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Comparative countries' tourism technical efficiency assessment: A stochastic output distance function approach☆

Alastaire Sèna Alinsato, Nassibou Bassongui*, Franck Nkeudjoua Wondeu

Laboratory of Public Economics, University of Abomey-Calavi, Benin

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ABSTRACT

This study aims at analysing the technical efficiency of the tourism industry worldwide. Using a sample of 111 countries worldwide from 2008 to 2016, we estimated the tourism industry technical efficiency score to measure of the industry performance from a translog output distance function modelling. Our results showed that high-income countries are more efficient because of higher qualified labour, and higher productivity of natural and cultural resources. Besides, our results support that African and Asian countries are less efficient than those from Europe and America. For international comparison purposes, our findings suggested that the level of income and the location of destinations should be incorporated as determinants and inputs of the tourism production function to the technical efficiency. In the political view, policymakers are encouraged to be aware of the income level of their citizens to improve the performance of their tourism sector.

Introduction

The tourism industry has known an important development across the world these last decades when tourists' flows analysis cannot be neglected, particularly by economists regarding its consequences on the economic system. Since the 1960s, the world's tourism industry has experienced steady growth by representing 7% of the world trade, and that performance is expected to double the next decades in emerging countries [1]. Even though it can have heterogeneities in tourism performances across regions and countries, it's evident that the tourism industry has become an essential instrument of economic policy owing to these statistics. Pearce et al. [2] indicated the positive externalities of the tourism industry for development through its impacts on the balance of payment, regional development, income levels, government revenue, and employment opportunities. Therefore, these socio-economic impacts of the tourism industry retained the interest of scholars by analysing its performance using various indicators of performance such as attractiveness, competitiveness, efficiency. While the first indicators is widely used in management sciences, the concept of efficiency has been used in economic literature to measure producers' performance. The most common is the non-parametric data envelopment analysis (DEA) method or the parametric stochastic frontier (SF) method.

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* Corresponding author.
E-mail address: bionassib@gmail.com (N. Bassongui).

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In the tourism industry, many authors employed efficiency measures for evaluating its performance across the world. The non-parametric data envelopment analysis (DEA) approach or the parametric stochastic frontier approach are the main performance measurement methods most used in the tourism industry. The property of the DEA, which makes it possible to estimate the production frontier in situations of multiple outputs and for several inputs without the imposition of additional restrictions, explains the common use of this estimation approach in the tourism industry.

Various studies have been carried out to evaluate the efficiency of the tourism sector by using the DEA approach and its derivatives. Nevertheless, most of them are micro-level studies, i.e. they focused on hotels, travel agencies, or particular destinations, notably the parks, museums as a unit of observation [3,4]. Nonetheless, due to the tourism industry's importance in the national domestic product, estimating tourism industry efficiency at the macro-level has become prominent these last three decades [5]. Hence, recent studies evaluated the efficiency of the tourism sector at the macro-level across countries [6–8]. Despite this rich literature, less attention has been devoted to the location and income level of destinations in the measurement of tourism efficiency, except the works of Assaf and Tsionas [9] and Mitra, [10] that took into consideration the income level. Indeed, these authors showed that ignoring the quality of destinations such as the income level, the quality of human resources into the measurement of the tourism performance leads to misrank countries. In a theoretical view, Crouch and Ritchie [11]'s tourism competitiveness model supports the role of prosperity in tourism competitiveness.

Notwithstanding the value of these studies, they only focused on endogenous variables on which policies can influence and ignored exogenous variables like the location of destinations. Yet, Li et al. [12] argued that poor areas could attract more tourists than wealthy ones because of this state. Hence, we assume that destinations can be attractive not because of the infrastructure or human resources quality but rather their location in islands, mountains and hills.

The question that raises this research is to whether incorporating the location and income level of destinations improves the comparison of countries based on their tourism performance. This work aims to extend those of Assaf and Tsionas [9] and Mitra, [10] by empirically examining the role of income level and the location of destinations in explaining tourism efficiency. We use a large sample of 108 countries worldwide over the period 2008–2016. The relevance of this paper is twofold. Empirically, it contributes to the literature of tourism efficiency by considering exogenous factors like the location of destinations when measuring tourism sector efficiency. On the political side, this paper could improve international agencies' results when ranking countries based on their tourism performance.

The rest of the paper is organized as follows. Section 2 presents a synthetic literature review. We present data and the methodology of the measurement of the technical efficiency in Section3. We present and discuss empirical results in Section 4. Finally, we end up the article with a conclusion followed by some implications.

Literature overview

The literature on the measurement of the technical efficiency of the tourism sector followed the methodological framework of the efficiency literature. Indeed, these studies used both the non-parametric DEA approach and the SFA framework to estimate the tourism sector the efficiency. Thus, these studies can be organised into two groups based on whether they considered the location and the income level of destinations as drivers of tourism efficiency or as inputs of the tourism production function. Indeed, Crouch and Ritchie [11] developed a tourism competitiveness model and showed a strong relationship between the quality of the destination measured by prosperity and tourism competitiveness. Mangion et al. [13] developed a hedonic price model to show that the quality of infrastructure and human resources matters in the measurement of price competitiveness of the tourism sector.

The first group estimates tourism sector efficiency by using income levels to measure the quality of destinations. Thus, Assaf and Josiassen [14] estimated and ranked a comprehensive sample of 120 countries worldwide based on their tourism sector performance through the bootstrap procedure of Simar and Wilson [15]. They identified the 20 most important drivers of tourism performance and highlighted the positive effect of gross domestic product per capita on tourism efficiency.Hadad et al. [16] applied data envelopment analysis and super efficiency method to rank 105 countries across the world including 34 developed countries and 71 developing countries based on their tourism sector efficiency. Their results showed that labour productivity is strongly correlated to countries tourism' efficiency in both developed and developing countries. Recently, Radovanov et al. [6] used output-orientated data envelopment analysis to evaluate the performance of 27 European and 5 Western Balkan countries during the period 2011–2017. They concluded that the income level and the quality of government services are correlated to tourism efficiency. Haibo et al. [7] also investigated the nexus between tourism sector efficiency and pollution issues by using data from 30 Chinese provinces over 2002–2016. Through a joint methodology encompassing the super-efficiency DEA model and the grey entropy weighted method, they showed significant differences in tourism efficiency between pollutant and non-pollutant provinces.

The second group of studies argues that the quality of destinations is an important driver of tourism efficiency on the one hand and as an input of the tourism production function. In this line, Assaf and Tsionas [9] measured and ranked the tourism industry performance of 101 destinations. The authors incorporated the quality of destinations directly into the frontier technology From the Bayesian stochastic frontier model. Their results showed that the quality of destinations significantly affects the efficiency scores. Recently, through a study across 170 countries based on a multi-output, multi-input DEA approach, Mitra [10] estimated tourism efficiency by incorporating the GDP per capita amongst the inputs used. They revealed that the ranking of countries based on the efficiency scores estimated shifted when ignoring the level of GDP.

Overall, the state of the literature shows that the income level of destinations are essential drivers of the tourism sector performance and can be incorporated as an input in the tourism production function. However, less attention has been devoted to the location of the destination as drivers or inputs of the tourism performance. This works attempts to fill this literature gap.

Methodology

The following section presents the different approaches to calculating the effectiveness and details the methodology used for this study.

Concept model

The property of the DEA, which makes it possible to estimate the production frontier in multi-output situations and for several inputs without the imposition of additional restrictions, reflects a more realistic representation of the tourism industry. However, this DEA approach does not consider any random variations that could influence the efficiency of a DMU, and the frontier estimated by this approach has no statistical properties. In this study, we will use the stochastic distance frontier. Introduced by Shephard [17], the distance frontier constitutes, through these different properties, a bridge between parametric and non-parametric approaches in the calculation of efficiency (possibility of modelling a multi-product technology, no constraint of heavy assumptions on the technology, not mandatory the presence of price information). Two orientations characterize the distance function [18]. The output-orientated one maximizes the optimal production from a fixed quantity of input, and the input-orientated one optimally minimises the inputs to obtain a fixed quantity of output. The output orientation is the choice in this study. Indeed, when the DMU control the inputs, the output-orientated approach is appropriate [19].

Let suppose a technology P^t of a DMU that combines the vector of inputs x where $x^t \epsilon\ R^K$ for producing the vector of output $y^t \epsilon R^M$. P^t can be formalised in Eq. (1) as follows:

$$P^t\left(x^t\right) = \left\{y^t \in \mathbb{R}^M : x^t \text{can produce } y^t\right\} \tag{1}$$

We assume that the technology satisfies the axioms presented in Färe and Primont [18], notably compactness and free disposability of inputs and outputs. The output distance function is defined on the output set $P^t(x^t)$ by Eq. (2)

$$D_0^t(x^t, y^t) = \min\left\{\theta : \left(\frac{y^t}{\theta}\right) \in P^t\left(x^t\right)\right\} \tag{2}$$

$D_0^t(x^t, y^t)$is the distance frontier DMU's output set to the efficient frontier and θ is a scalar parameter that denotes how much the output vector will be radially expanded to the feasible efficient frontier. Färe and Primont [18] assumed that $D_0^t(x^t, y^t)$is non-decreasing, positively linearly homogeneous, and convex in output y^t, and decreasing in input x^t.y is located on the outer boundary of the production possibility set if $D_0^t(x^t, y^t) = 1$.

The appropriate functional form of the distance frontier must be based on a set of properties, including flexibility, ease of computation, and the possibility of imposing homogeneity. Tovar and Martin-Cejas [20] and Assaf et al. [21] stated that the translogarithmic functional form meets these conditions. In a technology of M outputs and K inputs, the translogarithmic distance function could be represented by Eq. (3)

$$\begin{aligned} \ln D_0^t\left(x^t, y^t\right) = {} & \beta_0 + \sum_{m=1}^{M} \beta_m \ln y_{mit} + \tfrac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ & + \sum_{m=1}^{M}\sum_{k=1}^{K} \tau_{mk} \ln y_{mit} \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M} \varphi_{ym} \ln y_{mit} t + \sum_{k=1}^{K} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 \end{aligned} \tag{3}$$

Where $D_0^t(x^t, y^t)$is the output distance function, y^t is the vector of outputs, x^t is the vector of inputs, down script t indicates the time, i relates to the i^{th} DMU and $\beta, \alpha, \tau, \varphi$are the parameters to be estimated.

The homogeneity constraint implied that one of the outputs is arbitrarily chosen. If the output y_{Mit} is chosen, the following expression in Eq. (4) is obtained:

$$\begin{aligned} \ln D_0^t\left(x^t, \frac{y^t}{y_{Mit}}\right) = {} & \beta_0 + \sum_{m=1}^{M} \beta_m \ln y^*_{mit} + \tfrac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \ln y^*_{mit} \ln y^*_{nit} + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ & + \sum_{m=1}^{M-1}\sum_{k=1}^{K} \tau_{mk} \ln y^*_{mit} \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M} \varphi_{ym} \ln y^*_{mit} t + \sum_{k=1}^{K} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 \end{aligned} \tag{4}$$

After rearranging the terms of Eq. (4), we obtained the Eq. (5):

$$\begin{aligned} -\ln y_{Mit} = {} & \beta_0 + \sum_{m=1}^{M} \beta_m \ln y^*_{mit} + \tfrac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \ln y^*_{mit} \ln y^*_{nit} + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ & + \sum_{m=1}^{M-1}\sum_{k=1}^{K} \tau_{mk} \ln y^*_{mit} \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M} \varphi_{ym} \ln y^*_{mit} t + \sum_{k=1}^{K} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 - \ln D_0^t \end{aligned} \tag{5}$$

$-lnD_0^t$ is non-observable and can be interpreted as an error term. Thus, if $-lnD_0^t$ is replaced with a composed error term (u_{it}, v_{it}) where v_{it} captures the random noise and u_{it} represents the technical inefficiency, the Battese and Coelli [22] version of the traditional stochastic frontier model proposed by Aigner et al. [23] and Meeusen and Van den Broeck [24] will be obtained. Finally, Eq. (6) is obtained:

$$\begin{aligned}-\ln y_{Mit} &= \beta_0 + \sum_{m=1}^{M} \beta_m \ln y^*_{mit} + \tfrac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \ln y^*_{mit} \ln y^*_{nit} + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ &+ \sum_{m=1}^{M-1}\sum_{k=1}^{K} \tau_{mk} \ln y^*_{mit} \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M} \varphi_{ym} \ln y^*_{mit} t + \sum_{k=1}^{K} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 + u_{it} + v_{it}\end{aligned} \tag{6}$$

Where v_{it} is assumed to be independently and identically distributed as $\mathbb{N}(0, \sigma_v^2)$. The technical inefficiency u_{it} is assumed to be a non-negative random variable, independently distributed as truncations at zero of $|\ \mathbb{N}(0, \sigma_v^2)|$ [[22],[25]].

Following Battese and Coelli [22], the prediction of technical efficiency (TE) of DMU in each period is calculated as conditional expectation of $\exp(-u_{it})$ on the composed error term, ε_{it}. In case of DMU i in time period t, technical efficiency is specified in Eq. (7)

$$TE_{it} = E[(\exp(-u_{it}|\varepsilon_{it}] \tag{7}$$

where $\varepsilon_{it} = v_{it} + u_{it}$

Empirical specification

In this study, the translogarithmic function is specified with two outputs (y_1, y_2) and four inputs(x_1, x_2, x_3, x_4), where y_1, y_2 are the total number of international tourists' arrivals per year in the country and the receipts from the international tourists in current dollars US respectively. x_1, x_2, x_3, x_4 refer respectively to the index of tourist service infrastructure, the number of employees in the tourism industry, Natural resource endowment, and Cultural resources endowment. The Eq. (6) is therefore specified as follows:

$$\begin{aligned}-\ln y_{1it} &= \beta_0 + \beta_1 \ln(\tfrac{y_{2it}}{y_{1it}}) + \tfrac{1}{2}\beta_{11} \ln(\tfrac{y_{2it}}{y_{1it}}) \ln(\tfrac{y_{2it}}{y_{1it}}) + \sum_{k=1}^{K=4} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K=4}\sum_{l=1}^{K=4} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ &+ \sum_{k=1}^{K=4} \tau_{1k} \ln(\tfrac{y_{2it}}{y_{1it}}) \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M=1} \varphi_{ym} \ln(\tfrac{y_{2it}}{y_{1it}}) t + \sum_{k=1}^{K=4} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 + u_{it} + v_{it}\end{aligned} \tag{8}$$

The output was normalized by the total number of international tourists' arrivals per year(y_1). β, α, τ *and* φ are the parameters to be estimated and i stands for a country and t the period.

Taking into account heterogeneity issues

In econometric literature, ignoring the heterogeneity issue could lead to biased estimators. Especially in the efficiency models, not considering heterogeneity in DMUs technologies or the inefficiency term could lead to misleading efficiency scores in stochastic frontier models [26–28]. In the tourism sector, differences across countries in production opportunities such as access to markets may introduce heterogeneity issues [5]. Hence, as suggested by Greene [28], we took into account this issue by including a country-specific intercept in Eq. (8) which is rewritten as follows:

$$\begin{aligned}-\ln y_{1it} &= \beta_i + \beta_1 \ln(\tfrac{y_{2it}}{y_{1it}}) + \tfrac{1}{2}\beta_{11} \ln(\tfrac{y_{2it}}{y_{1it}}) \ln(\tfrac{y_{2it}}{y_{1it}}) + \sum_{k=1}^{K=4} \alpha_k \ln x_{kit} + \tfrac{1}{2}\sum_{k=1}^{K=4}\sum_{l=1}^{K=4} \alpha_{kl} \ln x_{kit} \ln x_{lit} \\ &+ \sum_{k=1}^{K=4} \tau_{1k} \ln(\tfrac{y_{2it}}{y_{1it}}) \ln x_{kit} + \varphi_1 t + \sum_{m=1}^{M=1} \varphi_{ym} \ln(\tfrac{y_{2it}}{y_{1it}}) t + \sum_{k=1}^{K=4} \varphi_{xk} \ln x_{kit} + \tfrac{1}{2}\varphi_{11} t^2 + u_{it} + v_{it}\end{aligned} \tag{9}$$

Finally, Eq. (9) is estimated by the method of maximum likelihood under the assumption of the half-normal distribution of the inefficiency term. This method consists of maximising the logarithmic of the joint probability density function as follows in Eq. (10)

$$Max\ LogL(Y, \phi) = Logf(Y, \phi) \tag{10}$$

With $L(Y, \phi)$ the likelihood function, ϕ the vector of parameters to be estimated through the data Y, and $f(.)$the density probability that is specified in Eq. (11) as follows:

$$f(Y, \phi) = \prod_{i=1}^{N} f_i(Y_i, \phi) \tag{11}$$

Data and variables description

Inputs

According to the neoclassical production theory, two inputs (capital and labour) are used to produce output [29,30]. This study used the tourist service infrastructure index of the Travel & Tourism Competitiveness Reports [31] to measure tourism

Table 1
Descriptive statistics.

Variable	Nature	Obs	Mean	Std. Dev.	Min	Max
Number of arrivals	Output	544	8,921,749.3	14,714,243	106,000	86,861,000
Tourism receipts	Output	549	1.053e + 10	2.372e + 10	1,700,000	2.514e + 11
Labour	Input	548	818.906	2864.401	4	25,734
Capital	Input	554	4.043	1.562	1	7
Natural resources	Input	554	4.202	16.326	1.673	387
Cultural resources	Input	554	2.823	1.584	1	6.944
Technical efficiency	Input	531	0.812	0.231	0.004	0.976

capital. This index encompasses four indicators: the Hotel rooms per 100 pop, the extension of recommended business trips, the presence of major car rental companies, and the ATMs accepting Visa cards per million pop. The choice of this index is in line with the study of Assaf and Tsionas [9], which considers the quality as part of the estimation of tourism performance. Labour is measured by the number of employees in the tourism industry [16].

Furthermore, when measuring tourism sector efficiency at the macro-level, other variables than labour and capital matter. Thus, we also use countries' cultural and natural resource endowments as complementary inputs apart from labour and capital,. The idea is that the more the country's endowment in terms of natural and cultural resources is, the more is the comparative advantage of that country to attract more international tourists. Some authors have confirmed this hypothesis worldwide [16,32,33]. Natural and cultural resource endowments are measured using a composite index obtained from the Travel & Tourism Competitiveness Reports [31].

The natural resources index includes the number of attractiveness measures i.e. the number of UNESCO natural World Heritage sites, the quality of the natural environment which proxies the beauty of its landscape, the richness of the fauna in the country as measured by the total known species of animals, and the percentage of nationally protected areas.

Various indicators are used for calculating the composite index of cultural resources such as the number of UNESCO cultural World Heritage sites, the number of large stadiums that can host significant sport or entertainment events, and a new measure of digital demand for cultural and entertainment the number of online searches related to a country's cultural resources can allow the level of interest to be inferred. The number of international association meetings taking place in a country is included to capture, at least partially, business travel.

Both natural and cultural resources indices are ranged from 1 to 7. Details on the methodology used to calculate these indices can be found in Travel & Tourism Competitiveness Report [31].

All the input data are available biannually and were taken from the Travel & Tourism Competitiveness Reports [31]. Overall, we used four variables as inputs: capital, labour, natural resources, and cultural resources.

Outputs

Following Radovanov et al. [6], Haibo et al. [7] and Soysal-Kurt [8], we use two tourism outputs, i.e. output in volume and tourism output in value. The tourism output in volume is measured by the total number of international tourists' arrivals per year in the country. The tourism output in value is measured by the receipts from the international tourists in current dollars US.

Data on the total number of international tourist arrivals and the receipts from the international tourists are taken from the world development indicator (WDI) database 2021. Regarding the input space is biannually, then we used the two years mean of each output.

Sampling

This study used country-level secondary data from a sample of 111 countries worldwide from 2008 to 2016. We used biannual data since input data are not available yearly. This sample includes both developed and developing countries. The choice of the period of the analysis and the including criteria of countries in the sample is based on the availability of data. Then, unbalanced panel data are used within a framework of an output distance function. The countries' list included in the sample is presented in Table A1 in the appendix.

Empirical results

This section presents the descriptive statistics and the estimation of the technical efficiency scores.

Univariate analysis

We present in Table 1 the results of descriptive statistics of all variables used in the estimations. The results indicate that some variables have high standard deviation values, such as the number of arrivals, the tourism receipts, the labour, and the natural resource endowments, implying heterogeneity within the sample in these variables. Such a result could be explained by the fact that our sample is composed of both developed and developing countries that are naturally characterized by a significant difference in income levels.

Table 2
Translog output distance parameters.

-Log(Number of Arrivals)	Coef.	Std.Err.	P>z	Significance
Receipts/Arrivals	0.665	0.097	0.000	***
(Receipts/Arrivals)^2	0.213	0.054	0.000	***
Capital	-1.138	0.374	0.002	***
Labour	-0.611	0.072	0.000	***
NaturalR	-0.163	0.273	0.550	
CulturalR	-0.661	0.272	0.015	***
Capital^2	2.008	0.741	0.007	***
Labour^2	-0.104	0.034	0.002	***
NaturalR^2	0.263	0.244	0.282	
CulturalR^2	-0.598	0.476	0.209	
Capital*Labour	-0.895	0.271	0.001	***
Capital*NaturalR	-0.511	1.006	0.611	
Capital*CulturalR	0.840	0.999	0.400	
Labour*NaturalR	0.191	0.207	0.356	
Labour*CalturalR	0.511	0.233	0.028	**
NaturalR*CalturalR	0.707	0.687	0.303	
Capital*(Receipts/Arrivals)	-0.178	0.168	0.291	
Labour*(Receipts/Arrivals)	0.055	0.032	0.086	*
NaturalR*(Receipts/Arrivals)	-0.285	0.131	0.030	**
CulturalR*(Receipts/Arrivals)	0.101	0.138	0.463	
Time	0.136	0.119	0.255	
Time^2	-0.044	0.038	0.257	
Time*Capital	-0.494	0.136	0.000	***
Time*Labour	0.049	0.027	0.068	**
Time*NaturalR	0.255	0.090	0.005	***
Time*CulturalR	-0.049	0.090	0.586	
Time*(Receipts/Arrivals)	-0.017	0.032	0.589	
Constant	-0.066	0.186	0.723	
Usigma (Constant)	-1.540	0.411	0.000	***
Vsigma(Constant)	-1.371	0.083	0.000	***
sigma_u	0.463	0.095	0.000	***
sigma_v	0.504	0.021	0.000	***
Gamma	0.458	0.107	0.000	***

Note: (*), (**), (***) indicate significance at 10%, 5% and 1% level.

Distance function parameters

We may wonder whether the inefficiency model is necessary for this study. Indeed, the translog output distance estimation results indicate that the Gamma coefficient is significantly different from zero at a 1% level (Gamma=0.458). Therefore, countries' tourism sector operates inefficiently, suggesting the efficiency modelling is the suitable one. To check of the translog specification's fitness, the generalised Likelihood Ratio (LR) test was run. The results of this test reported in Table A2 in the appendix strongly rejected at 1% level the null hypothesis of Cobb-Douglass specification. The translog output distance estimation results also indicate the first-order coefficients of all inputs are negative and that of the output is positive, confirming the validity of the output distance function. Indeed, the monotonicity requirements compel that the output distance function is assumed to be non-increasing in inputs, and non-decreasing in outputs. In sum, the translog output elasticities can be interpreted.

The results of the translog output distance function estimated through the maximum likelihood method are presented in Table 2. Before estimating our model, all variables were normalised at the sample geometric mean and taken at logarithmic. Hence, the first-order coefficients can be directly interpreted as elasticity.

We notice that apart from the coefficient of natural resources, all the inputs' coefficients are negative and statistically significant, indicating that these inputs contribute to the increase in tourism sector output in the sample. Indeed, the capital is the most important input, contributing for 1.24 followed by cultural resources and labour. An increase in tourist service infrastructure (capital) by 10% improves the number of international tourist arrivals by 12.38%. Similarly, we estimated a scale elasticity of 2.57, suggesting the presence of significant scale economies in the tourism industry. Hence, a 1% increase in tourism inputs improves tourism output by 2.57% ceteris paribus.

Countries' tourism technical efficiency

The results of the output distance function estimated an average technical efficiency of about 0.812 in the sample (Table 1). This result indicates that countries can improve their tourism sector output by 19% without increasing the level of inputs used. Our findings confirm previous studies that found countries' tourism sector operates inefficiently [9,14,16].

Table 3
Efficiency by income levels and regions.

Income Groups	Efficiency	Rank	Region Groups	Efficiency	Rank
Low	0.626	3	Africa	0.682	4
Middle	0.828	2	America	0.865	2
High	0.924	1	Asia	0.757	3
-	-	-	Europe	0.911	1

Table 4.
Input productivities by regions.

Region	K	Rank	L	Rank	NR	Rank	CR	Rank
Africa	728,332.74	4	15,467.387	4	699,163.55	4	1,079,826.5	4
America	1,546,357	2	17,636.567	3	1,625,982.1	3	1,994,171.9	3
Asia	2,507,772	3	42,212.684	2	2,328,681.7	2	2,773,843.8	2
Europe	2,574,294.5	1	72,110.676	1	3,802,542	1	3,288,151	1

Note: K= capital; L=labour; NR=natural resources; CR=cultural resources

From the results of the translog output distance function results, we ranked countries based only on their tourism sector's technical efficiency scores. The results presented in Table A1 in the appendix indicate that the best top 10 efficient countries are Georgia, Malta, Cyprus, Iceland, Mauritius, Portugal, Qatar, Romania, Greece, and Bulgaria. In comparison, the least top 10 efficient countries are Malawi, Cambodia, Vietnam, Zambia, Indonesia, Kyrgyz Rep, Nepal, China, Tanzania, and Ethiopia However, the average technical efficiency score hides significant heterogeneities across countries when the technical efficiency score ranges from 24.7% to 96.6%. Many drivers could explain the ranking of these countries, such as their inputs productivity, their level of development, or their geographical location.

For instance, some studies proved that countries' tourism sector efficiency is driven by their inputs productivity [16,34]. Using a sample of 34 developed and 71 developing countries within a DEA framework, Hadad et al. [16] showed that the more is labour productivity, the greater is countries' tourism sector efficiency in both developing and developed countries. Barros [34] found the same results using micro-level data. Other authors also showed that the income level gives a better explanation of countries' tourism sector efficiency disparities [14].

Tourism efficiency, level of development, and inputs' productivity

We recall that one of the main objectives of this study is to investigate the role of countries' level of development in explaining of countries' tourism sector efficiency. To that end, we grouped our sample into three sub-samples according to countries' income levels. We used the classification of the World Bank data to split the sample into low-income (Low), Middle income (Middle), and High-income countries when the country's income per capita is higher (High). Countries included in each group of income-level are presented in Table A3.

Results of the average technical efficiency in each group are presented in Table 3. We then run the Kruskal-Wallis equality-of-populations rank nonparametric test for comparing the average technical efficiencies across the 3 sub-samples. Results of this test (Table A2) strongly rejected at 1% level of significance the null hypothesis that countries' tourism sector efficiency varies with the level of income. Moreover, the Mann-Whitney test confirmed that the higher is the level of income, the greater is the tourism sector efficiency. To get some drivers of these results, we compared input productivity in these three groups of countries. Input productivity is defined as the inverse of the input intensity, i.e. the output produced by using one unit of an input, ceteris paribus. For instance, labour productivity is the ratio between the outputs quantities (number of international tourists) over labour used. Between two countries, the best use of an input is the one that input productivity is higher. Then the average input productivities for each sub-samples are presented in Table 4. As we can see from this Table 4, the ranking of the three groups of countries based on their technical efficiency scores does not change from that based on their input productivities, apart from capital productivity. Then, these results imply that the group of high-income countries are more efficient than their pairs of low-income countries because they have better labour productivity, natural resources productivity, and cultural resource endowments' productivity.

Tourism efficiency, countries' location, and inputs' productivity

Another objective of this study is to know whether or not there are differences in countries' efficiency across regions or income levels. This concern raises because of the features of the inputs used in the tourism production function. Indeed, one could think that as there are disparities in natural and cultural resources' endowments across regions, it's so reasonable to assume these disparities could lead to different levels of tourism sector efficiency across regions.

To test the relationship between tourism sector efficiency and countries' geo-localisation, the sample has been split into four sub-geographical samples: Africa, America, Asia, and Europe. The list of countries included in each group is presented in Table A3 in the appendix. Then, the average technical efficiencies of the tourism sector were calculated for each geographical

Table 5
Input productivities by income-levels.

Group	K	Rank	L	Rank	NR	Rank	CR	Rank
Low	938,849.27	3	13,500.597	3	754,656.77	3	1,140,389.7	3
Middle	2,572,621.3	1	30,923.837	2	2,386,745.2	2	2,874,416.4	2
High	2,241,641.4	2	66,260.467	1	3,321,925.4	1	2,989,640.4	1

Note: K= capital; L=labour; NR=natural resources; CR=cultural resources

sub-sample (Table 3). Results of the Krustman ranking test rejected the null hypothesis of no difference in technical efficiency across regions. The ranking shows that Europe and America are the two best efficient regions while Africa and Asia are at the bottom of the ranking. After that, we calculated the input productivity in each region. Results in Table 5 revealed that the disparities in tourism sector efficiency across regions are based on the disparities in regions' capital productivity. Especially, our results highlighted that European and American regions have the highest technical efficiency scores because they have the highest capital productivities. Otherwise, the African countries are the least efficient in the tourism sector because they have the lowest capital productivities. One explanation of this result could be that the level of infrastructure is low in Africa and Asia. Moreover, many authors confirmed that the low institutional quality plays a core role in the growth of productivity, especially in the African region that is characterised by a low institutional quality [35,36].

Conclusion

This study investigated countries' tourism sector efficiency. Using a sample of 111 countries worldwide over the period 2008–2016, we applied the distance function approach to estimate countries' technical efficiency scores. Then, we showed significant differences in the tourism sector performance across the groups of income-level. Especially, our results revealed that the more income-level is, the greater is the countries' tourism sector efficiency. Besides, we concluded that high-income countries are more efficient because they have higher qualified labour and a higher level of natural and cultural resources productivities. Hence, our findings support that African and Asian countries are less efficient than Europe and America because the latter has better capital productivity. The practical implication of this study is that future studies should be aware of incorporating of the income level and the location of destinations as determinants and inputs of the tourism production function in the measurement of the tourism sector efficiency. As policy implications, this study suggests low-income countries need to improve their labour, natural, and cultural resources management while countries from Africa and Asia increase their capital productivity for improving their tourism sector efficiencies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

Table A1
Countries 'ranking by efficiency.

Country	Efficiency	Rank	Country	Efficiency	Rank	Country	Efficiency	Rank
Georgia	0.9659	1	Thailand	0.9226	38	Albania	0.8614	75
Malta	0.9579	2	Jamaica	0.9223	39	Armenia	0.8462	76
Cyprus	0.9557	3	Netherlands	0.9207	40	Philippines	0.7987	77
Iceland	0.9528	4	Oman	0.9203	41	Botswana	0.7908	78
Mauritius	0.9506	5	United States	0.9182	42	Guatemala	0.7799	79
Portugal	0.9491	6	Chile	0.9182	43	Paraguay	0.7741	80
Qatar	0.9489	7	Morocco	0.9176	44	Austria	0.752	81
Romania	0.9487	8	Germany	0.9175	45	Malaysia	0.7457	82
Greece	0.9479	9	France	0.9161	46	Gambia. The	0.7434	83
Bulgaria	0.9469	10	Argentina	0.9151	47	Mali	0.7416	84
Croatia	0.9451	11	Sweden	0.9151	48	Azerbaijan	0.7387	85
Estonia	0.9442	12	United Kingdom	0.9151	49	Senegal	0.7381	86
Slovenia	0.9421	13	Jordan	0.9148	50	Nigeria	0.7154	87
Ireland	0.9418	14	Luxembourg	0.9141	51	Ghana	0.693	88
Italy	0.9412	15	Saudi Arabia	0.9125	52	Pakistan	0.6919	89
Hungary	0.9411	16	Singapore	0.9123	53	Cote d'Ivoire	0.6794	90
Serbia	0.9397	17	Kazakhstan	0.9088	54	Sri Lanka	0.6654	91
Montenegro	0.9391	18	Japan	0.9074	55	Bolivia	0.6509	92
Latvia	0.9383	19	Australia	0.9048	56	Burundi	0.6428	93
Tunisia	0.9363	20	Turkey	0.9024	57	Colombia	0.633	94
Czech Republic	0.9361	21	El Salvador	0.9023	58	Algeria	0.5945	95
Norway	0.935	22	Korea. Rep.	0.9017	59	Kenya	0.5605	96
Switzerland	0.9336	23	Panama	0.8966	60	Cameroon	0.5274	97
Trinidad and Toba	0.9319	24	Uruguay	0.8948	61	India	0.5205	98
Spain	0.9311	25	South Africa	0.8919	62	Zimbabwe	0.5145	99
Denmark	0.9299	26	Poland	0.8897	63	Bangladesh	0.5012	100
Kuwait	0.9286	27	Mexico	0.8891	64	Uganda	0.4871	101
Belgium	0.9262	28	Brazil	0.8859	65	Malawi	0.481	102
Costa Rica	0.925	29	Russian Fede	0.8827	66	Cambodia	0.4192	103
Lithuania	0.9248	30	Nicaragua	0.8773	67	Vietnam	0.3921	104
Slovak Republic	0.9247	31	Lesotho	0.8765	68	Zambia	0.3892	105
Dominica	0.9247	32	Mozambique	0.8732	69	Indonesia	0.3525	106
New Zealand	0.9243	33	Egypt	0.8722	70	Kyrgyz Rep	0.339	107
Canada	0.9242	34	Namibia	0.8709	71	Nepal	0.3069	108
Israel	0.9239	35	Venezuela. RB	0.8691	72	China	0.3045	109
Finland	0.9238	36	Madagascar	0.8657	73	Tanzania	0.2509	110
Bahrain	0.9232	37	Peru	0.8616	74	Ethiopia	0.2474	111

Table A2
Hypothesis tests.

Alternative Hypothesis (Ha)	Test	Statistics	*p*-value	Decision
Translog specification is better than the Cobb-Douglas one.	LR test for functional form	60.831	0.000	Ho* rejected
The average efficiency scores are different across the three groups Low, Middle, and High.	Kruskal-Wallis equality- rank test	170.020	0.000	Ho rejected
The average efficiency from the group "High" is greater than that from the group "Low".	Mann Whitney test	4369	0.000	Ho rejected
The average efficiency scores are different across the four regions (Africa, America, Asia, and Europe).	Kruskal-Wallis equality- rank test	102.383	0.000	Ho rejected
The average efficiency from the European region is greater than that from the African one.	Mann Whitney test	3721	0.000	Ho rejected

* H0 is the null hypothesis

Table A3
Samples by income levels and regions.

Groups by Income-level			Groups by geo-localisation			
LOW	MIDDLE	HIGH	AFRICA	AMERICA	ASIA	EUROPE
Algeria	Albania	Australia	Algeria	Argentina	Armenia	Albania
Bangladesh	Argentina	Austria	Botswana	Bolivia	Australia	Austria
Bolivia	Armenia	Bahrain	Burundi	Brazil	Azerbaijan	Belgium
Burundi	Azerbaijan	Belgium	Cameroon	Canada	Bahrain	Bulgaria
Cambodia	Botswana	Canada	Cote d'Ivoire	Chile	Bangladesh	Croatia
Cameroon	Brazil	Chile	Egypt	Colombia	Cambodia	Cyprus
Cote d'Ivoire	Bulgaria	Croatia	Ethiopia	Costa Rica	China	Czech Rep
Egypt	China	Cyprus	Gambia, The	Dominican R	Georgia	Denmark
El Salvador	Colombia	Czech Rep	Ghana	El Salvador	India	Estonia
Ethiopia	Costa Rica	Denmark	Kenya	Guatemala	Indonesia	Finland
Gambia, The	Dominican R	Estonia	Lesotho	Jamaica	Israel	France
Ghana	Georgia	Finland	Madagascar	Mexico	Japan	Germany
India	Guatemala	France	Malawi	Nicaragua	Jordan	Greece
Kenya	Indonesia	Germany	Mali	Panama	Kazakhstan	Hungary
Kyrgyz Rep	Jamaica	Greece	Mauritius	Paraguay	Korea, Rep,	Iceland
Lesotho	Jordan	Hungary	Morocco	Peru	Kuwait	Ireland
Madagascar	Kazakhstan	Iceland	Mozambique	Trinidad&Tob	Malaysia	Italy
Malawi	Malaysia	Ireland	Namibia	United States	Malta	Kyrgyz Rep
Mali	Mexico	Israel	Nigeria	Uruguay	Nepal	Latvia
Morocco	Montenegro	Italy	Senegal	Venezuela	New Zealan	Lithuania
Mozambique	Namibia	Japan	South Africa		Oman	Luxembourg
Nepal	Paraguay	Korea, Rep,	Tanzania		Pakistan	Montenegro
Nicaragua	Peru	Kuwait	Tunisia		Philippines	Netherlands
Nigeria	Russia	Latvia	Uganda		Qatar	Norway
Pakistan	Serbia	Lithuania	Zambia		Saudi Arabia	Poland
Philippines	SouthAfrica	Luxembourg	Zimbabwe		Singapore	Portugal
Senegal	Thailand	Malta			Sri Lanka	Romania
Sri Lanka	Turkey	Mauritius			Thailand	Russia
Tanzania	Venezuela	Netherlands			Vietnam	Serbia
Tunisia		New Zealand				Slovak Rp
Uganda		Norway				Slovenia
Vietnam		Oman				Spain
Zambia		Panama				Sweden
Zimbabwe		Poland				Switzerland
		Portugal				Turkey
		Qatar				UK
		Romania				
		Saudi Arabia				
		Singapore				
		Slovak Rep				
		Slovenia				
		Spain				
		Sweden				
		Switzerland				
		Trinidad&Tob				
		UK				
		USA				
		Uruguay				
34	**29**	**48**	**26**	**20**	**29**	**36**

Note: Numbers in bold indicate the number of countries in the sub-sample.

CRediT authorship contribution statement

Alastaire Sèna Alinsato: Conceptualization, Writing – review & editing, Supervision. **Nassibou Bassongui:** Data curation, Methodology, Software, Writing – review & editing. **Franck Nkeudjoua Wondeu:** Data curation, Methodology, Software, Writing – review & editing.

References

[1] OECD, Megatrends shaping the future of tourismOECD Tourism Trends and Policies 2018, OECD Publishing, Paris, 2018, doi:10.1787/tour-2018-6-en.
[2] P.L. Pearce, G. Moscardo, G.F. Ross, Tourism impact and community perception: an equity-social representational perspective, Aust. Psychol. 26 (3) (1991) 147–152, doi:10.1080/00050069108257240.
[3] Hwang, T.Y. Chang, Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan, Tour. Manag. 24 (4) (2003) 357, doi:10.1016/S0261-5177(02)00112-7.
[4] A.S. Shahraki, A. Keshtegar, Determining the efficiency of economic tourism industry in Chabahar free zone by using data envelopment analysis (DEA) method, Iran. Econ. Rev. 23 (4) (2019), doi:10.22059/ier.2019.73001.
[5] A.G. Assaf, L. Dwyer, Benchmarking international tourism destinations, Tour. Econ. 19 (6) (2013) 1233–1247, doi:10.5367/te.2013.0354.
[6] B. Radovanov, B. Dudic, M. Gregus, A.M. Horvat, V. Karovic, Using a two-stage DEA model to measure tourism potentials of EU countries and Western Balkan countries: an approach to sustainable development, Sustainability 12 (12) (2020) 4903, doi:10.3390/SU12124903.
[7] C. Haibo, D. Ke, W. Fangfang, E.C. Ayamba, The spatial effect of tourism economic development on regional ecological efficiency, Environ. Scie. Pollut. Res. (2020), doi:10.1007/s11356-020-09004-8.
[8] H. Soysal-Kurt, Measuring tourism efficiency of european countries by using data envelopment analysis, Eur. Sci. J. 13 (10) (2017) 31, doi:10.19044/esj.2017.v13n10p31.
[9] A.G. Assaf, E.G. Tsionas, Incorporating destination quality into the measurement of tourism performance: a Bayesian approach, Tour. Manag. 49 (2015) 58–71, doi:10.1016/j.tourman.2015.02.003.
[10] S.K. Mitra, A different perspective to measure tourism attractiveness, Curr. Issues Tour. 23 (14) (2020), doi:10.1080/13683500.2019.1656711.
[11] G.I. Crouch, J.R.B. Ritchie, Tourism, competitiveness, and societal prosperity, J. Bus. Res. 44 (3) (1999), doi:10.1016/S0148-2963(97)00196-3.
[12] Y. Li, R. Li, W. Ruan, C.H. Liu, Research of the effect of tourism economic contact on the efficiency of the tourism industry, Sustainability (Switzerland) 12 (14) (2020), doi:10.3390/su12145652.
[13] M.L. Mangion, R. Durbarry, M.T. Sinclair, Tourism competitiveness: price and quality, Tour. Econ. 11 (1) (2005), doi:10.5367/0000000053297202.
[14] A.G. Assaf, A. Josiassen, Identifying and ranking the determinants of tourism performance: a global investigation, J. Travel Res. 51 (4) (2012) 388–399, doi:10.1177/0047287511426337.
[15] L. Simar, P.W. Wilson, Estimation and inference in two-stage, semi-parametric models of production processes, J. Econom. 136 (1) (2007) 31–64, doi:10.1016/j.jeconom.2005.07.009.
[16] S. Hadad, Y. Hadad, M. Malul, M. Rosenboim, The economic efficiency of the tourism industry: a global comparison, Tour. Econ. 18 (5) (2012) 931–940, doi:10.5367/te.2012.0165.
[17] R.W. Shephard, Theory of Cost and Production Functions, Princeton University Press, Princeton, 1970 https://www.jstor.org/stable/j.ctt13x11vf.
[18] R. Färe, D. Primont, Multi-Output Production and Duality: Theory and Applications, Kluwer Academic Publishers, Boston, 1995.
[19] S.C. Kumbhakar, L. Orea, A. Rodríguez-Álvarez, E.G. Tsionas, Do we estimate an input or an output distance function? An application of the mixture approach to European railways, J. Prod. Anal. 27 (2) (2007) 87–100, doi:10.1007/s11123-006-0031-5.
[20] B. Tovar, R.R. Martín-Cejas, Technical efficiency and productivity changes in Spanish airports: a parametric distance functions approach, Transp. Res. Part E Logist. Transp. Rev. 46 (2) (2010) 249–260, doi:10.1016/j.tre.2009.08.007.
[21] A.G. Assaf, S.E. Atkinson, M.G. Tsionas, Endogeneity in multiple output production: evidence from the US hotel industry, Tour. Manag. 80 (2020) 104–124.
[22] G.E. Battese, T.J. Coelli, A model for technical inefficiency effects in a stochastic frontier production function for panel data, Empir. Econ. 20 (2) (1995), doi:10.1007/BF01205442.
[23] D.J. Aigner, C.A.K. Lovell, P. Schmidt, Formulation and estimation of stochastic frontier function models, J. Econom. 6 (1) (1977) 21–37, doi:10.1016/0304-4076.
[24] W. Meeusen, J. Van den Broeck, Efficiency estimation from cobb-douglas production functions with composed error, Int. Econ. Rev. 18 (2) (1977) 435–444, doi:10.2307/2525757.
[25] S.C. Kumbhakar, C.A.K. Lovell, Stochastic Frontier analysis: An Econometric Approach, Cambridge university press, Cambridge, 2000.
[26] J.W.B. Bos, H. Schmiedel, Is there a single frontier in a single European banking market? J. Bank. Finance 31 (7) (2007) 2081–2102, doi:10.1016/j.jbankfin.2006.12.004.
[27] S. Caiazza, A.F. Pozzolo, G. Trovato, Bank efficiency measures, M&A decision and heterogeneity, J. Prod. Anal. 46 (1) (2016), doi:10.1007/s11123-016-0470-6.
[28] W. Greene, Fixed and random effects in stochastic frontier models, J. Prod. Anal. 23 (1) (2005) 7–32, doi:10.1007/s11123-004-8545-1.
[29] P. Douglas, C. Cobb, A theory of production, Am. Econ. Rev. 18 (1928) 139–165 https://www.aeaweb.org/aer/top20/18.1.139-165.pdf.
[30] R.M. Solow, A contribution to the theory of economic growth, Q. J. Econ. 70 (1) (1956) 65–94.
[31] Forum. World Economic, Travel and Tourism Competitiveness Report 2017 - Reports -, World Economic Forum. In Denmark:Travel & Tourism Competitiveness Index, 2017.
[32] J. Priskin, Assessment of natural resources for nature-based tourism: the case of the central coast region of Western Australia, Tour. Manag. 22 (6) (2001) 637–648, doi:10.1016/S0261-5177(01)00039-5.
[33] T. Silberberg, Cultural tourism and business opportunities for museums and heritage sites, Tour. Manag. 16 (5) (1995) 361–365.
[34] C.P. Barros, Measuring efficiency in the hotel sector, Ann. Tour. Res. 32 (2005) 456–477.
[35] O. Rasmané, S. Relwendé, S. Hamidou, Private and public investment in sub-Saharan Africa: the role of instability risks, Econ. Syst. (2020) 100787, doi:10.1016/j.ecosys.2020.100787.
[36] H.S. Houngbedji, N. Bassongui, Investissement public et investissement privé en Afrique Subsaharienne: rôle de la qualité institutionnelle, Afr. Dev. Rev. (2021), doi:10.1111/1467-8268.12589.