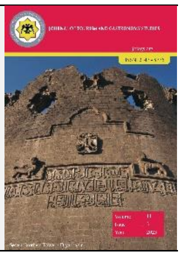
Journal of Tourism and Gastronomy Studies, 2023, 11 (3), 2171-2186

JOURNAL OF TOURISM AND GASTRONOMY STUDIES

ISSN: 2147 – 8775

Journal homepage: www.jotags.net



Tourism Efficiency: Bootstrap-Data Envelopment and Tobit Panel Data Analysis

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Article History

Received: 08.06.2023

Accepted: 23.09.2023

Keywords

Bootstrap

Data envelopment analysis

Efficiency

Tobit panel data analysis

Tourism

Abstract

Tourism is an important sector for countries, not only for cultural but also for economic activities. The tourism sector, which operates effectively, contributes to the development of the country's economy. Therefore, the study aims at calculating tourism efficiency and identifying factors that influence it. The study discussed 18 European countries that are among the world's major destination centers. Firstly, tourism efficiency scores were calculated with the data covering the period 2002-2019. Inputs are the number of tourists and tourism expenditures, and output is tourism revenues. Tourism sector efficiency was calculated with the standard Data Envelopment Analysis (DEA) model. Because of the possible statistical limitations of the DEA method, analysis was repeated with the Bootstrap-DEA method. The resulting efficiency scores were used as dependent variables in the Tobit model. The variables including per capita income, digitalization, energy consumption, financial development, political stability, and life expectancy at birth were handled as new trends of tourism efficiency in the Tobit panel data analysis. Boostrap DEA results, which yield more accurate results, gave efficiency results for a smaller number of countries than the efficiency analysis performed with standard DEA. Tobit panel data analysis results showed that income per capita, digitalization, political stability, and life expectancy at birth enhanced tourism efficiency. In the study, unlike the literature, tourism efficiency was not considered at the level of companies, but at the level of countries. In addition to the standard DEA analysis, the Bootstrap DEA method was used, which yielded superior results. Additionally, not only the efficiency values were calculated in the study, but also the factors affecting the tourism efficiency were determined.

Article Type

Research Article

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DOI: 10.21325/jotags.2023.1287

INTRODUCTION

The number of international tourists worldwide is expected to increase by 3.3% from 2010 to 2030 in the forecast for the tourism sector, one of the largest markets in the global world. By 2030, the number of tourists is projected to double at a rate of 4.4% per year in developing countries and 2.2% per year in developed economies. With these expected growth rates, tourist numbers are projected to reach 1.8 billion in 2030 (UNWTO, 2014). This uptrend sourcing from tourism's own internal dynamic is creating positive effects on the economy. What opportunities does the tourism sector offer for the economy? Foreign exchange revenues are the first to come to mind when it comes to tourism. As it is known, activities such as accommodation, eating, drinking, transportation, and entertainment constitute expenditure in tourist activities. Spending by tourists constitutes a revenue-generating effect for countries. Tourism revenues mean funds for investments and foreign trade deficits, as well as resources for investments. As the tourism sector has multiple backward and forward linkages, it is closely associated with sectors such as transport and construction. Investments other than ones such as airline services in the tourism sector are hardly costly. Profits are being made at a certain rate. Tourism is a labor-intensive sector and does not require over-skilled labor. Therefore, the employment effect is high. In summary, the tourism sector affects the economy through many channels (Gray, 1997; Mushtaq & Zaman, 2014).

What can countries do to attract more tourists? The first traditionally known factor for countries to achieve a more advanced tourism industry is to increase the level of income per capita. Although there are heterogeneous views on the relationship between tourism and economic growth, it is recognized that there is a positive relationship between tourism and economic growth when tourism-based growth occurs. Accordingly, tourism inflows bring in foreign currency, and capital goods boost imports and employment in particular. Thus, resident income increases (Bronzini et al., 2022). This is because economically strengthening individuals tend to travel more and more. For example, Zhang (2020) investigated the relationship between per capita disposable income in China and per capita tourism consumption expenditure. The study's findings showed a long-term relationship between the increase in income and tourism consumption. The 1% increase in revenues resulted in the tourism consumption increase by 1.131%. The rise in the average lifespan that accompanies rising per capita income allows people to demand tourism at least at a certain time in their lives. Rising life expectancy, coupled with an increase in the number of people surviving until retirement, increases the extent and strength of the active retirement period and the old age tourism market share (Williams & Hall, 2000).

As much as the increase in per capita income, it is necessary to transfer the income to pay systems in the tourism sector. Thus, the concept of financial development must be determined in the tourism sector. Financial development, as it is known, refers to the creation and expansion of institutions and instruments that drive financial growth along with increased use and accessibility of financial services (Beck, Feyen, Ize, & Moizeszowicz, 2008). Financial development can also improve tourism through the spread of technology and its effects on infrastructure growth. Financial development accelerates the spread of technology. Infrastructure improvement could also affect tourism. Financial development is driving tourism demand by stimulating investment in the tourism sector (Churchill et al., 2022). It can be said that there is a hypothesis of feedback causality between financial development and tourism. Financial development encourages direct financial sector activities such as foreign direct investment or progress in the stock market and banking activities and reduces energy use by affecting the energy efficiency and functioning of enterprises. This also leads to improvements that reduce carbon emissions. Financial development provides environmentally friendly modern technologies and production processes, which creates new opportunities for tourism (Khan et al., 2019).

Of course, the factors affecting tourists' consumption and destination decisions are not only economic. Historic and natural attractions, transportation opportunities, eating-drinking, and shopping opportunities, planned activities for tourists, hospitality, costs, conveniences, security, and other services also affect these decisions (Buhalis 2000; Heung, Qu & Chu 2001; Sirakaya & McLelland, 1997). Security, in particular, holds an important place in the choice of destination in today's world. Security is the precondition and guarantee of tourism activities, but it is the lifeblood of tourism development. This is because negative impressions of the destination for tourists not only reduce the likelihood of visits but also reduce the behavior of recommending them to others (Ding & Wu, 2022).

Events such as the Chornobyl accident, the volcanic eruption in Iceland, the magnitude 9 earthquake in Japan, and the Covid-19 pandemic have undoubtedly slowed tourism mobility in these countries. It is widely accepted that events that negatively affect life in tourist destinations, such as natural disasters, and pandemics, almost cease tourism activities. However, other than natural events, the impact of political crises on tourism in the world is known to be undeniably remarkable. For all countries regardless of the level of development, the image of the country is the main factor in the tourism sector to be able to be competitive. For example, after the September 11, 2001 attacks, the United States experienced a reduction in tourism revenues of more than $5 billion in 2002. Moreover, the effect continued in 2003. Meanwhile, the UK's Bretix decision in 2017 resulted in a decrease of 1.5 million in the total number of tourists in 2018. In short, political instability can make that country a non-preferred destination center despite having the most comfortable hotels in the world, the calmest and cleanest beaches, the oldest historical ruins, or the unique natural beauties. In addition, it could suddenly plunge countries into a "tourism crisis."What happened in Egypt and Lebanon, where there are seven wonders of the world, is a good example. Following the political instability in Egypt and Lebanon, it took only a few minutes for tourism firms to remove them from their programs. On the other hand, the population of tourists fleeing some countries may find themselves in new countries (substitution effect). For example, local and foreign tourists shifting from the Arab world to Turkey. As a result, political instability is one of the major factors that can cause countries to lose their tourism potential.

Another factor affecting tourism potential is technological advancements. The technology is likely to make it easier for travelers to access attractions. Transportation of tourists to previously difficult-to-reach places, tourism-specific infrastructure and construction activities related to accommodation, and systems that help reduce water and electricity consumption are designed with technology. The concept used as a new technological trend is digitalization. Digitalization has allowed tourist experiences to take on new dimensions and increasingly move to online platforms. The global spread and increasing use of the Internet, the development of certain apps, the rise in popularity of online travel agents, and the emergence of virtual tourism are driving online tourism into the spotlight. Today, technological advancement has gone beyond facilitating, streamlining, and improving tourists' comfort (Stipanuk, 1993; Firoiu & Croitoru, 2013). Undoubtedly, energy is used in all activities (infrastructure studies, construction activities, and even travel, etc.) in relation to tourism. Energy consumption is an integral part of the tourism sector. Greenhouse gas emissions and pollution as a result of energy consumption reveal that energy consumption is critical to tourism and environmental quality. The relationship between the development of tourism and environmental degradation due to energy consumption for sustainable tourism is one of the policy agendas and is accepted as one of the factors affecting tourism efficiency (Khanal et al., 2021; Zaman et al., 2016). The relationship of energy with tourism can be conceptualized in three aspects. First of all, the driving force of tourism is energy. As mentioned earlier, energy is used with fuels for basic infrastructure, electricity, transportation, heating, cooling, and other services. For this reason, energy supply and price affect the development of tourism in economies or drive it into recession. Second, energy is actually a constraint for tourism. The landscapes resulting from the work done to extract and process energy resources can create visual and environmental pollution. Third, energy can be interpreted as attractiveness. For example, modern facilities such as wind farms can be attraction centers for tourists (Frantál & Urbánková 2017).

In which countries tourism is managed successfully, as well as economic discourse and tourism activities of the countries, are important for development. On the other hand, countries that carry out successful tourism processes can be a source of inspiration for other countries. For this reason, the tourism performance of the countries is handled by efficiency calculations in the literature. For example, Hadad et al. (2012) conducted DEA analyses to measure the effectiveness of the tourism sector for 34 developed and 71 developing countries (a total of 105 countries) in 2009. While globalization and accessibility to the country are important for the efficiency of the tourism sector in developing countries, labor efficiency is also effective in tourism efficiency for both country groups.

Yi and Liang (2015) calculated tourism efficiency based on the Malmquist index for 21 cities in China during the period 2004-2010. The results showed that tourism efficiency was high for all cities and that there were differences between cities. Soysal-Kurt (2017) made an efficiency estimation with DEA in 29 European countries in 2013. Sixteen countries were found to be relatively efficient and 13 countries were found to be inefficient. Bayrak and Bahar (2018) examined the tourism activity in OECD countries from 2011-2015 with the DEA method. The findings of the analysis showed that the USA, Portugal, Australia, Spain, Turkey, New Zealand, and Luxembourg were efficient in all years. Bariši ́c and Cvetkoska (2020) investigated the income and employment impact of tourism and travel industry activity with the DEA method in 28 Europa Union member countries in 2017. It was determined that 13 European Union member states were relatively active. Rasoulzadeh et al. (2017) calculated efficiency for the tourism industry in the Middle East and East Asian countries with the DEA model in 2013. The results showed that the efficiency varies according to country, and there are some inefficiency results, especially for Iran. Hosseini and Hosseini (2021) examined tourism efficiency with a two-stage super-efficiency slacks-based measure approach in 24 developing countries with data from 2013, 2015, and 2017. The results of the analysis showed that the low tourism efficiency in the countries was due to the lack of infrastructure. Wang and Kim (2021) used DEA and Malmquist index methods to assess tourism efficiency and effectiveness in various provinces of China during the period 2016-2018. The results showed that productivity was high in the provinces, but the development of urban tourism was unbalanced and different from each other among the 15 cities. Wenhua (2021) analyzed tourism efficiency and effectiveness with the DEA and Malmquist index for 14 cities in China between 2004 and 2018. Although there is a growth trend in general, the researcher determined that there are regional differences in which productivity is not evenly distributed. Zhang and Fu (2021) used the DEA and Malmquist index to measure tourism efficiency and effectiveness in 31 regions in China over the period 2014-2016. They determined that tourism efficiency had increased in China, but policies should be developed at the regional level. Packovic et al. (2021) examined the tourism efficiency with the DEA method in 29 European countries with data from 2017. In most European countries, the tourism sector could not provide efficiency. Gao et al. (2022) calculated tourism efficiency with the Slacks-Based

Measure (SBM)-DEA model in 30 provinces in China from 2006-2019. They have found that tourism efficiency in China is fluctuating. It is foreseen that the development of industry, marketization, and urbanization in the provinces can increase efficiency. Pegkas (2022) determined regional efficiency scores with stochastic frontier analysis in Greece during the crisis years 2008-2016. The study revealed that the tourism industry in Greece has high average efficiency and the leading regions are the South Aegean and Crete.

Yang et al. (2022) determined tourism efficiency and influencing factors for 30 provinces in China from 2008-2018 using SBM-DEA, social network analysis, and spatial econometric regression methods. The findings showed that tourism efficiency was high in Southwest China and low in Northwest China. The number of patents, traffic, financial development, and macro control of the government have positively affected the efficiency of tourism.

This study intends to determine tourism efficiency and possible factors affecting the efficiency outlined above. The motivator for exploring tourism efficiency and factors that influence tourism efficiency can be summarized as follows: Tourism is among the fastest developing sectors in the world and is a major factor in the economic growth of countries due to the economic added value previously expressed. This is why the tourism sector is handled in the research. The possible benefit of tourism for countries is known. But what's really curious about the research is, do countries get the best out of the tourism sector with the resources available? So is the tourism sector efficient? And what are the factors influencing this efficiency? Because determining whether countries alone are efficient in the field of tourism is not an adequate research effort. Determining the factors that influence efficiency is a prerequisite for implementing the policies necessary to ensure the continuity of efficiency. Thus, this study not only offers an efficiency analysis but also contributes to the information gap in the relevant field, unlike other research in literature, by identifying the factors that influence this efficiency. On the other hand, the empirical analysis of the study reveals a Bootstrap efficiency untapped much in literature alongside a standard DEA analysis. Another superior aspect of the empirical analysis is that the efficiency results calculated by us are included as variables dependent on the model. Thus, instead of the standard panel regression model, a different perspective was tried to be brought to the literature with Tobit Panel estimation. It is hoped that the work will make a significant contribution to the tourism field given all these grounds that are mentioned.

Following the theoretical information presented in the introduction section, the study is organized as follows: Data and methods are described in the second section. Empirical analysis results are presented in the third section. The fourth and final section includes discussion, suggestions, and conclusion.

Data and methodology

In the empirical analysis part of the study, it is aimed to examine tourism efficiency and the factors determining the efficiency. To this end, tourism efficiency scores were first calculated for 18 European countries for the period 2002-2019. A balanced panel Tobit model was then predicted. In the balanced panel, the country and years that caused the discrete data were excluded. The study involves a two-stage analysis process:

Step 1: Measuring Efficiency Scores: DEA and Bootstrap DEA

In the first stage of the analysis, international tourism expenditures and the number of international incoming tourists were determined as inputs and international tourism revenues were determined as outputs, and DEA was performed to determine the tourism activities of the countries. Data from the 18 European countries (Albina, Armenia, Azerbaijan, Bulgaria, Finland, France, Greece, Germany, Hungary, Kazakhstan, North Macedonia, Norway, Poland, Portugal, Romania, Slovenia, Switzerland, and Ukraine) used as Decision-Making Units (DMUs) in the analysis were obtained from the World Bank.

DEA, the basic approach used in calculating efficiency values in the study, is a model that includes efficient and inefficient DMUs. The linear efficiency limit created by the efficient ones surrounds all observations, creating an "envelope", and the efficiency scores of all observations are determined according to this envelope curve (Hollingsworth, 2003). The most preferred DEA models are Charnes, Cooper, and Rhodes model (CCR) and Banker, Charnes, and Cooper model (BCC) models. These models can be calculated based on input and output. The input-oriented model is intended to generate existing output by changing inputs. Getting a certain output with the least resources is a situation that is easier to control. Therefore, this study favored an input-oriented CCR model. The approach that was first used only in measuring technical efficiency under the assumption of CCR was later modified by Banker, Charnes, and Cooper (1984), and the BCC assumption made it possible to measure scale efficiency under BCC.

DEA is a model that allows multi-input and multi-output efficiency analyses to be performed. In the model based on calculating the efficiency score of each DMU, the efficiency measurement of the DMU is carried out using the ratio of weighted total outputs to total inputs:

$$\text{Max } e_j = \frac{\sum_{r=1}^{s} u_{rj}\, Y_{rj}}{\sum_{i=1}^{m} v_{ij}\, X_{ij}} \qquad (1)$$

where j represents the number of output factors produced by the DMU, Y_{rj} represents r = 1,…,s DMU, and X_{ij} represents the number of input factors of i= 1,…,m. The weights loaded by j into the input and output factors are represented by v_{ij} and u_{rj} (Ramanathan, 2003).

The weights that the method gives to inputs and outputs cannot have a negative value, and the efficiency of any DMU cannot exceed 1. Thus, there are many weights sets to choose for DMUs, and there is often a tendency to give the highest weight to the least used inputs and the most produced outputs for DMUs. In DEA, which aims to measure how efficiently the DMU uses resources to create an output set, if the objective function value ($\sum_{r=1}^{s} u_r y_r$) equal to 1, it means that the DMU is efficient and if it is less than 1, DMU is inefficient (Yun, et al., 200). Another limit to be considered in the analysis is the number of DMUs. According to Sherman (1982), the sum of the numbers of inputs and outputs should be less than the number of DMUs. The total number of inputs and outputs used in the study is 3 and the number of DMUs is 18.

If it is difficult or impossible to obtain the sample distribution of a predictor by the asymptotic approach and the knowledge of the observations about the data generation process is not sufficient, the Bootstrap method, which is a statistically repeated sampling method, is used. This method, proposed by Efron (1979), is often used in complex problems. The basic idea of this method is to create an artificial sampling distribution of the predictor of interest by making a certain number of repeated samples from the bulk sampling at hand. The Bootstrap method, which is used to make some inferences about the sample distribution, was later developed by Efron and Tibshirani (1994) for some statistical inferences such as confidence interval. The data generation process can predict experimentally by resampling from the original dataset to produce a set of samples taken each time the Bootstrap is repeated and then applying the Bootstrap samples to the original estimators. Thus, the samples created by the Bootstrap method reflect the statistical characteristics of the main sample (Smeekes, 2009).

The Bootstrap DEA method was introduced by Ferrier and Hirschberg (1997), along with Simar and Wilson (1998), by constructing confidence intervals of DEA efficiency scores to overcome the main limitation of basic DEA analysis, namely the precision of sampling results. The Bootstrap DEA method was later developed further by Simar and Wilson (1999, 2000a, 2000b). In these studies, it was aimed to remove the dependence between the efficiency scores and to evaluate the statistical characteristics of the non-parametric efficiency scores arising from some unobservable data generation process. Thus, the method was developed with different studies to obtain the bias of DEA efficiency scores. Due to the statistical limitations of the DEA method, the Bootstrap DEA method is often used. In this method, which is based on repeating the original data B times, the DEA efficiency scores are recalculated every time they are repeated.

Based on the original DEA estimator θ DEA (x, y), the Bootstrap estimate of bias is calculated as follows:

$$\widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right) = B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}\ (x,y) - \hat{\theta}_{DEA}(x,y) \qquad (2)$$

where, $\hat{\theta}^*_{DEA,b}\ (x,y)$ denotes the Bootstrap value and B denotes the Bootstrap number of repetitions. Based on the formula, the unbiased estimator (x, y) can be calculated as follows:

$$\hat{\theta}_{DEA}(x,y) = \hat{\theta}_{DEA}(x,y) - \widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right) = 2\hat{\theta}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}\ (x,y) \ (3)$$

According to Simar and Wilson (2008), this bias correction approach may cause an additional error. Therefore, the sampling variance of the estimated Bootstrap values $\hat{\theta}^*_{DEA,b}(x,y)$ can be calculated as follows:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}\ (x,y)\right]^2 \qquad (4)$$

Step 2: Tobit Model

In the second stage of the analysis, new trend factors affecting the tourism efficiency scores determined in the first stage were investigated. At the first stage of the study, the efficiency values obtained with DEA were limited to 1 from above (right). These efficiency values, which will be used as a dependent variable, were limited, which led to the fact that the most appropriate choice for the model to be created in the second stage of the study was the Tobit Model.

Having to limit the dependent variable value from above or below while performing econometric analysis causes data loss. In such a case, the information about the dependent variable is found only for some observations, such a censored regression model is known as a Tobit model. The Tobit model, which is an extension of the Probit Model, was developed by James Tobin (Tobin, 1958).

The linear regression of a latent dependent variable (y^*) with the independent variable(s) is defined as follows.

$$y_i^* = x_i^{'}\beta + u_i \quad (i = 1, \ldots, n)$$

$$y_i = \begin{cases} y_i^*, & y_i^* > 0 \\ 0, & y_i^* \le 0 \end{cases}$$

$$u_i \sim IIN(0, \sigma^2) \qquad (5)$$

where y_i^* denotes the latent dependent variable, X_i denotes the descriptive variable(s) vector, β denotes the coefficients vector, u_i denotes error term that is Identically and Independently Normal (IIN) distributed, and Y_(i)denotes the observed dependent variable.

The Random Effects Panel Tobit model, which was created to determine the relationship between the tourism efficiency of 18 countries used in the analysis and the factors that are thought to affect it, is defined as follows:

$$y_{it}^{*} = x_{it}^{'}\beta + u_i + \varepsilon_{it}$$

$$y_{it} = \begin{cases} y_{it}^{*}, & y_{it}^{*} < 1 \\ 1, & y_{it}^{*} \geq 1 \end{cases}$$

$$u_i \sim IIN(0, \sigma_u^2) \text{ and } \varepsilon_{it} \sim IIN(0, \sigma_\varepsilon^2) \tag{6}$$

The model created as a result of the examination of both theoretical and applied research for the purpose of the study is as follows:

$$\mathrm{BOOTCCR_{it}} = \beta_0 + \beta_1 \mathrm{GDP_{it}} + \beta_2 \mathrm{LENR_{it}} + \beta_3 \mathrm{DGT_{it}} + \beta_4 \mathrm{FDI_{it}} + \beta_5 \mathrm{POL_{it}} + \beta_6 \mathrm{LIF_{it}} + \mathrm{u_i} + \varepsilon_{\mathrm{it}} \tag{7}$$

In the model,

$\mathbf{BOOTCCR_{it}}$	Tourism Bootstrap CCR efficiency value calculated by us for country i in year t
$\mathbf{GDP_{it}}$	Growth in per capita income of country i in year t (World Bank)
$\mathbf{LENR_{it}}$	Logarithmic value of energy consumption of country i in year t (International Energy Agency-IEA)
$\mathbf{DGT_{it}}$	The ratio of personal internet use to the population of country i in year t (World Bank)
$\mathbf{FDI_{it}}$	Financial development index of country i in year t (International Monetary Fund -IMF)
$\mathbf{POL_{it}}$	Political stability index of country i in year t (Worldwide Governance Indicators -WGI)
$\mathbf{LIF_{it}}$	Life expectancy at birth in country i in year t (World Bank)

In addition, $\mathrm{u_i}$ and $\varepsilon_{\mathrm{it}}$ are the error terms of the model, and $\mathrm{u_i}$ refers to the random effect and is the same in each period.

The original efficiency scores, which constitute the first step of the analysis and are calculated using DEA, are reported in Table 1, and the Bootstrap efficiency scores are reported in Table 2.

Table 1. Original CCR efficiency scores

Country	**ORIGINAL CCR**																		
	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	***Mean***
Albina	0.500	0.455	0.545	0.543	0.523	0.598	0.596	0.512	0.378	0.331	0.310	0.304	0.306	0.306	0.328	0.337	0.322	0.322	*0.418*
Armenia	0.280	0.262	0.347	0.365	0.511	0.487	0.479	0.471	0.478	0.469	0.419	0.393	0.390	0.380	0.393	0.392	0.394	0.392	*0.406*
Azerbaijan	0.107	0.103	0.097	0.107	0.175	0.201	0.193	0.265	0.254	0.321	0.492	0.474	0.525	0.563	0.581	0.553	0.472	0.332	*0.323*
Bulgaria	0.289	0.320	0.347	0.387	0.380	0.469	0.459	0.509	0.693	0.732	0.660	0.639	0.616	0.514	0.504	0.475	0.474	0.457	*0.496*
Finland	0.371	0.472	0.477	0.447	0.473	0.543	0.592	0.519	0.541	0.592	0.570	0.847	0.812	0.627	0.591	0.672	0.733	0.741	*0.590*
France	0.235	0.225	0.313	0.297	0.304	0.319	0.319	0.299	0.279	0.287	0.299	0.296	0.278	0.319	0.299	0.297	0.295	0.283	*0.291*
Germany	0.610	0.672	0.742	0.773	0.793	0.828	0.880	0.804	0.750	0.773	0.696	0.721	0.730	0.594	0.602	0.610	0.627	0.605	*0.712*
Greece	0.829	0.905	0.971	0.947	**1.000**	0.790	0.771	0.672	0.704	0.738	0.843	0.985	0.991	0.938	0.890	**1.000**	0.986	0.995	*0.886*
Hungary	0.295	0.264	0.279	0.302	0.372	0.315	0.337	0.373	0.393	0.410	0.432	0.456	0.477	0.487	0.472	0.479	0.513	0.527	*0.399*
Kazakhstan	0.180	0.188	0.184	0.190	0.208	0.206	0.231	0.228	0.213	0.207	0.182	0.188	0.182	0.170	0.208	0.222	0.232	0.251	*0.204*
North Macedonia	0.262	0.336	0.354	0.344	0.423	0.477	0.496	0.471	0.439	0.435	0.425	0.434	0.440	0.372	0.367	0.366	0.363	0.351	*0.397*
Norway	0.350	0.375	0.399	0.455	0.432	0.499	0.538	0.467	0.456	0.542	0.613	0.616	0.634	0.487	0.432	0.431	0.525	0.491	*0.486*

Table 1. Original CCR efficiency scores (Cont.)

Poland	0.250	0.249	0.221	0.210	0.190	0.258	0.252	0.244	0.220	0.255	0.246	0.250	0.252	0.233	0.242	0.258	0.271	0.273	*0.243*
Portugal	0.571	0.604	0.656	0.615	0.652	0.925	0.975	0.931	0.935	**1.000**	**1.000**	0.973	0.972	0.918	0.938	**1.000**	**1.000**	0.949	*0.867*
Romania	0.154	0.158	0.156	0.261	0.265	0.271	0.260	0.218	0.201	0.216	0.214	0.257	0.218	0.210	0.205	0.200	0.186	0.178	*0.213*
Slovenia	0.513	0.542	0.581	0.603	0.636	0.682	0.721	0.724	0.657	0.656	0.590	0.600	0.580	0.527	0.503	0.498	0.490	0.491	*0.589*
Switzerland	0.616	0.708	0.184	0.717	0.722	0.771	0.902	0.881	0.890	**1.000**	0.937	0.926	0.956	0.888	0.793	0.762	0.765	0.761	*0.788*
Ukraine	0.218	0.218	0.213	0.226	0.245	0.262	0.294	0.231	0.234	0.242	0.243	0.218	0.111	0.083	0.076	0.078	0.083	0.094	*0.187*
Mean	*0.368*	*0.392*	*0.393*	*0.433*	*0.461*	*0.494*	*0.516*	*0.490*	*0.484*	*0.512*	*0.510*	*0.532*	*0.526*	*0.479*	*0.468*	*0.480*	*0.485*	*0.472*	

According to Table 1, the average original efficiency value in 2002 was 0.368. The corresponding period efficiency value was well below the full efficiency value (1.000) and there is no country capable of reaching the full efficiency level during this period. In the terms of 2003, 2004, 2005, 2007, 2008, 2009, 2010, 2013, 2014, 2015, 2016, and 2019, the average levels of efficiency are still quite low and there are no countries that can reach the full efficiency level. Only Greece was able to reach the full efficiency level in 2006. During the studied period, 2011 had the highest average efficiency (0.512). In the relevant year, Portugal and Switzerland rose to the full efficiency level. In 2012, there was a partial decline in the average efficiency level, and the number of full efficient countries declined to 1 "(Portugal). In 2017, Greece and Portugal became fully efficient, and this continued with only the full efficiency of Greece in 2018. Since the beginning of the studied period (2002), there has been an increase of approximately 39% until 2011, when the highest average efficiency was observed, while after 2011, there was an approximately 8% decrease in the average efficiency level until the end of the studied period (2019). During the whole studied period, Portugal achieved their full efficiency value in 2011, 2012, 2017, and 2018, Greece in 2006 and 2017, and Switzerland in 2011. Apart from the relevant countries, there are no countries that can reach the full efficiency level during the studied period.

The Bootstrap CCR scores are given in Table 2. Since Bootstrap efficiency measurement contains a more accurate calculation, lower efficiency values were encountered compared to the original CCR measurement. According to this measurement, it is observed that no country reached the full efficiency level during the studied period. The highest level of efficiency in the corresponding period is observed in Portugal in 2017 (0.952). The lowest efficiency is observed in Ukraine in 2019 with a score of 0.087. During the process, decreases and increases in Bootstrap CCR values were detected. Considering the studied period as a whole, it was found that the highest average efficiency occurred in 2013 with a score of 0.506. The lowest efficiency period is 2003 and 2004. Greece reached the highest average efficiency level 9 times and Portugal reached the highest average efficiency level 7 times in the 18 review periods. Switzerland achieved its highest efficiency level in 2011 and 2012. Albina, Armenia, Azerbaijan, Bulgaria, Finland, France, Germany, Hungary, Kazakhstan, North Macedonia, Norway, Poland, Romania, Slovenia, and Ukraine had never been among the most efficient countries.

Table 2. Bootstrap CCR efficiency scores

Country	BOOTSTRAP CCR																		
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	*Mean*
Albina	0.475	0.435	0.522	0.521	0.501	0.574	0.572	0.489	0.351	0.310	0.295	0.289	0.292	0.294	0.317	0.326	0.310	0.311	*0.399*
Armenia	0.265	0.250	0.326	0.346	0.482	0.463	0.457	0.449	0.457	0.450	0.400	0.376	0.373	0.363	0.374	0.372	0.373	0.372	*0.386*
Azerbaijan	0.101	0.096	0.089	0.103	0.169	0.195	0.187	0.257	0.242	0.304	0.471	0.455	0.503	0.539	0.557	0.531	0.450	0.310	*0.309*
Bulgaria	0.278	0.311	0.336	0.375	0.368	0.453	0.442	0.493	0.643	0.685	0.619	0.610	0.590	0.490	0.482	0.457	0.457	0.440	*0.474*
Finland	0.353	0.453	0.458	0.429	0.454	0.519	0.564	0.495	0.517	0.565	0.545	0.798	0.766	0.590	0.555	0.629	0.690	0.692	*0.560*
France	0.223	0.213	0.302	0.288	0.294	0.310	0.309	0.290	0.271	0.278	0.290	0.287	0.269	0.309	0.290	0.288	0.285	0.274	*0.282*
Germany	0.584	0.645	0.712	0.742	0.760	0.795	0.845	0.772	0.718	0.741	0.666	0.690	0.698	0.562	0.570	0.579	0.596	0.574	*0.680*
Greece	**0.796**	**0.869**	**0.939**	**0.915**	**0.962**	0.754	0.736	0.641	0.672	0.704	0.805	**0.950**	**0.951**	**0.889**	0.833	0.915	0.919	**0.934**	*0.844*
Hungary	0.278	0.246	0.262	0.284	0.352	0.295	0.312	0.349	0.370	0.386	0.409	0.432	0.451	0.462	0.447	0.453	0.486	0.499	*0.376*
Kazakhstan	0.175	0.183	0.178	0.184	0.201	0.199	0.222	0.218	0.203	0.199	0.170	0.177	0.170	0.162	0.198	0.212	0.223	0.239	*0.195*
North Macedonia	0.250	0.320	0.336	0.327	0.398	0.443	0.466	0.440	0.417	0.414	0.405	0.413	0.419	0.353	0.349	0.349	0.345	0.333	*0.377*
Norway	0.331	0.352	0.378	0.433	0.411	0.476	0.516	0.446	0.436	0.520	0.588	0.591	0.608	0.466	0.412	0.410	0.502	0.469	*0.464*
Poland	0.235	0.235	0.207	0.195	0.177	0.243	0.243	0.233	0.210	0.243	0.232	0.234	0.237	0.214	0.222	0.238	0.253	0.252	*0.228*
Portugal	0.554	0.586	0.630	0.586	0.620	**0.862**	**0.917**	**0.868**	**0.867**	0.924	0.930	0.920	0.924	0.873	**0.894**	**0.952**	**0.950**	0.902	*0.820*
Romania	0.143	0.146	0.144	0.252	0.257	0.263	0.252	0.212	0.195	0.208	0.208	0.249	0.209	0.204	0.199	0.190	0.176	0.167	*0.204*
Slovenia	0.488	0.505	0.541	0.560	0.590	0.637	0.685	0.693	0.622	0.619	0.548	0.558	0.540	0.503	0.479	0.474	0.467	0.468	*0.554*
Switzerland	0.591	0.677	0.176	0.684	0.689	0.735	0.857	0.836	0.845	**0.933**	**0.880**	0.870	0.901	0.831	0.744	0.715	0.721	0.719	*0.745*
Ukraine	0.206	0.206	0.203	0.216	0.234	0.251	0.282	0.222	0.225	0.234	0.236	0.211	0.106	0.079	0.073	0.074	0.078	0.087	*0.179*
Mean	*0.351*	*0.374*	*0.374*	*0.413*	*0.440*	*0.470*	*0.492*	*0.467*	*0.459*	*0.484*	*0.483*	*0.506*	*0.500*	*0.454*	*0.444*	*0.454*	*0.460*	*0.447*	

In the study, the effects of GDP, LENR, DGT, FDI, POL, and LIF variables, which were independent variables, on Bootstrap tourism efficiency values (BOOTCCR), which were dependent variables, were determined by partial correlation analysis.

Table 3. Correlation Matrix

	BOOTCCR	GDP	LENR	DGT	FDI	POL	LIF
BOOTCCR	1.0000						
GDP	0.3189	1.0000					
LENR	-0.0863	-0.2474	1.0000				
DGT	0.3193	0.5005	-0.1932	1.0000			
FDI	0.4546	0.4024	-0.6334	0.4990	1.0000		
POL	0.4399	0.2342	-0.3946	0.3561	0.6177	1.0000	
LIF	0.6426	0.4354	-0.2691	0.6534	0.7001	0.6060	1.0000

GDP: Growth in per capita income, **LENR:** Energy consumption, **DGT:** The ratio of personal internet use, **FDI:** Financial development index, **POL:** Political stability index, **LIF:** Life expectancy at birth.

According to the obtained partial correlation coefficients, there is a positive correlation between tourism efficiency and GDP, DGT, POL, and LIF, and the correlation coefficients are 0.3189, 0.3193, 0.4546, 0.4399, and 0.6426, respectively. The relationship between tourism efficiency and LENR was negative and the correlation coefficient was found to be 0.0863.

In Tobit model estimation, hypothesis testing implemented with the "maximum likelihood ratio test" (LR). The hypotheses formed for the estimation of the model given in Equation 7 are as follows:

H0: “The model is generally insignificant (the parameters together are insignificant)”

H1: “The model is generally significant (the parameters are significant together)”

The results obtained from the estimation of the model given in Equation (7) with the maximum likelihood method using the balanced panel data set for the period 2002-2019 are reported in Table 4.

Looking at the Wald statistical value used to test the significance of the overall model, the probability value (0.0000) of the Wald value, which has a distribution of 6 degrees of freedom X^2, is less than the significance level of the determined α (0.01), so the null hypothesis (H_0) that the model is insignificant (parameters are insignificant together) is rejected, and the model is generally concluded to be significant at a significance level of 1%

Table 4. Random effect panel Tobit Model estimation results

Number of obs		324			
Number of groups		18			
Log-Likelihood		*282.05942*			
Wald χ^2 (6)	*66.57*			***Prob*** > χ^2	*0.0000*
BOOTCCR	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**
GDP	.0029312	.0013862	2.11	0.034	-.005648 -.0002143
LENR	-.0042205	.0024187	-1.74	0.081	-.0089612 .0005201
DGT	.0771163	.0250528	3.08	0.002	-.126219 -.0280137
FDI	.1047483	.1111267	0.94	0.346	-.1130561 .3225527
POL	.0442284	.0164983	2.68	0.007	.0118924 .0765644
LIF	.0311841	.0051268	6.08	0.000	.0211358 .0412323
_cons	-1.822549	.362721	-5.03	0.000	-2.533177 -1.111921
/sigma_u	.1409689	.0240763	5.86	0.000	.0937803 .1881575
/sigma_e	.0912085	.0036872	24.74	0.000	.0839817 .0984352
Rho	.7049086	.0731181			.5490588 .8299224
LR test of sigma _u=0: chibar 2(01)			*323.00*	***Prb> =chibar 2***	*0.000*

BOOTCCR: Bootstrap **CCR** efficiency scores, **GDP:** growth in per capita income, **LENR:** energy consumption, **DGT:** The ratio of personal internet use, **FDI:** financial development index, **POL:** political stability index, **LIF:** life expectancy at birth.

Table 4 includes the coefficient estimates, standard errors, z statistics, P values, and 95% confidence intervals.

Since the P values of all independent variables except the FDI variable are smaller than the α significance levels (0.01, 0.05, and 0.10), it was determined that the coefficients of these variables were statistically significant and their plus and minus signs were in accordance with the expectations.

GDP, DGT, POL, and LIF variables positively affect tourism efficiency. According to the results obtained from the analysis, if there is an increase of 1 unit in the relevant variables, an increase of 0.03, 0.77, 0.10, 0.04, and 0.03 units is realized in tourism efficiency, respectively. The effect of the LENR variable on tourism efficiency is negative, and the change of 1 unit has the effect of reducing tourism efficiency by 0.04 units.

Discussions and Conclusions

During a certain time of the year, people desire to take a break from their busy schedules, slow down, and vacation. They need to relax, travel, have fun and increase their cultural development. Tourism allows people to meet their needs. Tourism activities are a source of economic output alongside having a pleasant time for individuals. Theoretical and applied research reveals an irreplaceable relationship between tourism and economic growth. Tourism is affecting economic growth through multiple channels. The most important benefit of tourism activities is that it generates foreign currency gains. It is a source of payment for countries with trade deficits. On the other hand, it is the financing tool for imported capital goods. Tourism is a revenue item for governments because of its foreign currency-generating impact. Tourism means new investments. New investments, on the other hand, are creating jobs. Moreover, the tourism sector has a relationship with sectors such as transport, finance, and construction. This means a high multiplier impact on the economy. Therefore, it is clear that an efficient tourism sector will provide much greater added value to the economic structure. Therefore, the study identified whether the tourism sector was efficient in the 2002-2019 period for 18 European countries and what the factors impacting the efficiency were. The relevant countries and periods were selected according to the available data set of the period. Efficiency calculations were carried out using the DEA method, which is the most popular method used in the calculation of relative efficiency for decision-making units, and Boostrap DEA methods, which give stronger results. To be able to measure the efficiency, input and output variables were determined in the first step. In the study, the inputs and outputs were selected by following the literature. The inputs are the number of incoming tourists and tourism expenditures, and the output is tourism revenues. The efficiency values obtained by Boostrap DEA analysis were used as a dependent variable for the Tobit model. In the Tobit panel data analysis, the variables of per capita income, digitalization, energy consumption, financial development, political stability, and life expectancy at birth were analyzed with tourism efficiency scores. The results showed that per capita income, digitalization, political stability, and life expectancy at birth had a positive effect on tourism efficiency. The only variable that shows a negative relationship between tourism efficiency and energy consumption is energy consumption. There was no statistically significant relationship between the financial development index and tourism efficiency. Churchill et al. (2022) stated that there may be a negative or positive relationship conceptually between tourism and financial development depending on the mechanism by which financial development is transferred to tourism. In addition, when examined empirically, it was predicted that the impact of financial development on tourist arrivals, in particular, would not be known. From this point of view, the inability to decipher a significant relationship between tourism efficiency and financial development is in accordance with the literature. Today, human activities are an important cause of environmental degradation such as climate change and global warming. Especially the sector where fossil fuels are mostly used is transportation. This explains the effect of an increase in energy consumption on reducing the efficiency of tourism.

Based on the findings of this study, policy measures that countries can take for a more effective tourism sector can be listed as follows. First, increasing per capita income and distributing fairly will increase the welfare of individuals and thus enable them to add tourism activities to their spending plans. Secondly, driven by the fact that the life expectancy at birth extends the average lifespan, existing markets need to be redesigned to meet the needs of the aging population. Developing new types of services in travel, accommodation, information-communication technologies, and staff training will be beneficial, taking into account problems such as the constraint in older people's physical activities and some chronic illnesses. Thirdly, the creation of sustainable tourism awareness for continuity of tourism destinations should be ensured by the adoption of an energy strategy that is respectful of nature and man, where carbon emissions are reduced, and where edible sources of energy are preferred over fossil fuels. Fourth, in the tourism sector, sales, customer relations, follow-up of customer satisfaction, instant follow-up throughout the tourism service, personalization of services, and structuring of digital technologies in the short, long and medium term should be planned for competitive advantage. Fifth, tourism should serve the purpose of improving people's quality of life. In countries where there is political confusion, risk of terrorist attacks, and political and ideological turmoil, the determination of how sensitive tourists are to these situations should be done well, and how to manage the risks in tourism accordingly should be determined.

To recap, tourism is seen as a locomotive sector in keeping the economy alive. Tourism is the entirety of activities that support economic growth for countries, mitigate regional differences, create jobs, preserve historical and cultural heritage and nature, and offer many more advantages. A key criterion in the efficient continuity of tourism activities is that they must be sustainable. For tourism activities to be sustainable, the understanding of tourism that spans the entire year needs to be adopted. In cases where their income is low relative to the number of incoming tourists, developing some activities can be effective to attract tourists, meet their demands and needs, and increase their stay days. Another suggestion worthy of discussion includes legal regulations which can be used to holistically solve tourism-related problems. Infrastructure investments and environmental protection may deserve special attention in this respect. Given the changing world standards and consumer demands, tourism investments can be suggested to be market-based. The last but not the least, a tourism vision can be designed to preserve the historical, natural, cultural, and social structure.

Finally, this study reflects the results of an effort made toward tourism efficiency. It contains some limitations that may be overcome in future potential research. The research can be expanded in further research attempts by addressing different countries, periods, and factors. Obtaining data that is older or provides future predictions will make the research more comprehensive.

Decleration

All authors of the article contributed equally to the article process. The authors have no conflicts of interest to declare.

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