development is characterized by significant regional heterogeneity, with

tourism activity concentrated in a limited number of regions, particularly Almaty and Astana. This uneven distribution reflects structural constraints related to infrastructure availability, accessibility, and investment concentration, which are associated with regional tourism performance and recovery dynamics. In this context, sustainability is interpreted primarily in its economic dimension, focusing on revenue generation efficiency, structural balance, and long-term sectoral resilience.

Despite the growing body of international literature on tourism recovery, empirical evidence focusing on Central Asia remains limited. Existing studies predominantly rely on descriptive approaches or global comparisons and rarely apply rigorous econometric methods. Moreover, previous research often examines tourism demand, infrastructure development, and regional disparities separately rather than within a unified analytical framework. This limitation is particularly relevant for small-sample emerging economies, where data constraints require parsimonious and methodologically consistent empirical approaches.

Accordingly, the study addresses three research questions. First, what is the short-run and long-run association between travel expenditure and tourism demand in Kazakhstan? Second, how is the COVID-19 shock associated with short-run changes in tourism demand? Third, what do infrastructure dynamics and regional clustering reveal about the spatial pattern of post-pandemic tourism recovery?

The objective of this study is to evaluate post-pandemic tourism recovery in Kazakhstan by examining the association between tourism demand and travel expenditure, while using infrastructure index construction and regional cluster analysis to contextualize spatial disparities in recovery. The empirical analysis is based on annual time-series data for 2000–2023 and applies a parsimonious autoregressive distributed lag (ARDL) framework to estimate short-run dynamics and long-run equilibrium associations. Complementary infrastructure and regional analyses are used to describe structural conditions and spatial heterogeneity, rather than to establish direct causal effects.

This study makes three contributions. First, it provides new empirical evidence on post-pandemic tourism recovery in Kazakhstan, a Central Asian economy that remains underrepresented in tourism demand research. Second, it estimates the expenditure–demand association using a parsimonious ARDL framework suitable for small annual samples and structural shocks. Third, it complements the national time-series analysis with infrastructure and regional evidence, thereby showing how aggregate recovery is accompanied by spatially uneven development.

2. Literature Review

2.1. Tourism Vulnerability to External Shocks

Tourism constitutes a significant driver of economic growth; however, its structural dependence on international mobility, open borders, and stable consumer expectations makes it highly vulnerable to external shocks. Previous crises have demonstrated the sensitivity of tourism to geopolitical instability, financial disruptions, and global health emergencies. The COVID-19 pandemic exposed this systemic vulnerability more clearly than any prior global shock (Arbulú et al., 2021; Zhang et al., 2021; Pham et al., 2021). The pandemic led to an unprecedented collapse in tourism flows, resulting in severe economic losses and widespread disruption across the sector, while also revealing fragmented and insufficiently coordinated crisis management frameworks within the tourism industry (Drammeh, 2024).

2.2. Economic Consequences of the COVID-19 Pandemic

Empirical evidence indicates that the COVID-19 pandemic led to unprecedented contractions in international tourism flows and expenditure. Tourism income declined

by approximately 60–80% during 2020–2021 (Škare et al., 2021), with significant spillover effects on gross domestic product (GDP), employment, and fiscal revenues (Gössling et al., 2021; Hall et al., 2020; Lenzen et al., 2020).

Global statistics further confirm the scale of the disruption: international tourist arrivals fell by around 74% in 2020, while tourism export revenues declined by nearly US dollars (USD) 1 trillion, putting over 120 million jobs at risk (UNWTO, 2020). Simulation studies suggest that tourism shocks contributed to GDP reductions of up to 1–2% in highly tourism-dependent economies (Rodousakis & Soklis, 2022).

2.3. Post-Pandemic Structural Transformation of Tourism

The pandemic triggered a reassessment of tourism development models. While pre-crisis strategies often emphasized visitor volume growth, post-pandemic tourism research increasingly highlights resilience, sustainability, diversification, and adaptive capacity as core elements of recovery (Brouder, 2020; Prayag, 2020; Gössling & Schweiggart, 2022; Ragmoun, 2022). This shift reflects the recognition that returning to pre-pandemic growth patterns is insufficient unless tourism systems become more capable of responding to future shocks.

In the post-pandemic context, domestic and regional tourism have gained importance as relatively resilient market segments. These forms of tourism helped compensate for the slow recovery of international mobility and supported local destinations during periods of uncertainty. Recent studies also emphasize the role of market diversification, community-based recovery, and coordinated policy support in strengthening tourism resilience after COVID-19 (Chiawo et al., 2023).

Digital transformation has also become an important driver of post-pandemic tourism recovery. Smart tourism systems, digital platforms, and data-based management tools improve destination marketing, demand forecasting, visitor management, and service personalization. These technologies allow destinations to adapt more effectively to changing tourist behaviour and to strengthen competitiveness in a more uncertain global environment (Gretzel et al., 2015; Xiang et al., 2015; Yepez & Leimgruber, 2024).

More broadly, the pandemic accelerated structural changes in tourism systems by increasing the importance of flexibility, innovation, sustainability, and regional balance. Post-pandemic recovery is therefore not limited to the restoration of tourist flows, but also involves changes in demand structure, investment priorities, infrastructure capacity, and destination management. This perspective is particularly relevant for emerging tourism economies, where recovery depends not only on renewed demand but also on the ability to reduce structural vulnerabilities and support more balanced regional development.

2.4. Regional Context: Tourism Development and Recovery in Kazakhstan

Despite Kazakhstan's significant tourism potential, empirical research remains limited and largely descriptive. Existing studies rarely integrate infrastructure development, investment dynamics, and regional disparities within a unified econometric framework, highlighting a clear research gap.

Prior to the pandemic, Kazakhstan experienced steady growth in tourism flows, supported by public investment and international initiatives such as EXPO-2017. However, the COVID-19 shock caused a sharp contraction in tourism activity, followed by a gradual recovery in subsequent years (Bureau International des Expositions, n.d.; UNWTO, 2021; World Bank, 2022).

Recent evidence suggests that tourism recovery in Kazakhstan has been uneven across regions. Infrastructure availability, transport accessibility, and investment concentration are closely associated with regional tourism performance (Faber & Gaubert, 2019). Leading

destinations such as Almaty and Astana benefit from developed infrastructure and international connectivity, whereas peripheral regions remain constrained by limited investment and accessibility.

These patterns indicate that, despite aggregate recovery, structural imbalances persist, underscoring the need for differentiated policy approaches to improve the spatial distribution of tourism activity.

Recent studies further confirm that tourism recovery exhibits strong spatial heterogeneity, with mobility restrictions, regional accessibility, and transport connectivity shaping uneven recovery trajectories across destinations (Yang et al., 2020; Sun et al., 2021; Chang et al., 2020). This evidence highlights the importance of regional-level analysis when evaluating post-pandemic tourism dynamics.

2.5. Public Policy and Recovery Dynamics

Government policy responses played a significant role in stabilizing tourism sectors during the pandemic. Fiscal support measures such as subsidies, concessional loans, and tax relief helped reduce the financial burden on tourism enterprises and supported investment during the recovery phase (OECD, 2020; Fornaro & Wolf, 2020).

Empirical evidence suggests that the effectiveness of such policies varies across countries depending on economic resilience and institutional capacity. In less resilient economies, fiscal stimulus and monetary easing tend to generate stronger recovery effects, highlighting the importance of combining short-term support with long-term structural reforms (Okafor et al., 2022).

In addition, recent empirical evidence suggests that policy stringency, containment measures, and institutional responses significantly influence tourism recovery patterns, particularly through their impact on mobility and consumer confidence (Hale et al., 2021).

The effectiveness of policy responses is shaped not only by the scale of fiscal support, but also by broader macroeconomic conditions, institutional capacity, and the consistency of implementation. Therefore, post-pandemic tourism recovery requires coordinated policy frameworks that combine short-term stabilization with long-term structural development strategies.

2.6. Infrastructure, Investment, and Tourism Competitiveness

Infrastructure development plays a central role in tourism competitiveness. Transport accessibility, air connectivity, accommodation capacity, and service quality directly influence tourist flows and destination attractiveness (Faber & Gaubert, 2019; Khadaroo & Seetanah, 2007). Inadequate infrastructure can constrain tourism development even in resource-rich destinations.

Empirical evidence consistently shows that infrastructure investment contributes to tourism growth by reducing travel costs, improving accessibility, and enhancing overall destination competitiveness. Moreover, infrastructure affects not only physical accessibility but also perceived service quality and visitor experience, thereby influencing demand patterns (Dogru et al., 2017).

Following the pandemic, increased investment risks slowed capital inflows into tourism sectors (Aburumman, 2020), reinforcing the importance of coordinated public-private investment strategies. Recent research further indicates that infrastructure affects not only physical accessibility but also perceived destination competitiveness, while digital technologies enhance service delivery and tourist experience (Chan et al., 2022; Martins et al., 2017; Adeola et al., 2018).

2.7. Implications for Post-Pandemic Tourism Development

Tourism recovery depends not only on the restoration of visitor flows but also on strengthening investment activity, improving infrastructure quality, and ensuring balanced regional development. Long-term institutional reforms and sustainable development strategies therefore play a crucial role in enhancing sectoral resilience (OECD, 2020; UNWTO, 2021; Rogerson & Baum, 2020).

In this context, recent studies emphasize that recovery dynamics are associated with both demand-side factors, such as tourism expenditure, and supply-side conditions, including infrastructure capacity and regional accessibility. However, these dimensions are often analysed separately, limiting the ability to capture their joint effects.

Building on these insights, the present study applies a combined empirical strategy. The ARDL model is used to examine the association between tourism demand and travel expenditure, while infrastructure index construction and regional cluster analysis provide complementary evidence on structural and spatial conditions. This design allows the study to connect national demand dynamics with regional heterogeneity, while avoiding an overstated causal interpretation of infrastructure and regional factors.

In this context, tourism recovery should be understood as a multidimensional process involving both demand-side adjustments and supply-side transformations. The growing importance of digital technologies and smart tourism systems further supports this integrated perspective, enabling destinations to enhance resilience, improve service delivery, and better respond to changing tourist preferences (Gretzel et al., 2015; Xiang et al., 2015).

2.8. Theoretical Framework

This study is grounded in tourism demand theory, which conceptualizes tourism flows as a function of economic capacity, relative prices, travel costs, and behavioural consumption patterns (Morley, 1992; Lim, 1997; Song & Li, 2008). Within this framework, travel expenditure serves as a proxy for effective demand, reflecting both purchasing power and consumer preferences. This interpretation is consistent with tourism demand modelling literature, where visitor flows are commonly explained through economic and behavioural determinants of demand.

From a macroeconomic perspective, tourism demand can be interpreted within a partial equilibrium framework, where expenditure represents realized demand under given structural constraints. At the same time, infrastructure and institutional factors operate as supply-side conditions that shape destination competitiveness, accessibility, service capacity, and the ability of regions to convert tourism demand into economic outcomes (Dwyer & Kim, 2003).

The distinction between demand-side and supply-side drivers is particularly relevant in the post-pandemic context, where recovery dynamics are influenced by both structural capacity and changes in consumer behaviour. By focusing on the expenditure–demand relationship, the study adopts a reduced-form approach that isolates core demand dynamics while treating infrastructure and regional disparities as complementary structural factors.

In this context, travel expenditure is interpreted not simply as a monetary aggregate, but as an indicator of effective demand intensity. Higher expenditure reflects stronger purchasing capacity and broader engagement with tourism services, which supports accommodation, transport, and complementary activities and thereby reinforces observed tourism demand. This interpretation helps distinguish expenditure-driven recovery from a purely volume-based increase in visitor numbers.

3. Methodology

3.1. Data and Sources

This study employs two complementary datasets. The first dataset consists of annual national time-series indicators for Kazakhstan covering 2000–2023, including total visitors, travel expenditure, GDP per capita, and a harmonised tourism infrastructure index. These indicators are used across the baseline and extended ARDL specifications. The second dataset contains regional tourism indicators for 2024 and is used for descriptive regional comparison and hierarchical cluster analysis. Data were obtained from the Bureau of National Statistics of Kazakhstan and from the official compendium Kazakhstan: Country-Specific: Basic Indicators (Compendium) 1995–2024 (December 2025) (UNWTO, 2025), published in Tourism Statistics.

For the econometric analysis, tourism demand is proxied by total visitors (TV), while travel expenditure (*TravEXP*) is used as the main explanatory variable. A COVID-19 dummy variable is included to capture the pandemic shock in 2020–2021. GDP per capita (*GDPpc*) and the tourism infrastructure index (*InfraIndex*) are introduced only in extended robustness specifications and are not treated as baseline regressors. Additional descriptive indicators, including domestic tourism consumption and tourism contribution to GDP, are used to contextualize the structure of tourism recovery.

The sample period for the econometric analysis is restricted to 2000–2023 due to data availability and consistency across the main variables. Earlier observations are excluded because of missing values and potential structural inconsistencies associated with the transition period. Continuous variables are transformed into natural logarithms to stabilize variance and enable elasticity-based interpretation of coefficients. The COVID-19 dummy is not logarithmically transformed because it is a binary variable.

Because the annual sample is relatively small, a parsimonious baseline specification is adopted. Travel expenditure is retained as the main explanatory variable because it directly reflects tourism-related spending and allows the model to focus on the expenditure–demand association. Additional variables, including GDP per capita and the infrastructure index, are introduced only as robustness checks in order to avoid overfitting and preserve model stability.

3.2. Regional Cluster Analysis

To assess regional heterogeneity in tourism development, hierarchical cluster analysis is conducted using Ward’s minimum variance method and Euclidean distance. The analysis is based on two regional indicators: tourist arrivals and tourism service revenue.

Tourist arrivals are standardized using z-score normalization:

$$Z_i^{(T)} = \frac{T_i - \mu_T}{\sigma_T} \quad (1)$$

Tourism service revenue is log-transformed to reduce skewness:

$$R_i^{(ln)} = \ln(R_i) \quad (2)$$

The log-transformed revenue variable is then standardized using z-score normalization. Euclidean distance is computed as:

$$d_{ij} = \sqrt{(Z_i^{(T)} - Z_j^{(T)})^2 + (Z_i^{(R)} - Z_j^{(R)})^2} \quad (3)$$

where $Z_i^{(T)}$ and $Z_i^{(R)}$ denote the standardized values of tourist arrivals and log-transformed tourism service revenue, respectively.

The optimal number of clusters is determined based on dendrogram inspection and within-cluster variance minimization. A three-cluster solution is retained because it provides an interpretable classification of regions into relatively high, moderate, and low tourism development groups.

Cluster analysis enables the identification of relative development patterns across regions and provides a basis for comparing spatial disparities in tourism activity. The results are used as complementary evidence to contextualize regional differences in post-pandemic recovery, rather than as causal evidence of the effect of infrastructure or regional policy on tourism demand.

3.3. Infrastructure Index Construction

To evaluate infrastructure development, a composite tourism infrastructure index is constructed based on four indicators: change in road length, change in the number of airports, change in the number of hotels, and change in the number of tourist sites. These indicators are expressed as annual change indices, where the previous year equals 100.

Each indicator is assigned an equal weight of 0.25 due to the absence of empirical evidence supporting differential elasticities in the context of Kazakhstan. This approach ensures methodological neutrality and avoids imposing arbitrary weighting assumptions. Alternative weighting schemes, such as principal component analysis (PCA), were not applied due to the limited sample size and the objective of maintaining interpretability. Descriptive statistics of the infrastructure indicators used in the index construction are presented in Table 1.

Table 1. Descriptive statistics of annual tourism infrastructure change indicators used for index construction.

Indicator	Mean Annual Change Index	Standard Deviation
Change in road length	100.89	1.18
Change in the number of airports	100.83	1.58
Change in the number of hotels	101.12	9.21
Change in the number of tourist sites	97.19	10.13

Note: The indicators are expressed as annual change indices, where the previous year equals 100. Descriptive statistics are calculated for the period 2000–2024. Standard deviation is calculated for the population.

For each year, the composite annual infrastructure change index is calculated as the arithmetic mean of the four indicators:

$$G_t = \frac{1}{4} \sum_{i=1}^4 x_{it} \quad (4)$$

where x_{it} represents the annual change index of infrastructure indicator i in year t . Since four indicators are used and each indicator is assigned an equal weight, the composite annual infrastructure change index is calculated as their arithmetic mean.

The cumulative tourism infrastructure index is then constructed using 2000 as the base year:

$$InfraIndex_{2000} = 100 \quad (5)$$

$$InfraIndex_t = InfraIndex_{t-1} \times \frac{G_t}{100}, t > 2000 \quad (6)$$

where $InfraIndex_t$ represents the cumulative tourism infrastructure index in year t , and G_t is the composite annual infrastructure change index. This procedure converts annual infrastructure change indices into a cumulative index that reflects the overall evolution of tourism infrastructure over time.

Infrastructure is treated primarily as a structural and supply-side condition. In the baseline ARDL model, infrastructure is not included in order to preserve a parsimonious demand-side specification and avoid overfitting in a small annual sample. However, to address concerns about the separate treatment of infrastructure, the tourism infrastructure index is introduced in an extended infrastructure-augmented ARDL specification as a robustness check. In this specification, the logarithm of the infrastructure index is used. The infrastructure-augmented model is not treated as the preferred baseline model because infrastructure may be endogenous to tourism demand and because the number of annual observations remains limited.

3.4. Econometric Specification

The empirical analysis follows a structured time-series approach to reduce the risk of spurious regression and ensure consistent interpretation of the estimated associations. The baseline log-linear model is specified as:

$$\ln(TV_t) = \alpha + \beta \ln(TravEXP_t) + \varepsilon_t \quad (7)$$

where tourism demand is proxied by total visitors (TV), and travel expenditure ($TravEXP$) is used as the main explanatory variable.

Prior to estimation, the stationarity properties of the variables are examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. This step is necessary because non-stationary time-series data may generate spurious statistical relationships. The results indicate that the variables are either non-stationary at levels or only marginally stationary, but become stationary after first differencing. Importantly, none of the variables is integrated of order two, $I(2)$, which supports the use of the ARDL bounds testing approach.

Given the small annual sample and the time-series properties of the variables, the Autoregressive Distributed Lag (ARDL) approach is employed. The ARDL framework is appropriate in this context because it allows the estimation of both short-run dynamics and long-run equilibrium associations. The optimal lag structure is selected using the Bayesian Information Criterion (BIC), while an alternative lag structure selected by the Akaike Information Criterion (AIC) is used as a robustness check.

To account for the pandemic shock, a dummy variable (d_{covid}) is introduced, taking the value of one for 2020–2021 and zero otherwise. This variable captures the short-run disruption associated with the COVID-19 pandemic period.

The error-correction representation of the baseline ARDL model is specified as:

$$\begin{aligned} \Delta \ln(TV_t) = & \lambda (\ln(TV_{t-1}) - \theta \ln(TravEXP_{t-1})) + \sum_{i=1}^p \phi_i \Delta \ln(TV_{t-i}) \\ & + \sum_{j=0}^q \psi_j \Delta \ln(TravEXP_{t-j}) + \gamma d_{covid} + \varepsilon_t \end{aligned} \quad (8)$$

where the error-correction term captures the speed of adjustment toward the long-run equilibrium association. Given the small sample size and the structural shock associated with COVID-19, an adjustment coefficient slightly exceeding unity in absolute value may reflect short-run overshooting dynamics rather than model instability.

The preferred baseline specification remains parsimonious because the annual sample is limited. GDP per capita is not included in the baseline model, but it is introduced in a separate GDP-augmented ARDL specification as a robustness check. This allows the study to assess whether the expenditure–demand association remains stable after accounting for a basic macroeconomic control.

The tourism infrastructure index is also excluded from the preferred baseline model because infrastructure represents a structural supply-side condition and may be endogenous to tourism demand. However, to address the reviewers' concern about the separate treatment of infrastructure, the infrastructure index is included in an additional infrastructure-augmented ARDL specification as a robustness check.

Therefore, the baseline ARDL is interpreted as a reduced-form association model focusing on expenditure-related tourism demand dynamics. Although the ARDL framework accounts for dynamic adjustment through lagged variables and the error-correction mechanism, it does not fully eliminate possible endogeneity or reverse causality between tourism demand and travel expenditure. For this reason, the estimated coefficients are interpreted as conditional associations rather than strict causal effects.

3.5. Robustness Checks

To assess the reliability of the empirical results, several diagnostic and robustness checks are conducted. First, serial correlation is examined using the Breusch–Godfrey Lagrange multiplier (LM) test, and heteroskedasticity is assessed using the White test. Second, the existence of a long-run relationship is evaluated using the ARDL bounds testing approach. Third, parameter stability is examined using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests.

In addition to the baseline ARDL model selected by BIC, the model is re-estimated under alternative specifications. These include an ARDL model without the COVID-19 dummy and an alternative lag structure selected by AIC. To address concerns about omitted macroeconomic variables, GDP per capita is introduced in an extended ARDL specification. To strengthen the link between the econometric and infrastructure analyses, the tourism infrastructure index is also included in a separate infrastructure-augmented ARDL specification. These extended models are interpreted as robustness checks rather than as replacements for the baseline model, because the annual sample remains limited and the inclusion of additional regressors reduces degrees of freedom.

3.6. Hypothesis Development

H₁. *Travel expenditure is positively and statistically significantly associated with tourism demand in Kazakhstan.*

H₂. *The COVID-19 dummy is negatively associated with short-run changes in tourism demand.*

H₃. *Tourism demand and travel expenditure exhibit a stable long-run equilibrium association.*

4. Results

4.1. Regional Analysis

Regional analysis reveals substantial spatial disparities in tourism activity and revenue generation across Kazakhstan's 20 regions in 2024, as illustrated in Figure 1. Almaty City clearly dominates both indicators, accounting for approximately 19.5% of tourism revenue and 10.3% of total tourist arrivals, confirming its role as the country's primary tourism hub. This leading position is supported by advanced infrastructure, high-quality accommodation, and strong international connectivity. Astana City follows with a relatively balanced structure, where tourist arrivals (11.45%) slightly exceed revenue (10.5%), reflecting its specialization in business and administrative tourism. Karaganda and Turkistan regions also demonstrate relatively high shares in both indicators, indicating diversified tourism demand and stable service capacity.

In contrast, peripheral regions such as Ulytau, North Kazakhstan, and Abay exhibit significantly lower shares of both tourist arrivals and revenue, suggesting limited infrastruc-

ture development and weaker integration into national and international tourism markets. Other regions, including Pavlodar, Mangystau, and Kostanay, occupy intermediate positions, reflecting moderate levels of tourism activity with potential for further growth.

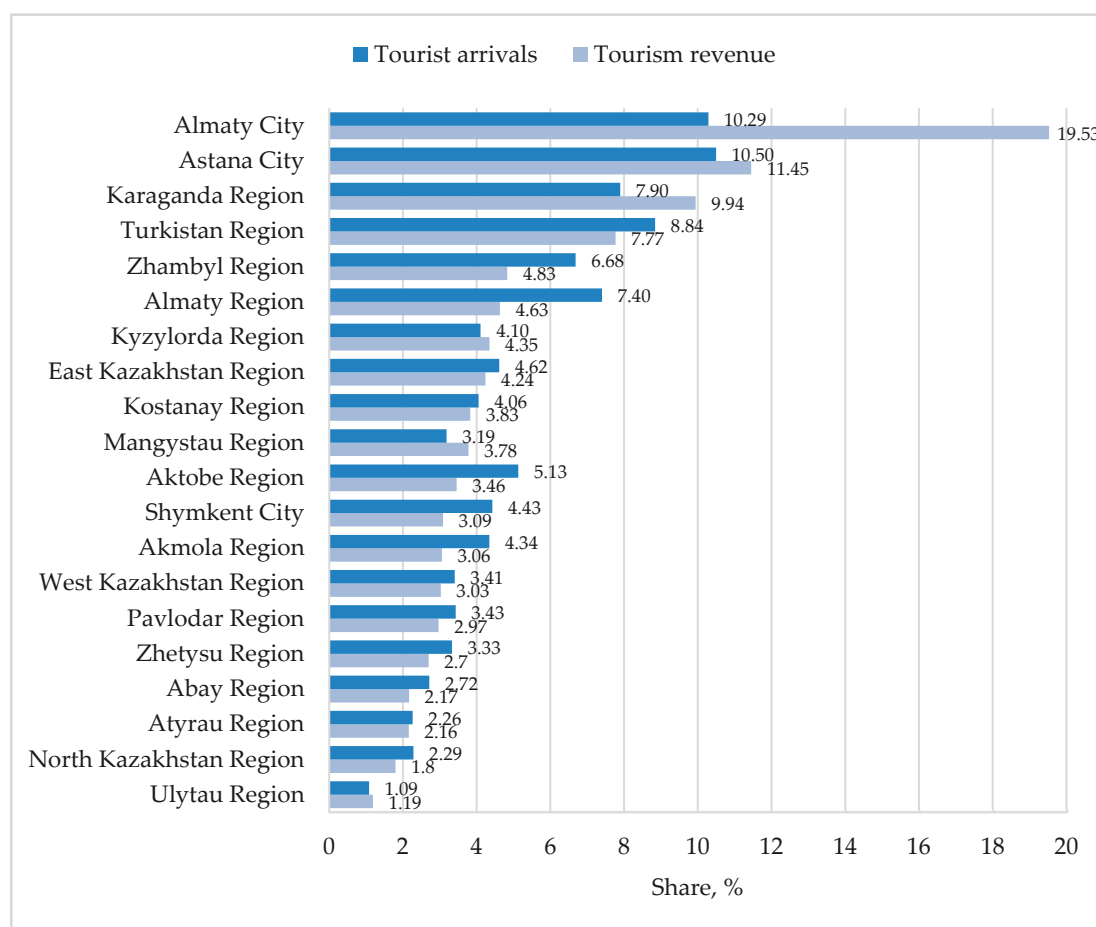


Figure 1. Regional distribution of tourist arrivals and tourism service revenue in Kazakhstan in 2024, %. Source: Bureau of National Statistics of the Republic of Kazakhstan (n.d.-b).

The regional distribution suggests that tourist concentration alone does not guarantee proportional revenue generation. Differences between the shares of arrivals and revenue point to variation in spending intensity, length of stay, and service capacity across regions. This pattern reinforces the importance of infrastructure quality and regional specialization in shaping the economic outcomes of tourism recovery.

4.2. Cluster Analysis

The cluster structure of Kazakhstan's regions based on tourism indicators is presented in Figure 2 using Ward's hierarchical clustering method with Euclidean distances. The results identify three distinct and interpretable clusters, reflecting different levels of tourism development and structural capacity across regions.

The first cluster includes Almaty City, Astana City, Turkistan Region, Karaganda region, Zhambyl region, and Almaty region. These regions are grouped at relatively low linkage distances, indicating a high degree of similarity in tourism performance. They are characterized by comparatively high tourist arrivals and revenue levels, supported by better-developed infrastructure, higher accessibility, and a more diversified tourism offer.

The second cluster consists of a larger group of regions, including Zhetysay, Pavlodar, West Kazakhstan, Mangystau, East Kazakhstan, Kyzylorda, Kostanay, Aktobe, Shymkent City, and Akmola. These regions form a cohesive group with moderate tourism indicators.

Their clustering suggests relatively similar levels of tourism development, where natural and regional resources contribute to tourism activity, but infrastructure and service capacity remain less advanced compared to the leading regions.

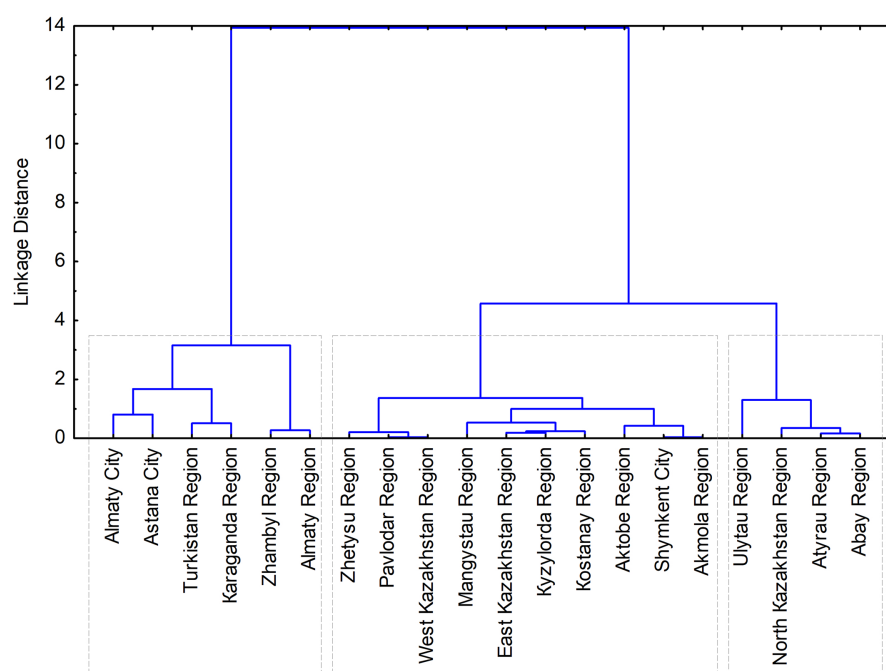


Figure 2. Hierarchical clustering of Kazakhstan's regions by tourist arrivals and tourism revenue, based on Ward's method and Euclidean distance; three-cluster solution. Source: [Bureau of National Statistics of the Republic of Kazakhstan \(n.d.-b\)](#).

The third cluster includes Ulytau, North Kazakhstan, Atyrau, and Abay regions. These regions are grouped together at higher linkage distances from the leading clusters, indicating lower similarity in tourism performance and generally weaker indicators. They are characterized by relatively low tourist inflows and limited tourism revenue, reflecting infrastructural constraints, lower investment activity, and weaker integration into national tourism networks.

These clustering results provide empirical evidence of pronounced regional disparities and highlight the importance of differentiated policy approaches tailored to the specific development level of each cluster.

4.3. Infrastructure Dynamics

Figure 3 shows the cumulative tourism infrastructure index for Kazakhstan over the period 2000–2024, with 2000 used as the base year. The index declined during the early 2000s, remained relatively stable during the following period, and increased after the mid-2010s, reaching approximately 110 by 2024. This pattern suggests that infrastructure development recovered gradually after an earlier decline, although the index should be interpreted as a composite descriptive measure rather than as direct evidence of causal effects on tourism demand.

The comparative dynamics of actual and projected tourism indicators are presented in Figure 4. The actual series cover the period 2000–2024, while the projected series represent a counterfactual no-COVID-19 scenario for 2020–2024. The figure shows a clear pandemic-related disruption in 2020–2021. Actual tourism revenue declined sharply in 2020, while visitor numbers fell even more substantially and reached their lowest point in 2021. This confirms the strong sensitivity of Kazakhstan's tourism sector to mobility restrictions and pandemic-related shocks.



Figure 3. Dynamics of the tourism infrastructure index in Kazakhstan, 2000–2024 (2000 = 100). Source: Authors' calculations based on data from the [Bureau of National Statistics of the Republic of Kazakhstan](#) (n.d.-b).

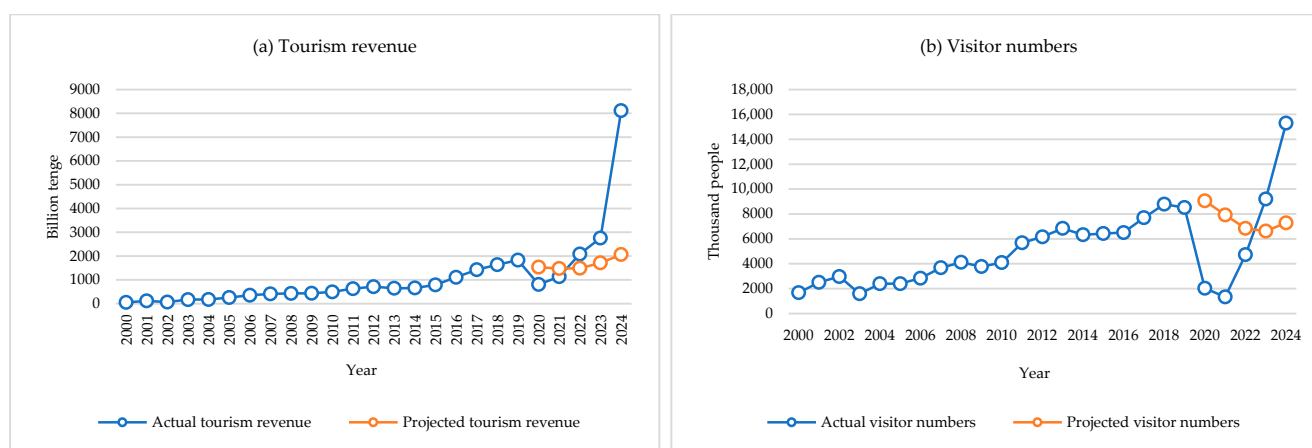


Figure 4. Actual and projected dynamics of Kazakhstan's tourism indicators under a counterfactual no-COVID-19 scenario: actual series, 2000–2024; projected series, 2020–2024. (a) Tourism revenue; (b) visitor numbers. Authors' calculations based on data from the [Bureau of National Statistics of the Republic of Kazakhstan](#) (n.d.-b).

The post-pandemic recovery became visible from 2022 onward. Tourism revenue exceeded the projected no-COVID-19 trajectory from 2022, while actual visitor numbers remained below the projected trajectory during 2020–2022 and exceeded it from 2023 onward. In 2024, actual visitor numbers exceeded the projected value by approximately 109.8%, while actual tourism revenue exceeded the projected value by approximately 292.6%. This indicates that the post-pandemic rebound was particularly strong in revenue terms, suggesting not only a recovery in visitor volumes but also a substantial increase in tourism-related spending.

Figure 5 provides additional descriptive evidence on the structure of tourism recovery by comparing the share of domestic tourism consumption and the contribution of tourism to GDP. The share of domestic tourism consumption was highly volatile over the study period, with particularly high values in the mid-2000s and early 2010s, followed by a sharp decline in 2013. After the pandemic period, the indicator initially decreased slightly from 12.0% in 2020 to 11.5% in 2021, but then increased steadily, reaching 17.3% in 2024. This suggests a partial recovery of domestic tourism consumption.

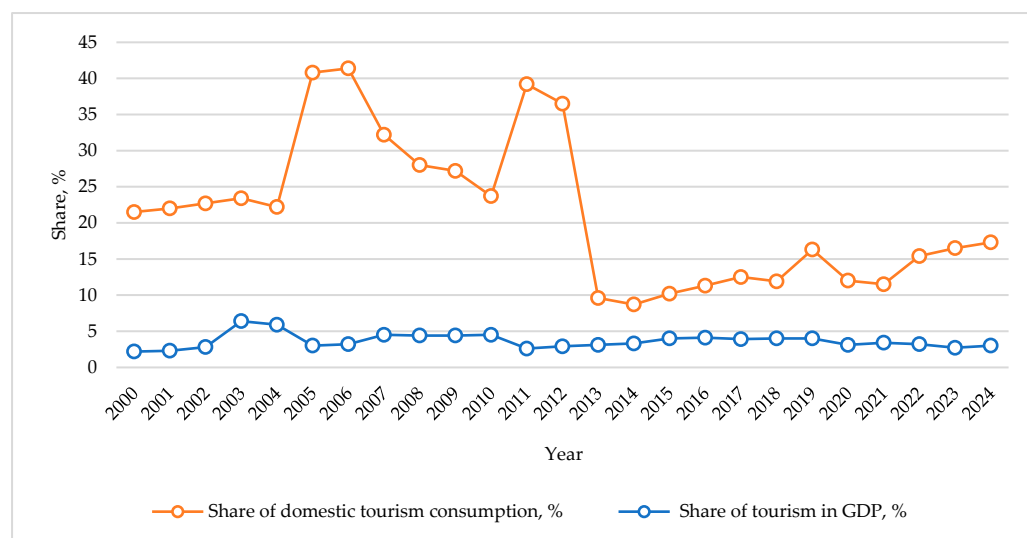


Figure 5. Domestic tourism consumption and tourism contribution to gross domestic product (GDP) in Kazakhstan, %. Source: Authors' calculations based on data from the [Bureau of National Statistics of the Republic of Kazakhstan](#) (n.d.-a).

At the same time, tourism's contribution to GDP remained relatively moderate after 2014, fluctuating mostly around 3–4%. In 2024, it reached approximately 3.0%, indicating that the recovery of tourism activity and domestic consumption did not translate into an equally large increase in tourism's overall GDP share. Taken together, Figures 3–5 suggest that Kazakhstan's post-pandemic tourism recovery was accompanied by infrastructure expansion, a strong rebound in visitor numbers and revenue in 2024, and a gradual recovery of domestic tourism consumption.

4.4. Econometric Results

The econometric results examine the association between tourism demand and travel expenditure in Kazakhstan over the period 2000–2023. Table 2 presents the definitions, transformations, and model use of the variables included in the baseline and extended ARDL specifications.

Table 2. Variable definitions and transformations.

Variable	Definition	Measurement/Coding	Transformation	Use in Model
<i>TV</i>	Total visitors/tourism demand	Number of visitors	$\ln(TV)$	Dependent variable
<i>TravEXP</i>	Travel expenditure	Monetary value	$\ln(TravEXP)$	Main explanatory variable
<i>GDPpc</i>	GDP per capita	Constant LCU	$\ln(GDPpc)$	Extended robustness check
<i>InfraIndex</i>	Tourism infrastructure index	Index value	$\ln(InfraIndex)$	Extended robustness check
<i>d_{covid}</i>	COVID-19 dummy	1 for 2020–2021, 0 otherwise	Not log-transformed	Shock/control variable

Note: All continuous variables are transformed into natural logarithms to reduce scale differences and allow elasticity-based interpretation. The COVID-19 dummy is not logarithmically transformed because it is a binary variable.

Descriptive statistics are reported in Table 3. The variables show moderate variation over the sample period, which supports their use in time-series analysis. The COVID-19 dummy has a mean of 0.083, reflecting its value of one only for 2020–2021 and zero for all other years.

Figure 6 illustrates the dynamics of total tourist arrivals in Kazakhstan over the period 2000–2023. The figure shows a general upward trend before the pandemic, followed by

a sharp decline in 2020 and 2021. This decline reflects the disruption associated with the COVID-19 shock and mobility restrictions. From 2022 onward, tourist arrivals began to recover, and by 2023 they exceeded the pre-pandemic level. This pattern indicates that tourism demand was highly sensitive to the pandemic shock but also recovered rapidly after the easing of restrictions.

Table 3. Descriptive statistics of variables used in the autoregressive distributed lag (ARDL) models.

Variable	Obs.	Mean	Std. Dev.	Min	Max
$\ln(TV)$	24	15.379	0.465	14.336	16.105
$\ln(TravEXP)$	24	20.821	0.581	19.690	21.622
$\ln(GDPpc)$	24	13.285	0.289	12.608	13.595
$\ln(InfraIndex)$	24	4.477	0.087	4.394	4.697
d_{covid}	24	0.083	0.282	0	1

Note: Descriptive statistics are reported for the variables used in the baseline and extended ARDL specifications. All continuous variables are expressed in natural logarithms. The sample covers annual observations for 2000–2023.

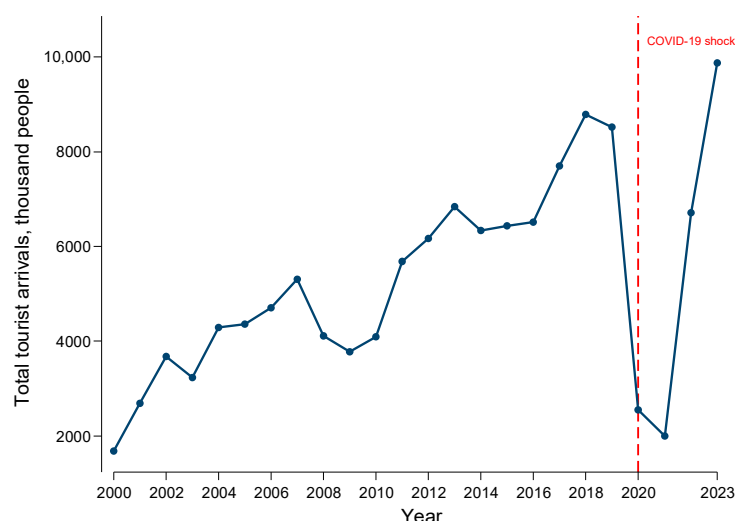


Figure 6. Dynamics of total tourist arrivals in Kazakhstan, 2000–2023.

The stationarity properties of the variables are examined using the Augmented Dickey–Fuller and Phillips–Perron tests, with the results reported in Table 4. The results indicate that the variables are generally non-stationary at levels but become stationary after first differencing. GDP per capita is stationary after first differencing at the 10% significance level, whereas the remaining variables provide stronger evidence of stationarity after first differencing. Accordingly, the variables can be treated as integrated of order one, $I(1)$, which supports the application of the ARDL bounds testing approach.

The baseline ARDL results are presented in Table 5. The long-run coefficient of travel expenditure is positive and statistically significant. The estimated coefficient of 0.589 indicates that a 1% increase in travel expenditure is associated with an approximately 0.589% increase in total tourist arrivals in the long run, holding the dynamic structure of the model constant. This finding supports the interpretation that tourism demand in Kazakhstan is closely associated with expenditure-side dynamics.

The COVID-19 dummy variable has a negative and statistically significant coefficient of -0.281 . This indicates a negative short-run association between the pandemic period and tourism demand. The result is consistent with the disruption caused by mobility restrictions and pandemic-related uncertainty.

The error-correction term is negative and statistically significant. Its coefficient of -1.071 provides evidence of adjustment toward the long-run equilibrium association.

Although the absolute value slightly exceeds unity, this may reflect short-run overshooting in a small annual sample affected by the COVID-19 shock, rather than model instability.

Table 4. Unit root test results.

Variable	ADF Unit Root Test		PP Unit Root Test		Decision
	Level	1st Difference	Level	1st Difference	
$\ln(TV)$	−3.038 (0.122)	−3.850 *** (0.002)	−3.042 (0.121)	−3.786 *** (0.003)	I(1)
$\ln(TravEXP)$	−2.476 (0.340)	−3.975 *** (0.002)	−2.518 (0.319)	−3.915 *** (0.002)	I(1)
$\ln(GDPpc)$	−2.947 (0.148)	−2.709 * (0.073)	−3.053 (0.118)	−2.677 * (0.078)	I(1) at 10%
$\ln(InfraIndex)$	−3.210 (0.083)	−3.258 ** (0.017)	−3.010 (0.129)	−3.297 ** (0.015)	I(1)

Note: *p*-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. ADF denotes Augmented Dickey–Fuller; PP denotes Phillips–Perron. ADF and PP tests at levels are estimated with a linear trend, while first-difference tests are estimated without a trend. The COVID-19 dummy is excluded because it is a binary variable. The results indicate that none of the variables is integrated of order two, supporting the use of the ARDL bounds testing approach.

Table 5. Baseline ARDL estimation results: long-run and short-run coefficients.

Variable	Coefficient	Std. Error	t-Statistic	<i>p</i> -Value
Long-run coefficient				
$\ln(TravEXP)$	0.589 ***	0.051	11.61	0.000
Short-run coefficients				
$\Delta \ln(TV)(-1)$	0.203 **	0.081	2.51	0.023
COVID-19 dummy	−0.281 **	0.121	−2.31	0.034
Constant	3.366 **	1.203	2.80	0.012
Error-correction term				
ECM(−1)	−1.071 ***	0.091	−11.74	0.000

Note: *p*-values are reported in the last column; ** and *** denote statistical significance at the 5% and 1% levels, respectively. ECM denotes the error-correction term.

Post-estimation diagnostics for the baseline ARDL model are reported in Table 6. Following the bounds testing approach of Pesaran et al. (2001), the F-statistic and t-statistic exceed the upper critical bounds, supporting the presence of a long-run association between tourism demand and travel expenditure. The Breusch–Godfrey LM test does not indicate statistically significant serial correlation, and the White test does not indicate statistically significant heteroskedasticity. The CUSUM and CUSUMSQ tests remain within the 5% critical bounds, supporting parameter stability.

Table 6. Post-estimation diagnostics for baseline ARDL.

Test	Statistic	<i>p</i> -Value/Result
Pesaran bounds F-statistic	F = 70.018	<0.001
Pesaran bounds t-statistic	t = −11.744	<0.001
Breusch–Godfrey LM test	$\chi^2(1) = 2.203$	0.138
White heteroskedasticity test	$\chi^2(11) = 14.070$	0.229
CUSUM stability test	Within 5% bounds	Stable
CUSUMSQ stability test	Within 5% bounds	Stable

Note: Diagnostics are reported for the baseline ARDL(2,0) model selected using BIC. The bounds test refers to the Pesaran ARDL bounds testing procedure. The CUSUM and CUSUMSQ statistics remain within the 5% critical bounds.

Together, the unit root tests and ARDL bounds test reduce the risk that the estimated relationship is driven only by common trending behaviour. However, because the model is

reduced-form and possible reverse causality cannot be fully eliminated, the results should be interpreted as conditional associations rather than causal effects.

Figure 7 presents the CUSUM and CUSUMSQ stability tests for the estimated ARDL model. Both statistics remain within the 5% critical bounds, supporting the stability of the estimated coefficients and residual variance.

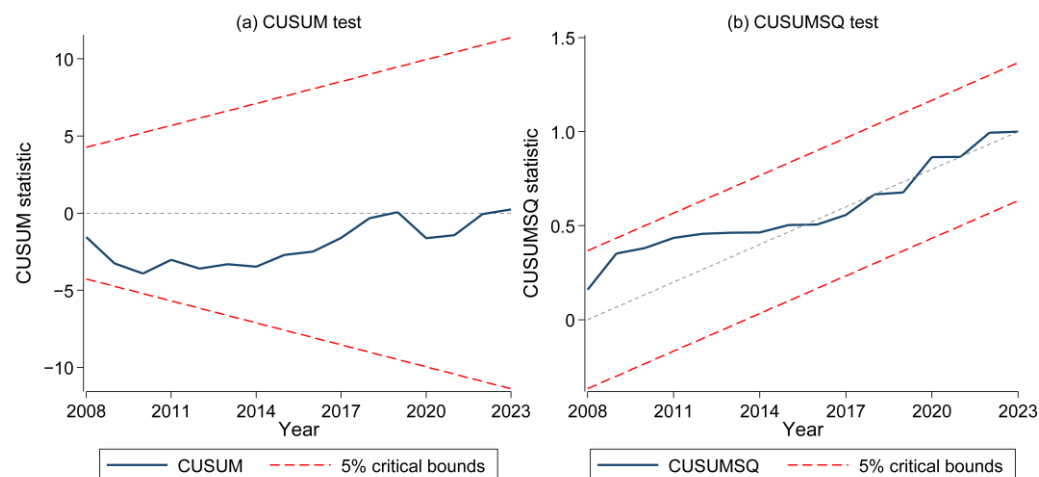


Figure 7. CUSUM and CUSUMSQ stability tests for the estimated ARDL model: (a) CUSUM test; (b) CUSUMSQ test. The black dashed line indicates the reference line.

Figure 8 plots the residuals of the estimated ARDL model. The residuals fluctuate around zero without a clear systematic pattern, supporting the adequacy of the dynamic specification.

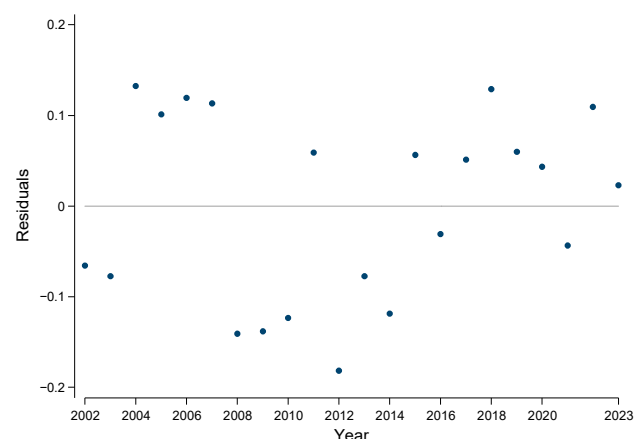


Figure 8. Residuals of the estimated ARDL model. The points represent model residuals, and the horizontal line indicates the zero reference line.

Table 7 reports robustness checks for the baseline specification. The long-run coefficient of travel expenditure remains positive and statistically significant when the COVID-19 dummy is excluded. The coefficient also remains unchanged when the lag structure is selected using AIC rather than BIC. These results suggest that the main expenditure–demand association is not driven only by the inclusion of the COVID-19 dummy or by the baseline lag-selection criterion.

The GDP-augmented ARDL specification is reported in Table 8. Travel expenditure remains positive and statistically significant after GDP per capita is included. By contrast, GDP per capita is not statistically significant in this extended specification. This result supports the stability of the expenditure–demand association, although it should not be

interpreted as evidence that macroeconomic conditions are irrelevant. Rather, it suggests that, within this small annual sample, the inclusion of GDP per capita does not eliminate the positive association between travel expenditure and tourism demand.

Table 7. Robustness checks of the baseline ARDL specification.

Variable/Statistic	Without COVID Dummy	AIC Lag Selection
$\ln(\text{TravEXP})$	0.593 *** (0.070)	0.589 *** (0.051)
COVID-19 dummy	—	−0.281 ** (0.121)
ECM(−1)	−0.800 *** (0.185)	−1.071 *** (0.091)
Observations	22	22
Selected model	ARDL(1,2)	ARDL(2,0)
Bounds F-statistic	9.368	70.018
BG LM <i>p</i> -value	0.173	0.138
White test <i>p</i> -value	0.698	0.229

Note: Standard errors are reported in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively. BG LM denotes the Breusch–Godfrey LM test for serial correlation. The White test refers to heteroskedasticity.

Table 8. Robustness check results using GDP-augmented ARDL specification.

Variable	Coefficient	Std. Error	t-Statistic	<i>p</i> -Value
Long-run coefficients				
$\ln(\text{TravEXP})$	0.464 **	0.159	2.91	0.011
$\ln(\text{GDPpc})$	0.478	0.379	1.26	0.227
Short-run coefficients				
$\Delta \ln(\text{TV})(-1)$	0.198 **	0.081	2.45	0.027
$\Delta \ln(\text{GDPpc})$	1.796	1.114	1.61	0.128
COVID-19 dummy	−0.417 *	0.211	−1.97	0.067
Constant	−0.677	2.607	−0.26	0.799
Error-correction term				
ECM(−1)	−1.003 ***	0.096	−10.42	0.000

The GDP-augmented specification is ARDL(2,0,1), estimated using BIC lag selection for the period 2002–2023. The model includes 22 observations, with $R^2 = 0.949$, adjusted $R^2 = 0.928$, and root MSE = 0.110. The bounds F-statistic is 49.386, the BG LM *p*-value is 0.409, and the White test *p*-value is 0.400. Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. GDPpc denotes GDP per capita. GDPpc is included only as a macroeconomic robustness check and is not treated as a baseline regressor.

The infrastructure-augmented ARDL specification is reported in Table 9. Travel expenditure remains positive and statistically significant, while the tourism infrastructure index is also positive and statistically significant. This result provides additional robustness evidence that tourism demand is positively associated with infrastructure conditions. However, because infrastructure may itself respond to tourism demand, the coefficient should be interpreted as an association rather than as evidence of a direct causal infrastructure effect.

Overall, the robustness checks reported in Tables 7–9 support the reliability of the baseline ARDL findings. The coefficient of travel expenditure remains positive and statistically significant across alternative specifications, including the model without the COVID-19 dummy, the AIC-selected model, the GDP-augmented model, and the infrastructure-augmented model. This consistency supports the interpretation that Kazakhstan’s tourism recovery is closely associated with expenditure-side demand dynamics.

The empirical findings are consistent with the three proposed hypotheses. Travel expenditure is positively and significantly associated with tourism demand, supporting H1. The COVID-19 dummy is negative and statistically significant in the baseline model, supporting H2. The ARDL bounds test and the significant error-correction term provide

evidence of a stable long-run association between tourism demand and travel expenditure, supporting H3. These findings should be interpreted as evidence of robust conditional associations rather than causal effects.

Table 9. Robustness check results using infrastructure-augmented ARDL specification.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Long-run coefficients				
$\ln(\text{TravEXP})$	0.523 ***	0.066	7.96	0.000
$\ln(\text{InfraIndex})$	1.284 **	0.487	2.64	0.017
Short-run coefficients				
COVID-19 dummy	−0.663 ***	0.114	−5.84	0.000
Constant	−0.964	1.441	−0.67	0.512
Error-correction term				
ECM(−1)	−0.844 ***	0.079	−10.63	0.000

The infrastructure-augmented specification is ARDL(1,0,0), estimated using BIC lag selection for the period 2001–2023. The model includes 23 observations, with $R^2 = 0.946$, adjusted $R^2 = 0.933$, and root MSE = 0.106. The bounds F-statistic is 62.021, the BG LM p -value is 0.597, and the White test p -value is 0.277. Note: ** and *** denote statistical significance at the 5% and 1% levels, respectively. *InfraIndex* denotes the tourism infrastructure index. This specification is used as an extended robustness check to link the infrastructure analysis with the ARDL framework.

5. Discussion

The findings indicate that Kazakhstan's post-pandemic tourism recovery should be interpreted not only through changes in visitor numbers, but also through the expenditure structure behind tourism demand. The positive long-run association between travel expenditure and total visitors suggests that the recovery process was linked to the restoration of tourism consumption. This interpretation is consistent with Figure 5, which shows a partial recovery of domestic tourism consumption after the pandemic period, while tourism's contribution to GDP remained relatively moderate. These findings are consistent with tourism demand theory, which links tourism flows to income, expenditure capacity, and consumption behaviour (Morley, 1992; Song & Li, 2008). In contrast to purely volume-based interpretations of recovery, the results suggest that expenditure-side dynamics provide a more informative view of Kazakhstan's post-pandemic rebound. This interpretation is also consistent with post-pandemic evidence showing that recovery has depended not only on the return of mobility, but also on expenditure recovery, destination competitiveness, and consumer confidence (Gössling & Schweiggart, 2022; Chiawo et al., 2023; Yopez & Leimgruber, 2024).

The COVID-19 dummy and the error-correction term provide additional insight into the adjustment process. The negative coefficient of the COVID-19 dummy confirms the strong short-run disruption associated with the pandemic period. At the same time, the significant error-correction term suggests that deviations from the long-run expenditure–demand association were corrected relatively quickly after the shock. This supports the interpretation of dynamic recovery, although it should not be treated as evidence of a strict causal mechanism.

Infrastructure represents an important structural condition in this recovery process. Although it is not included in the preferred baseline model, the infrastructure-augmented robustness check shows a positive and statistically significant association between the infrastructure index and tourism demand. This strengthens the link between the econometric findings and the descriptive infrastructure analysis. However, the result should be interpreted cautiously because infrastructure may also respond to tourism demand, meaning that possible reverse causality cannot be fully excluded.

These regional results are consistent with studies emphasizing the role of accessibility and infrastructure in uneven tourism recovery. National recovery was spatially uneven: tourism activity and revenue remain concentrated in better-connected and more developed regions, especially Almaty and Astana, while several peripheral regions continue to show lower levels of tourism activity and revenue generation. The cluster analysis therefore complements the national ARDL results by showing that aggregate recovery can coexist with persistent regional disparities.

Theoretically, the study supports a multidimensional interpretation of tourism recovery. Recovery is not simply the restoration of visitor numbers, but a process involving expenditure dynamics, structural capacity, and regional conditions. This is particularly relevant for emerging tourism economies, where national-level recovery indicators may hide uneven regional development.

From a policy perspective, the results suggest that demand stimulation alone is unlikely to ensure balanced recovery. Policies aimed at increasing visitor flows should be combined with infrastructure upgrading, improved accessibility, and service-capacity development in lagging regions. For leading destinations such as Almaty and Astana, policy priorities may focus on higher-value tourism and expenditure retention, whereas peripheral regions require targeted investment in connectivity, accommodation capacity, and tourism facilities.

6. Conclusions

This study examined post-pandemic tourism recovery in Kazakhstan by combining ARDL modelling with infrastructure index construction and regional cluster analysis. The baseline ARDL results provide evidence of a positive long-run association between travel expenditure and tourism demand. The COVID-19 dummy is negative and statistically significant, indicating a short-run disruption associated with the pandemic shock. The significant error-correction term and the ARDL bounds test further support the presence of a stable long-run association between tourism demand and travel expenditure.

The robustness checks strengthen the reliability of the baseline results. The coefficient of travel expenditure remains positive and statistically significant across alternative specifications, including the model without the COVID-19 dummy, the AIC-selected model, the GDP-augmented specification, and the infrastructure-augmented specification. In the GDP-augmented model, GDP per capita is not statistically significant, while travel expenditure remains significant. In the infrastructure-augmented model, the infrastructure index is positively and significantly associated with tourism demand. These results support the interpretation that Kazakhstan's tourism recovery was closely associated with expenditure-side demand dynamics, while also being linked to structural infrastructure conditions.

At the same time, the findings show that recovery was not spatially uniform. Tourism activity and revenue remain concentrated in major urban and better-connected regions, particularly Almaty and Astana, while several peripheral regions continue to show weaker tourism activity and revenue generation. The regional and cluster analyses therefore indicate that national-level recovery can coexist with persistent spatial disparities.

The study has several limitations. The annual time-series sample is relatively small, additional macroeconomic controls are included only as robustness checks, and the infrastructure index is not part of the preferred baseline model. Potential reverse causality between tourism demand, travel expenditure, and infrastructure cannot be fully ruled out. Therefore, the findings should be interpreted as evidence of robust conditional associations rather than strict causal effects. Future research could use longer time series, regional panel data, higher-frequency observations, or stronger identification strategies to examine causal mechanisms more directly.

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