

Modelling International Tourism Efficiency in China

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Abstract Efficient cross-border tourism flows are a critical dimension of a country's economic integration into the global economy. This paper introduces an innovative application of the stochastic frontier gravity model (SFGM) to analyze and measure international tourism efficiency. By integrating natural determinants (e.g., geographical distance, economic size, and price indices) with man-made factors (e.g., social, political, economic, and policy preferences), the study provides a comprehensive framework for assessing tourism efficiency relative to theoretical gravity frontier levels. The findings reveal that, while China has achieved approximately 80% of its tourism potential on average, significant inefficiencies persist, particularly across different origin countries and regions. The study highlights the complementary relationship between human and goods flows, emphasizing the importance of cultural proximity and trade intensity in reducing inefficiencies. Furthermore, it demonstrates the robustness of the SFGM framework in capturing the dynamic and uneven patterns of tourism efficiency over time. By addressing gaps in the application of SFGM to tourism research, this paper advances the theoretical and methodological understanding of tourism efficiency and provides actionable policy recommendations for enhancing China's tourism market integration.

Keywords stochastic frontier gravity model; tourism efficiency

Received October 8, 2024, accepted April 18, 2025

Supported by National Natural Science Foundation of China (71988101, 71971007)

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1 Introduction

Tourism, as a vital component of both national and global socio-economic systems, plays a crucial role in economic and social development. Onetiu and Predonu^[1] argued that tourism activities, by utilizing available resources, generated not only economic benefits, such as increased net income and tourism revenue, but also social benefits. An efficient tourism industry is expected to attract more tourists, serving as a key driver of economic growth and enhancing the competitiveness of a country's tourism sector by maintaining or expanding its international market share^[2]. Consequently, measuring tourism efficiency and productivity provides essential statistical insights that inform both micro-level strategies and macro-level policy formulation.

Since initiating its policy of openness to the outside world in 1978, China has implemented a series of effective economic reforms and policies aimed at removing country-specific social, political, and institutional constraints that hinder cross-border flows of capital, goods, and people^[3,4]. Among these, international tourism flows represent a key dimension of China's economic integration into the global economy. With the deepening and expansion of regional and global cooperation^[5–8], China's international tourism has grown significantly. Visitor arrivals to China increased from 1.81 million in 1978 to 145.31 million in 2019, representing an 80-fold increase. This raises an important question: Has China, as one of the most liberalized economies, fully realized the potential and efficiency of its international tourism flows with its major tourist origin countries? Furthermore, it is crucial for every country to understand its full tourism potential and efficiency levels with other nations and specific regions.

Tourism liberalization policies are crucial to the development of a country's tourism industry. As part of its economic opening-up process, China has implemented a range of tourism liberalization measures to promote international tourism. Notably, since the early 1990s, the Chinese government has adopted a selective and incremental approach to liberalizing outbound travel^[5]. By the end of 2015, 121 countries had been designated as approved destinations for Chinese citizens traveling for leisure under the approved destination status (ADS) program.

These initiatives raise several important questions: To what extent have these policies enhanced China's international tourism potential and efficiency? In which geo-preferential groups has China achieved relatively greater success in realizing its tourism potential? For Chinese policymakers, understanding the determinants of tourism efficiency and potential is essential for evaluating the prospects and scope for future growth in tourism flows from different countries to China. However, these remain empirical questions that require rigorous measurement and testing. This study aims to contribute to this line of research.

The paper makes significant contributions to the study of tourism efficiency, with a specific focus on China's international tourism flows. Firstly, it extends the application of the stochastic frontier gravity model (SFGM) to tourism research, advancing the theoretical understanding of efficiency measurement in the industry. By demonstrating the relevance of production frontier concepts to cross-border tourism flows, the study bridges gaps between economic theory and tourism research. Furthermore, the paper enhances the SFGM framework by incorporating

time-variant, country-specific efficiency measures, enabling a more dynamic analysis of tourism performance over time.

Secondly, using panel data from 21 origin countries spanning 1995–2019, the study offers a comprehensive empirical evaluation of China's inbound tourism efficiency. It estimates country-specific and regional efficiency scores, shedding light on the uneven distribution of tourism efficiency across countries and regions. The analysis identifies key inefficiency drivers, distinguishing between natural factors (e.g., geographical distance, economic size, and price indices) and man-made factors (e.g., social, political, economic, and policy preferences). This dual perspective provides a holistic understanding of the determinants of tourism flows.

For China's international tourism, the findings emphasize the critical role of man-made factors such as cultural proximity, trade intensity, and policy measures like the approved destination status (ADS) program. These factors are shown to significantly reduce inefficiencies and uncertainties in tourism flows. Strengthening social, political, economic, and cultural ties with origin countries emerges as a key strategy for enhancing tourism performance. The paper also offers evidence-based recommendations for improving China's integration into the global tourism market.

Overall, the study contributes to both theoretical and practical knowledge, providing a robust framework for analyzing and enhancing international tourism flows, with particular emphasis on China's role in the global tourism economy. The structure of this paper is as follows: Section 2 provides a brief review of relevant literature. Section 3 outlines the specification and application of the stochastic frontier approach to gravity modeling, detailing the explanatory variables used to estimate tourism potential and efficiency at the macro level. Section 4 presents the estimation results, including the computation and ranking of tourism efficiencies across countries, geographical regions, and time periods. Finally, Section 5 offers conclusions and policy recommendations for improving tourism efficiency.

2 Literature Review

Efficiency is a critical concept in both economic and social development. Originally introduced by Farrell^[9] in the context of technical efficiency in production, the concept has since been extended to encompass managerial, financial, and market efficiency at the micro level (e.g., for individuals, firms, and institutions) and economic and social efficiency at the macro level (e.g., for specific industries, nations, or global comparisons)^[10]. In empirical studies, two principal approaches—data envelopment analysis (DEA) and stochastic frontier analysis (SFA)—have been widely applied to operationalize Farrell's efficiency concept by constructing production frontiers and calculating efficiency scores relative to these frontiers^[11,12]. These approaches define efficiency as the deviation of an observed indicator from an estimated frontier function, which represents the maximum output that could potentially be achieved given a specific level of inputs^[13]. The frontier estimation serves as a benchmark, representing best practices that lead to superior efficiency or performance within the sample^[14].

The measurement of tourism efficiency has recently emerged as an important area of research within tourism studies. Several recent studies have provided comprehensive literature reviews on efficiency and performance in the tourism industry^[15–17]. According to these reviews, the assessment and measurement of efficiency have primarily focused on micro-level units, such as hotels, restaurants, and travel agencies, to evaluate their performance^[18–20]. In particular, a significant portion of these studies has employed the data envelopment analysis (DEA) method, a non-parametric approach that evaluates relative efficiencies without requiring assumptions about functional forms^[15,21–23]. Wu et al.^[24] conducted a review of studies applying DEA to assess hotel efficiency between 1989 and 2009.

In contrast, a review of the relevant literature reveals that comparatively fewer studies have focused on assessing and ranking efficiency at the macro level in the tourism field. Soysal-Kurt^[25] highlighted some exceptions, including studies measuring the efficiency of 103 Italian regions^[2], evaluating the efficiency of different regions in China^[26], analyzing the efficiency of French regions between 2003 and 2007^[27], examining tourism efficiency more broadly^[28], and conducting a DEA-based evaluation of 27 European Union (EU) countries^[29]. Furthermore, while some studies in the past decade have applied stochastic frontier analysis (SFA) to assess and rank efficiency in the tourism industry^[2], such research remains relatively limited. Specifically, the applications of SFA demonstrate a focus on dynamic modeling^[30], nonparametric approaches^[31,32], and addressing statistical challenges^[33], expecting to improve tourism efficiency analysis. For instance, using a stochastic frontier gravity model, Wu et al.^[34] studied evaluated the inbound tourism efficiency of European countries, identifying economic scale and geographic distance as key factors.

Traditionally, stochastic frontier analysis (SFA), introduced by Meeusen and Van Den Broeck^[12] and Aigner et al.^[14], and grounded in Farrell's^[9] theory of efficiency measurement, has been widely used to assess production efficiency in the field of production economics. This parametric method is fundamentally based on quantitative economic theory, providing a framework for economic justification and hypothesis testing^[12]. While SFA-based applications offer the advantage of accounting for statistical noise caused by severe measurement errors, uncontrollable factors, or unexpected events, the assumptions rooted in economic theory determine the form of the frontier. However, the limited application of SFA for estimating relative efficiency in the tourism industry indicates that the economic underpinnings of this approach remain underdeveloped in this field. In SFA-based frontier efficiency models, the choice of variables, measures, and the functional form of the frontier is critical, as these elements define the inputs and outputs used in the analysis. Based on a systematic review of empirical studies, Mortimer^[35] observed that, in estimating hospital efficiency, the mis-specification of functional forms can lead to significant issues, particularly when analyzing heterogeneous samples or data with measurement errors.

Recent research has demonstrated that the concept of SFA for measuring production efficiency can be applied to estimating the conventional gravity equation, referred to as the stochastic frontier gravity model (SFGM), to evaluate trade and foreign direct investment (FDI) poten-

tial and performance^[36]. Grounded in international economic and trade theory, SFGM enables the estimation of appropriate benchmarks and, consequently, the measurement of efficiency. Empirical studies have shown that SFGM is one of the most effective tools for assessing potential and performance, particularly in explaining international trade^[37–41], FDI flows^[36,42–44], and international service export performance^[45].

International tourism flows, essentially a form of cross-border human movement, are often categorized as trade in services in most studies. Consequently, following the theoretical framework used for international merchandise trade flows, the gravity model has been widely adopted to analyze international tourism demand and identify its key determinants^[46,47]. However, to the best of our knowledge, the SFGM approach has not yet been applied or statistically validated in the empirical tourism literature. This gap is particularly evident in the context of assessing and ranking efficiency at the macro level, which is often overlooked in tourism research.

Building on the theoretical framework and empirical estimation techniques of the stochastic frontier gravity model (SFGM), this paper aims to address the overlooked issue of establishing an economic efficiency ranking for the tourism sector at the macro level. Similar to its application in analyzing trade and FDI efficiency, as discussed by Fan et al.^[43], SFGM can be employed as a production function for modeling cross-border tourism flows. This approach seeks to maximize tourism potential and efficiency by incorporating factors such as economic size, geographical distance, and other resistances or determinants specified in the gravity model. More importantly, by identifying appropriate frontier benchmarks, SFGM addresses the limitations of the conventional gravity equation by accounting for the influence of unobservable variables on tourism flows. From an econometric perspective, this method helps eliminate the bias inherent in traditional gravity models^[48]. Consequently, it enables the estimation of time-variant, country-specific tourism efficiency, providing a more comprehensive understanding of tourism performance.

3 Model Specifications of SFGM for Estimating Tourism Efficiency

Since its introduction, the gravity model has undergone significant theoretical refinements and empirical improvements, resulting in better alignment with observed data. However, as reviewed by Olanike and Kareem^[49], the model's reliance on strong theoretical assumptions, such as frictionless trade or iceberg transport costs, has led to unsatisfactory proxies for trade frictions and resistances in empirical applications. Armstrong^[36] highlighted that many subjective resistances, such as imperfect information and internal constraints, were difficult to quantify and were often omitted in traditional gravity model specifications. When unobservable trade resistance variables are not adequately accounted for in empirical gravity equations, recent literature suggests using SFA as a suitable method to address the bias caused by unobservable trade resistances and to estimate their effects^[37]. Following the SFGM applied to international trade and FDI, the log-linearizing form of actual tourism flow from origin o to destination d ,

$\ln T_{\text{dot}}$, is defined by the following equation:

$$\ln T_{\text{dot}} = \beta_0 + \beta_1 \ln \text{GDPpc}_{\text{dt}} + \beta_2 \ln \text{GDPpc}_{\text{ot}} + \beta_3 \ln \text{Pop}_{\text{dt}} + \beta_4 \ln \text{Pop}_{\text{ot}} + \beta_5 \ln D_{\text{do}} + \sum_{k=6}^K \beta_k R_k + v_{\text{dot}} - u_{\text{dot}}, \quad (1)$$

where the explained variable T_{dot} could be specified as variables like tourist arrivals, overnight stays or receipts from tourism^[50,51]. In the tourism flow case, GDP per capita ($\ln \text{GDPpc}_{\text{dt}}$, $\ln \text{GDPpc}_{\text{ot}}$) and population ($\ln \text{Pop}_{\text{dt}}$, $\ln \text{Pop}_{\text{ot}}$) are included as a measure of market size of the gravity model^[52]; D_{do} is geographical distance; R_k stands for a range of observable and unobservable variables to proxy and capture the effect of bilateral tourism resistances (BTR) and multilateral tourism resistances (MTR), which might limit or promote tourism between particular origin-destination pairs; the v_{dot} represents a two-sided error term, $v_{\text{dot}} \sim \text{iid}N(0, \sigma_v^2)$. For further empirical estimation, we rewrite the Equation (1) as follows:

$$\ln T_{\text{dot}} = \mathbf{x}'_{\text{dot}} \boldsymbol{\beta} + v_{\text{dot}} - u_{\text{dot}} = \ln T_{\text{dot}}^{\text{SF}} - u_{\text{dot}}, \quad (2)$$

where $\mathbf{x}_{\text{dot}} = (1, \ln \text{GDPpc}_{\text{dt}}, \ln \text{GDPpc}_{\text{ot}}, \ln \text{Pop}_{\text{dt}}, \ln \text{Pop}_{\text{ot}}, \ln D_{\text{do}}, R_k)'$, denoting the core variables that determine the frontier of tourism flows; $\boldsymbol{\beta}$ is the vector of parameters.

In SFA specification, $\ln T_{\text{dot}}^{\text{SF}}$ represents the frontier level of tourist flows. By definition, u_{dot} is a non-negative, one-sided inefficiency term that captures the combined effects of unobserved BTR factors and other MTR spatial interdependence biases. These biases cause bilateral tourism flows to fall below, but never exceed, their potential level. Typically, u_{dot} is assumed to follow a half-normal distribution, an exponential distribution, or, more generally, a non-negative truncated-normal distribution^[53].

In our case, the u_{dot} is a nonnegative truncation of a normal random variable, being possibly parameterized by a function of tourism-increasing or reducing variables affecting the country's ability to tourism flow. In our analysis, heteroscedasticity could be modeled through a non-constant, μ_{dot} , or a non-constant, σ_{dot}^2 .

$$u_{\text{dot}} \sim N^+(\mu_{\text{dot}}, \sigma_{\text{dot}}^2). \quad (3)$$

Based on a specific data, if the added flexibility significantly improves the estimation, both μ_{dot} and σ_{dot}^2 are also allowed to be observation-specific. Specifically, variables used for a flexible approach to model heteroscedasticity in Equation (3) are parameterized as the following:

$$\mu_{\text{dot}} = b_0 + \mathbf{z}'_{\text{dot}} \boldsymbol{\delta}, \quad (4)$$

$$\sigma_{\text{dot}}^2 = \exp(b_1 + \mathbf{z}'_{\text{dot}} \boldsymbol{\gamma}), \quad (5)$$

where b_0 and b_1 are constant and $\mathbf{z}_{\text{dot}}$ is a vector of non-stochastic variables. Both $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are the corresponding set of parameters. Following the heteroscedasticity specification in Wang^[54], the parameterizations specify μ_{dot} and σ_{dot}^2 with the same variables, $\mathbf{z}_{\text{dot}}$. Basically,

this specification assumed that variables affecting both the mean and log of the variance of the truncated distribution. The maximum likelihood estimation (MLE) technique is used for estimating parameters.

Based on the stochastic frontier estimation, the one-sided effects are used to calculate the tourism efficiency index (TEI). The TEI measures how closely a country's international tourism performance approaches the optimal level, characterized by minimal resistance or inefficiencies under current conditions such as transportation and institutional practices^[55]. For the logarithm dependent variable, the measure is defined as follows:

$$\text{TEI}_{\text{dot}} = \frac{\exp(\mathbf{x}'_{\text{dot}}\boldsymbol{\beta} - u_{\text{dot}})}{\exp(\mathbf{x}'_{\text{dot}}\boldsymbol{\beta})} = \exp(-u_{\text{dot}}). \quad (6)$$

Clearly, $\text{TEI}_{\text{dot}} \in [0, 1]$ measures the efficiency level of international tourism, with 0 ($u_{\text{dot}} \rightarrow \infty$) indicating the least efficient, and 1 ($u_{\text{dot}} = 0$) the most efficient. In addition, high efficiency scores indicate international tourism flows is close to reaching its maximum, whereas low efficiency scores suggest deviations from frontier, which imply to the scope for further country-specific improvement^[56]. The alternative specification used in our analysis is assumed that u_{dot} follows an exponential distribution. The only parameter in exponential distribution is denoted by η ($\eta > 0$). Specifically, the mean and the variance of u_{dot} are η_{dot} and η_{dot}^2 . Also, η_{dot} is specified as the following equation:

$$\eta_{\text{dot}}^2 = \exp(\alpha_0 + \mathbf{z}'_{\text{dot}}\boldsymbol{\alpha}), \quad (7)$$

where α_0 is constant and $\mathbf{z}_{\text{dot}}$, as above specification of the truncated distribution, is a vector of non-stochastic variables. $\boldsymbol{\alpha}$ is the corresponding set of parameters. For the empirical specification of international tourism flows in China, two models are developed for the stochastic frontier gravity estimation. The first model, represented by Equation (2), measures the frontier level of China's international tourism flows. The second model, represented by Equations (4) and (5), identifies the factors and resistances affecting tourism flows. Additionally, the dataset used in the analysis is described.

In this empirical study, the dependent variable is specified as Chinese international tourist arrivals. For China as the only destination for $\mathbf{x}_{\text{dot}}$ specification, both $\ln \text{Pop}_{\text{dt}}$ and $\ln \text{GDPpc}_{\text{dt}}$ are cross-time fixed. Therefore, $\ln \text{Pop}_{\text{dt}}$ are excluded from equation to avoid the possible multicollinearity problem. Additionally, TR terms (R_k) is specified with three kinds of factors. Following Nguyen and Kalirajan^[57], this study first includes comprehensive measures of “beyond the border” constraints proxied by the relative price factors. The relative price P_{dot} is computed as the ratio of $\text{CPI}_{\text{dt}}/\text{NER}_{(\text{d}/\$)\text{t}}$ to $\text{CPI}_{\text{ot}}/\text{NER}_{(\text{o}/\$)\text{t}}$. Specifically, NER is the nominal exchange rate; CPI is the consumption price index. Secondly for panel data, individual country fixed-effects (γ_d and γ_0) and time-specified term (γ_t) are introduced to approximate the multilateral resistances and time effect^[58].

Thirdly, other two control variables for the R_k specification are included partly for the heterogeneity bias of origin and destination specific. For China destination-side, 2003-year

dummy (SARS variable in equation) is introduced for the negative effect caused by one-off 2003 severe acute respiratory syndrome epidemic (SARS) event. For the origin-side specification, the worldwide governance indicators (WGI, Risk_{ot} in our equation) are introduced as the quality of origins' governance and political risk^[40,59]. Specifically, Risk_{ot} is the average of six indicators from WGI, falling between -2.5 and 2.5 .

In summary, based on the discussion above for China's international tourism flows, the stochastic frontier model of the Equation (2) is specified as follows:

$$\ln T_{\text{dot}}^{\text{SF}} = \beta_0 + \beta_1 \ln \text{GDPpc}_{\text{dt}} + \beta_2 \ln \text{GDPpc}_{\text{ot}} + \beta_3 \ln \text{Pop}_{\text{dt}} + \beta_4 \ln D_{\text{do}} + \beta_5 \ln P_{\text{ot}} + \beta_6 \text{SARS} + \beta_7 \text{Risk}_{\text{ot}} + \gamma_d + \gamma_o + \gamma_t + v_{\text{dot}}. \quad (8)$$

For z_{dot} specification, although there is some ambiguity regarding which theoretical variables should be included to explain the gap between actual and potential tourism flows, empirical studies on trade and FDI efficiency often follow a general rule of thumb. Armstrong^[36] reviewed the SFGM specification, suggesting that the frontier could be estimated using fundamental or core determinants from the conventional gravity equation, such as geographical distance, economic size, and other BTR/MTR factors. Specifically, BTR and MTR determinants, often referred to as natural determinants or objective resistances, are typically time-fixed effects or factors that cannot be altered in the short to medium term. In contrast, most man-made determinants, or subjective resistances, primarily social, political, economic, or policy-related factors between origin and destination, are recommended for inclusion in Equations (4) and (5) to account for inefficiencies^[36,43]. As a typical export-oriented industry, the efficiency or potential of a country's inbound tourism is influenced not only by the supply of tourism resources and the demand for tourist services but also, more critically, by the specific social, political, and economic relationships between origin-destination pairs. Consequently, this study specifies the inefficiency term for tourism resistance using four key factors, economic, political, cultural, and policy-related determinants, relevant to Chinese international tourism demand.

The economic factors, FDI_{dot} and ExportRatio_{dot} (the ratio of China's export value to an origin country's export value relative to China's total trade value), reflect the economic interactions between China and the sampled countries. Generally, more open economies are likely to experience higher levels of business travel. Secondly, ADS_{dot} tourism liberalization policy factor, which reflects the political-preferential relationship between China and its origin countries, is represented by a dummy variable. This variable takes a value of 1 for the year of and after the ADS agreement with China, and 0 otherwise. It is used to control for the heterogeneity in Chinese tourist arrivals before and after the ADS agreement. In this study, we aim to examine how the tourism liberalization of a country facilitates its inbound tourism flows, ultimately leading to greater tourism efficiency^[5]. Thirdly, the percentage of ethnic Chinese in the total population (Culture_{do} in estimation equation) is used as a proxy for the social ties between China and the origin country in terms of trade, FDI, and human flows^[59–62]. This variable is also a dummy, equal to 1 when the percentage of ethnic Chinese in the origin country's

population exceeds 1%, and 0 otherwise. Theoretically, Chinese inbound tourist arrivals are expected to be positively correlated with this variable.

In summary, based on the discussion above, the tourism resistances and factors for inefficiency term is specified as economic, political and culture link to tourism between China and its origins, $\mathbf{z}_{\text{dot}} = (\text{Culture}_{\text{do}}, \ln \text{ExportRatio}_{\text{dot}}, \ln \text{FDI}_{\text{dot}}, \text{ADS}_{\text{dot}})'$. Generally, the coefficients of four social-, political- or economic-preferential factors between origin and destination in both μ_{dot} and σ_{dot}^2 inefficiency functions are obviously expected to be negative values. The variables and data sources are detailed in Table 1.

Table 1 Variables definition and data source

Variable	Definition	Expected sign	Data source
TA _{dot}	International tourist arrivals from origin countries to China		CNTA
Frontier determinants of gravity model			
GDPpc _{d(o)t}	GDP per capita (PPP, in 2017 constant international dollars)	(+)	WDI
Pop _{ot}	Population of origin	(+)	WDI
D_{do}	Distance between tourist origin countries and China in kilometers	(−)	http://www.distancefromto.net/
P_{dot}	The relative price between China and its tourism origin as defined in Equation (5). The proxy measures the tourist living costs in China relative to that in the origin country and is also adjusted by the relevant exchange rates.	(−)	Our elaboration on World Bank data
SARS	One-off SARS event in 2003 year: 2003 year dummy	(−)	-
Risk _{ot}	Political risk indicator: Between −2.5 and 2.5	(+)	WGI
Inefficiency determinants			
ExportRatio _{dot}	The ratio of export (China to origin countries) to total trade value of China	(−)	CSY 2020
FDI _{dot}	Annual inward foreign direct investment from origin to China	(−)	CSY 2020
ADS _{dot}	A dummy variable taking value of 1 the year and after having an ADS agreement with China and 0 otherwise	(−)	CNTA
Culture _{do}	Cultural similarity/proximity: A dummy variable that is equal to one when percentage of ethnic Chinese in total origin countries' population is more than 1%, and 0 for otherwise	(−)	Ohio library and Wiki

Note: World Bank Development Indicator (WDI); World Bank Governance Indicators (WGI); China Statistical Yearbook 2020 (CSY 2020).

4 Estimations and Results

The SFGM specified in Equation (2) and the inefficiency models represented in Equations (4) and (5) are estimated simultaneously using a one-step approach based on balanced panel data of Chinese international tourism flows from 21 origin countries during the period 1995~2019.

Table 2 presents the maximum likelihood estimation (MLE) results for various models, excluding the estimates for country and year dummies. As shown in Table 2, from Model (4) to Model (1), a more flexible and less restricted specification for the inefficiency effect u_{dot} is introduced.

Specifically, Model (4) serves as the benchmark model. It is essentially a linear model that includes only the core gravity variables of tourism flows and excludes the one-sided deviation effect ($u_{\text{dot}} = 0$). Model (3) is a half-normal model, which assumes μ_{dot} to be equal to 0 and allows σ_{dot}^2 to be observation-specific. Models (1) and (2) focus on estimating the tourism inefficiency effect u_{dot} , allowing the mean and variance functions of its pre-truncated distribution to be observation-specific, respectively. However, the model does not permit both the mean and

Table 2 Estimation results of Equation (4), (5) and (8)

Variables	(1) $\gamma = 0$	(2) $\delta = 0$	(3) $\mu_{\text{dot}} = 0$	(4) $\mu_{\text{dot}} = 0$	(5) Exponential distributions	(6)
Main function:						
$\ln \text{GDPpc}_{\text{dt}}$	0.32*** (6.91)	0.40*** (9.98)	0.40*** (9.81)	0.50*** (11.38)	0.43*** (12.64)	0.45*** (11.88)
$\ln \text{GDPpc}_{\text{ot}}$	1.20*** (22.49)	1.10*** (30.98)	1.09*** (31.40)	1.10*** (27.23)	1.12*** (32.02)	1.12*** (21.52)
$\ln \text{Pop}_{\text{ot}}$	0.55*** (18.46)	0.52*** (23.14)	0.52*** (23.47)	0.47*** (18.12)	0.53*** (23.02)	0.36*** (12.35)
$\ln D_{\text{do}}$	-1.00*** (-17.52)	-1.06*** (-36.59)	-1.06*** (-36.53)	-1.10*** (-28.82)	-1.07*** (-37.42)	-1.05*** (-24.03)
$\ln P_{\text{dot}}$	-0.14*** (-7.33)	-0.15*** (-14.16)	-0.14** (-13.83)	-0.13** (-8.98)	-0.15*** (-14.75)	-0.09** (-5.85)
$\ln \text{Risk}_{\text{ot}}$	-0.74*** (-14.51)	-0.63*** (-17.26)	-0.62*** (-17.66)	-0.67*** (-16.36)	-0.66*** (-18.52)	-0.76*** (-14.07)
SARS	-0.24** (-3.28)	-0.21** (-3.49)	-0.21** (-3.43)	-0.20** (-2.97)	-0.21** (-3.68)	-0.17** (-1.68)
Constant	-9.08*** (-11.13)	-7.98*** (-13.24)	-7.80*** (-13.57)	-7.47*** (-12.02)	-8.45*** (-15.40)	-5.85*** (-7.25)
Function of μ_{dot}						
$\text{Culture}_{\text{do}}$	-1.14*** (-11.75)					
$\ln \text{FDI}_{\text{dot}}$	-0.00 (-0.18)					
$\ln \text{ExportRatio}_{\text{dot}}$	-0.38*** (-8.98)					
$\ln \text{ADS}_{\text{dot}}$	-0.27** (-3.56)					
Constant	-0.30 (-1.63)	-0.15 (-0.85)	0.00 -	0.00 -		

Table 2 (Continued)

Variables	(1) $\gamma = 0$	(2) $\delta = 0$	(3) $\mu_{\text{dot}} = 0$	(4) $\mu_{\text{dot}} = 0$	(5) Exponential distributions	(6)
Function of σ_{dot}^2 and η_{dot}^2						
Culture _{do}		-1.74*** (-11.00)	-1.79*** (-11.52)		-2.45*** (-11.18)	
ln FDI _{dot}		-0.01 (-0.28)	-0.01 (-0.15)		-0.02 (-0.24)	
ln ExportRatio _{dot}		-0.54*** (-6.73)	-0.57*** (-7.34)		-0.70*** (-6.18)	
ln ADS _{dot}		-0.34** (-2.03)	-0.36** (-2.07)		-0.37 (-1.56)	
Constant	-1.58*** (-17.20)	-1.94*** (-4.58)	-2.13*** (-5.62)	0.00 -	-3.15*** (-6.05)	-1.20*** (-6.14)
σ_v	-5.79*** (-8.53)	-4.90*** (-10.99)	-5.07*** (-10.81)	-5.08*** (-10.90)	-4.34*** (-15.02)	-2.66*** (-8.50)
No. of Obs.	525	525	525	525	525	525
Log-likelihood value	-213.8	-299.9	-300.4	-401.1	-328.7	-414.5
LR test	374.64	202.39	201.45	-	171.56 ^a	40.44 ^b
<i>p</i> -value	0.0000	0.0000	0.0000	-	0.0000	0.0000

Notes: Numbers in parentheses are *t* statistics; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

^aLR test for Model (6) against Model (5) is the chi-squared statistics with the degrees of freedom 4;

^bLR test is Likelihood ratio test of σ_u^2 that there is no inefficiency component in the composed error term.

variance functions to be heteroscedastic simultaneously. Based on our dataset, this additional flexibility is redundant and does not significantly improve the estimation.

The generalized likelihood ratio (LR) test, presented in the lower panel of Table 2, is used to evaluate the suitability of the stochastic frontier analysis (SFA) for gravity model estimation^[53]. Specifically, the benchmark Model (4) serves as the null hypothesis, assuming no inefficiency effects ($u_{\text{dot}} = 0$), while alternative Models (1)–(3) incorporate flexible inefficiency effects. For Models (1)–(3), the number of parameters used to specify the distribution of μ_{dot} (degrees of freedom) is 5, 6, and 6, respectively. The LR test results reject the null hypothesis for all three models at the 1% significance level, confirming the appropriateness of the SFA estimation. Additionally, a flexible model accounting for heteroscedasticity is preferred over the benchmark Model (4).

Models (5) and (6) provide alternative specifications, assuming that the one-sided inefficiency term (u_{dot}) follows an exponential distribution, which is one of the most commonly used distributions in stochastic frontier analysis (SFA). These models are used to test whether the estimation results are sensitive to different distributional assumptions^[53]. Consistent with the

findings of Kumbhakar, Wang, and Horncastle^[41], the alternative distributions in Models (5) and (6) have no significant impact on the stochastic frontier estimation.

Overall, the core gravity parameters align closely with theoretical predictions, and the coefficients of the core gravity variables are similar in magnitude. Econometrically, this consistency supports the findings of Kumbhakar, Subal, and Lovell^[53], which demonstrate that the stochastic frontier model produces estimates consistent with those of the linear model and is unaffected by alternative distributional assumptions. As shown in Table 2, all coefficients of the core gravity variables in frontier Equation (8) are statistically significant at the 1% level and exhibit the expected signs (expect the sign on the index of political risk, $Risk_{ot}$).

As expected, the three market size proxies ($\ln GDP_{pc_{dt}}$, $\ln GDP_{pc_{ot}}$ and $\ln Pop_{ot}$) have a statistically significant and positive influence on tourism, indicating that richer and larger countries tend to have higher levels of international tourism between them. Additionally, in all models, the estimated coefficients on $\ln GDP_{pc_{ot}}$ (income elasticity) are greater than 1, aligning with the existing literature. This finding confirms that traveling to China, as a normal good in consumption, remains a luxury for most tourists from various origins. Furthermore, the consistently negative coefficients of $\ln D_{do}$ and $\ln P_{dot}$ suggest that tourists prefer nearby destinations with lower expenses. Notably, the estimated coefficient on $\ln P_{dot}$ ranges from -0.15 to -0.09 . It is statistically significant at the 1% level.

Regarding the estimates of the inefficiency effect u_{dot} , it is decomposed into the mean (μ_{dot}) and the variance (σ_{dot}^2 and η_{dot}^2) of its pre-truncated distribution and exponential distribution. As shown in Models (4) and (6), the mean and variance functions are parameterized by four social, political, economic, and policy preferential factors. Table 2 indicates that the estimates for all four variables are negative for both the mean and variance of the tourism inefficiency functions, aligning with theoretical expectations (except for the FDI variable). These results suggest that strengthening social, political, economic, and policy preferential links not only reduces the level of inefficiency but also decreases its uncertainty in Chinese international tourism flows. In other words, these factors help narrow the gap between actual Chinese international tourism flows and the frontier estimates.

Overall, the effects of cultural proximity ($Culture_{do}$) and trade intensity ($\ln ExportRatio_{dot}$) on the mean and variance functions are both robust, with coefficients significantly negative at the 1% level. Notably, the relatively larger magnitude of cultural proximity indicates significant efficiency gains in Chinese international tourism for origin countries with a higher percentage of ethnic Chinese. Furthermore, the significant impact of trade intensity on reducing Chinese tourism inefficiency suggests that human and goods flows are complementary, particularly for China as a global manufacturing hub. For the ADS policy determinant, the coefficient is significant for both the mean and variance functions of tourism inefficiency at the 1%–5% level across different models, except for Model (5), where it is not significant. These findings suggest that, in general, the preferential ADS policy reduces both the level of tourism inefficiency and the uncertainty in realizing the potential of the tourism frontier.

In summary, the economic, political, and cultural relationships between tourism origin and destination significantly reduce the inefficiency of Chinese international tourism performance. Among the models tested (Models (1)–(6)), Model 1 is identified as the most suitable for estimation of TEI_{dot} , as it achieves the highest log-likelihood value (−213.8). Therefore, the efficiency scores derived from Model 1 serve as the foundation for evaluating tourism efficiency between China and its tourist source countries.

Using stochastic frontier estimation, tourism efficiency for each observation is calculated as the ratio of actual tourism flow volume to its potential volume, which represents the maximum predicted tourism flow^[36]. For further analysis and comparison, the estimated tourism efficiency indexes (TEIs) for each tourist source country are aggregated to evaluate the impact of country groups across major geographical regions.

Since the estimated country-specific TEIs are compared across countries and over time, it is important to examine whether the rankings of observation-specific TEIs are sensitive to different model specifications. To address this, Spearman rank correlation coefficients were calculated for the TEIs derived from Models (1), (2), (3), and (5) in Table 2. Models (4) and (6) were excluded because they violate the dataset’s heteroscedasticity assumptions. The results, presented in Table 3, indicate that the rankings change minimally when TEIs are computed using different model specifications. This suggests that, for this dataset, the relative efficiency measures across observations are not heavily influenced by the choice of distribution. These findings align with the evidence provided by Kumbhakar, Subal, and Lovell^[53]. Therefore, the TEI analysis based on Model (1) offers reliable relative efficiency measures for individual countries or groups of countries.

Table 3 Spearman rank correlation coefficients of TEIs from according models

	TEI(1)	TEI(2)	TEI(3)	TEI(5)
TEI(1)	1			
TEI(2)	0.9398	1		
TEI(3)	0.9407	0.9994	1	
TEI(5)	0.9153	0.9327	0.939	1

Figure 1 shows the frequency distribution of TEI, which is right-skewed with a mean of 0.80 and a standard deviation of 0.03. The mean value of 0.80 suggests that approximately 20% of potential tourism arrivals are lost due to tourism resistances. Overall, tourism efficiency across all sample countries is relatively high, with a standard deviation of about 10%, indicating that the efficiency frontier is not far from most countries in the sample. The high efficiency scores reflect a low level of resistance to tourism flows into China from partner countries, highlighting China’s strong integration into international and regional markets.

Figure 2 and Table 4 illustrate the evolution of tourism efficiency for each tourist-origin country and geographical region, averaged over the years 1995–2019. At the country level, Table 4 shows that the highest estimated efficiency, exceeding 90% and referred to as frontier

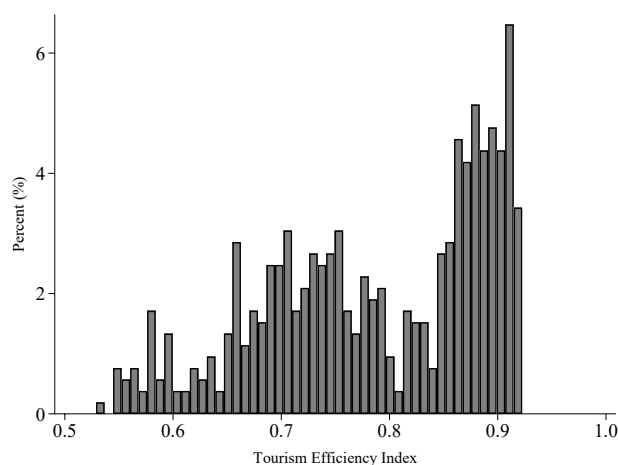


Figure 1 The distribution of TEI

tourism efficiency, is achieved by the USA (0.91), followed by Singapore, Australia, and the Philippines. This indicates the greatest export potential and likelihood for international tourist arrivals to China. In contrast, countries such as Switzerland and the Netherlands have the lowest TEI ratings, falling below 0.70. Additionally, India demonstrates significant variability in efficiency, with a standard deviation of 0.06, highlighting its unstable performance compared to other countries in the sample.

Figure 2 and Table 4 reveal that European countries generally exhibit low and highly unstable tourism efficiency indexes, with the exception of Russia (0.83), whose TEI is slightly above the overall sample average. For Chinese policymakers, this suggests that there is significant potential to improve policies and institutions to promote tourism service development in most countries within this region. In contrast, Asian countries display a wide variability in TEI, with a substantial range of 0.29, indicating a highly uneven pattern of tourism efficiency. The region includes top-performing countries such as Malaysia, Singapore, and the Philippines, which achieve efficiency indexes as high as 0.89, alongside countries like India and Mongolia, which record much lower average TEIs. Additionally, the volatility of average TEIs is more pronounced in Asia compared to other regions. By comparison, the Americas and Oceania demonstrate higher and more stable tourism efficiency levels across all subgroups in the sample, reflecting a more homogeneous pattern of tourism efficiency. Notably, Oceania experienced continuous improvement in its TEI between 1995 and 2007.

An analysis of the estimated country-specific TEIs over time and across countries reveals several key features of Chinese international tourism. Firstly, the period under study includes the 2008–2009 global financial crisis, which had a distortionary impact on tourism patterns in China. During the sub-period 1995–2007, the mean TEI for the total and sub-regional samples gradually increased, reaching relatively high levels in 2007 (0.83 for the total sample). However, this upward trend was interrupted by two notable setbacks: The 1998 Asian financial crisis and the 2003 SARS outbreak, with Mongolia being the only exception among tourism origins.

Table 4 TEI estimates from SFGM for each country, 1995–2019

Rank	Country	Mean	Standard deviation	1995	2007	2019	1995–2007 % Change	2007–2019 % Change
1	USA	0.91	0.01	0.88	0.92	0.90	5.37	−2.93
2	Australia	0.90	0.03	0.84	0.93	0.90	9.86	−2.92
2	Canada	0.89	0.02	0.83	0.91	0.90	9.67	−0.82
2	Malaysia	0.89	0.02	0.86	0.92	0.87	7.01	−5.04
5	Philippines	0.89	0.01	0.88	0.91	0.86	3.64	−5.70
5	Singapore	0.89	0.02	0.88	0.92	0.86	3.51	−6.23
7	Japan	0.88	0.03	0.82	0.92	0.85	11.45	−7.65
8	Indonesia	0.86	0.04	0.80	0.90	0.88	13.21	−2.78
9	New Zealand	0.86	0.04	0.77	0.89	0.88	15.45	−1.04
10	Korea	0.85	0.05	0.72	0.92	0.85	27.15	−7.84
11	Russia	0.83	0.04	0.76	0.88	0.82	14.95	−5.77
12	UK	0.78	0.03	0.76	0.82	0.75	7.49	−8.07
13	Thailand	0.76	0.04	0.75	0.78	0.73	4.56	−5.70
14	Sweden	0.73	0.05	0.67	0.80	0.67	18.10	−15.70
15	Italy	0.72	0.05	0.68	0.75	0.77	11.21	1.99
16	Germany	0.71	0.06	0.65	0.76	0.70	16.82	−7.40
17	France	0.70	0.05	0.62	0.76	0.70	21.29	−7.47
18	India	0.70	0.06	0.57	0.77	0.70	34.15	−8.42
19	Mongolia	0.70	0.05	0.74	0.69	0.70	−6.63	1.44
20	Netherlands	0.69	0.04	0.59	0.73	0.67	24.79	−7.81
21	Switzerland	0.58	0.02	0.59	0.60	0.56	2.37	−7.95
	Total Mean	0.80	0.03	0.75	0.83	0.79	11.48	−5.40

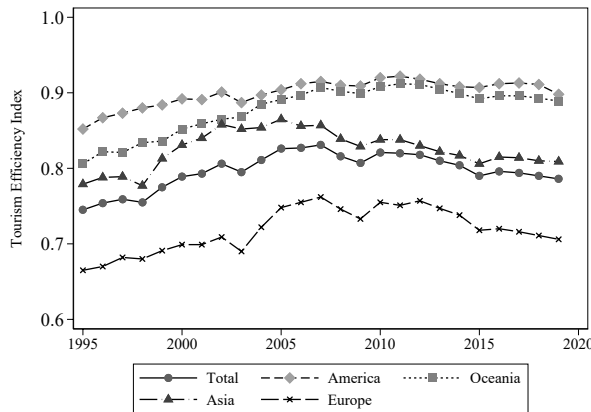


Figure 2 Evolution of tourism efficiency index by regions

In contrast, as shown in Figure 2 and Table 4, the estimated TEIs contracted significantly during and after the 2008–2009 global financial crisis, decreasing by approximately 5.4 percentage points from 2008 to 2019 for the total sample. A primary reason for this persistent decline

is that international tourism demand, as a form of luxury consumption, is more sensitive to economic downturns compared to the trade of essential goods. Indeed, a comparison of 2007 and 2019 in Table 4 highlights a sharp decline in tourism efficiency across all trading relationships. Notably, the contractions in TEIs for Europe and Asia were far greater than those for the Americas and Oceania during this period.

5 Conclusion

A country's openness is characterized by higher rates and greater efficiency in the cross-border flows of capital, goods, and people. International tourism flows, as a key form of cross-border human movement, represent one of the most important dimensions of a country's economic integration into the global economy. As one of the most liberalized economies, China is assumed to have achieved significant potential and efficiency in its international tourism flows with its tourist origin countries. Empirically, the degree of a country's tourism integration at the macro level is a hypothesis that requires estimation and testing.

This paper examines the efficiency of China's inbound international tourism using a stochastic frontier gravity model (SFGM), offering new insights into the factors driving tourism efficiency and inefficiency. The findings highlight several key conclusions about the performance and potential of China's international tourism flows. Firstly, China has achieved approximately 80% of its potential tourism flows with its partner countries on average. However, significant inefficiencies and barriers persist, underscoring the need for further efforts to deepen tourism market integration.

Secondly, the analysis identifies both natural and man-made factors affecting tourism efficiency. Natural factors include geographical distance, economic size, and price levels, while man-made factors encompass social, political, economic, and policy variables. Enhancing these man-made factors can substantially reduce inefficiencies and uncertainty in tourism flows. Notably, cultural proximity—such as a higher proportion of ethnic Chinese in origin countries—and trade intensity have proven particularly effective in addressing inefficiencies. This underscores the complementary relationship between the movement of people and goods, especially in light of China's status as a global manufacturing hub. Policies like the approved destination status (ADS) program have also played a crucial role in mitigating inefficiencies and boosting tourism flows. These findings emphasize the importance of sustained policy efforts to further enhance tourism efficiency.

Thirdly, tourism efficiency scores vary widely across countries and regions. Asian countries such as Malaysia, Singapore, and the Philippines perform strongly, whereas others, like India and Mongolia, lag behind. Over time, these efficiency scores have been volatile, with significant setbacks during events such as the 1998 Asian financial crisis, the 2003 SARS outbreak, and the 2008–2009 global financial crisis. Notably, despite earlier improvements, tourism efficiency declined markedly after the 2008 global financial crisis, with sharper contractions in Europe and Asia compared to the Americas and Oceania.

Efficient cross-border tourism flows are vital for a country's economic integration into the global economy. For Chinese policymakers, the findings highlight the need to strengthen social, political, economic, and cultural ties with origin countries to reduce inefficiencies and enhance tourism market integration. Addressing regional disparities and improving resilience to external shocks require targeted policy measures.

Despite offering valuable insights, the study has certain limitations. Firstly, while the SFGM approach is innovative, it has not been widely applied or statistically validated in tourism studies, limiting the generalizability of the findings. Broader applications of this model across different countries and regions are necessary to improve its robustness. Secondly, the empirical SFGM specification struggles to quantify subjective resistances such as imperfect information, internal constraints, and unobservable trade resistance variables, which are often excluded from traditional gravity models. These omissions may introduce biases into the results. Thirdly, the heterogeneity of tourism flows across countries and regions complicates the estimation of efficiency scores. This variation likely reflects structural differences not fully accounted for by the model. Addressing these limitations in future research could enhance the robustness and applicability of the findings while providing deeper insights into global tourism efficiency patterns.

Conflict of Interest The authors declare no conflict of interest.

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