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Short-run and long-run performance of international tourism: Evidence from Bayesian dynamic models

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HIGHLIGHTS

- We model the short-run and long-run technical efficiency using a new dynamic stochastic frontier model.
- Most tourism destinations improve their technical efficiency in the long-run.
- A shock in technical efficiency has a considerable effect in certain destinations.

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ABSTRACT

Measuring the technical efficiency of the tourism industry is essential for evaluating tourism sustainability and reshaping tourism activities. This paper introduces for the first time a new dynamic stochastic frontier model to 1-measure and compare the short-run and long-run technical efficiencies of leading tourism destinations, and 2-provide impulse response functions and persistence measures to trace out the dynamic effect of shocks in technical inefficiency. We develop our model in a Bayesian framework using carefully constructed Markov Chain Monte Carlo (MCMC) techniques. We report efficiency results and persistence scores for individual destinations and discuss how different destinations recover from shocks in tourism performance.

1. Introduction

The literature on tourism performance is now fairly well established. Studies benchmarking tourism destinations have initially focused on issues such as customer satisfaction (Milman & Pizam, 1995) competitiveness (Kozak & Rimmington, 1999; Ritchie & Crouch, 2003), or some simple indicators such as tourism arrivals, tourism receipts, foreign exchange earnings, changes in market share (Dwyer & Kim, 2003) and tourism satellite accounts (Dwyer, Forsyth, & Spurr, 2007a, 2007b). Recognizing however that these measures have limitations, the recent literature has introduced more comprehensive methods of tourism performance such as Data Envelopment Analysis (DEA) and Stochastic Frontier (SF) (see, for example, Assaf & Cvelbar Knežević, 2011; Hwang & Chang, 2003). Both these methods have the advantage of accounting for multiple tourism inputs and outputs. They measure performance (i.e. technical efficiency) by estimating a production technology (also known as the production frontier), where firms that sit on the frontier are deemed to be the most technically efficient. The methods have been applied to study the performance of tourism firms across several international countries (Anderson, Fish, Xia, & Michello, 1999; Anderson, Fok, & Scott 1999; Assaf & Agbola, 2011; Barros, 2006; Barros & Alves, 2004; Chen, 2007; Pérez-Rodríguez & Acosta-González, 2007; Sigala, Airey, Jones, & Lockwood, 2004).

Table 1 summarizes the key studies in the literature. These studies have focused either on single or multiple tourism destinations. For example, Barros et al. (2011) measured the technical efficiency of the French tourism industry, while Assaf and Josiassen (2012) extended the analysis to compare the technical efficiency of 120 international tourism destinations. Both these studies reemphasized the need of using multiple-input/output performance metrics such as technical efficiency to measure tourism performance. As argued by Fuchs (2004, p.56) tourism involves subsystems within destinations that combine a number of input resources in order to transform them to desired output levels. "Consequently, both input resources as well as the economic

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Table 1
Review of efficiency studies on tourism destinations.

Study	Methodology	Input/output variables	Sample	Key findings
Fuchs (2004)	DEA	Inputs: a. Labor b. Infrastructure c. Natural environment Outputs: a. Sales b. Occupancy c. Market Share d. Profit	21 Tyrolean tourism destinations	The DEA is a powerful and reliable method for benchmarking tourism destinations
Barros et al. (2011)	DEA bootstrap	Inputs: a. Accommodation Capacity b. Arrivals Outputs: a. Nights Slept	22 French destinations	Several drivers of efficiency in French regions. The principal driver comprises the sea, sun and strategy based on beaches endowment.
Cracolici, Rietveld, & Nijkamp (2006)	SF and DEA	Inputs: a. Number of museums, monuments and archaeological sites b. Tourist school graduates divided by working age population c. Labor units employed in the tourism sector Outputs: a. Number of bed nights	103 Italians Regions	Different results between DEA and SF. For instance, DEA showed a lower efficiency score than SF. Specifically, with the DEA method, cultural and artistic destinations method performed much lower than with the SF method.
Botti, Peypoch, Robinot, and Solonadrasana (2009)	DEA	Inputs: a. Accommodation Capacity b. Arrivals Outputs: a. Nights Slept	22 French destinations	The main conclusion is that there is room for efficiency improvement in 12 French regions
Assaf and Josiassen (2012)	DEA Bootstrap	Inputs: a. Number of employees b. Capital investments made by governments on the tourism industry in a particular year c. Total number of accommodation establishments Outputs: a. Total number of international tourists b. Total number of domestic tourists c. Average length of stay of international tourists d. Average length of stay of domestic tourists.	120 international tourism destinations	The study highlighted the determinants of tourism performance. The most positively impacting determinants are crime rate, fuel price level, and hotel price index, while the most negatively impacting determinants are government expenditures on the tourism industry, stringency of environmental regulation
Peypoch (2007)	Luenberger productivity index based on DEA	Inputs: a. Number of tourist bed-nights in hotels b. Number of tourist bed-nights in campsites Outputs: a- Tourism receipts	A Sample of French and 8 other international tourism destinations	Innovations in tourism supply did not contribute to increase in tourist expenditure.

output of these production-consumption processes should be considered simultaneously by comprehensive destination efficiency measures".

Motivated by the above, the present study aims to offer two important contributions to the literature on tourism performance (i.e. technical efficiency). Firstly, we introduce a new stochastic frontier dynamic model that allows for the measurement of both short-run and long-run (i.e. steady-state) technical efficiencies. The current literature (Table 1) though rich has mainly focused on DEA or simple versions of the SF method. With DEA, for example, it is difficult to distinguish between short-run and long-run technical efficiencies. The few studies on SF, including those that focused on firm-level data, have also never addressed the measurement of long-run technical efficiency, despite its critical importance in many discussions of competition and policy implications.

Secondly, from the same model, we also derive impulse response functions and persistence measures which allow us to trace out the dynamic effect of shocks in technical inefficiency. With our new model developments we can now monitor how different tourism destinations react to a decline in tourism performance. Does the drop in performance persist? Or does it revert back to original level in the long-term? Different destinations react differently to shocks (e.g. economic downturn, terrorist attack, outbreak of a disease, etc.), and some recover more quickly than others (Assaf, Pestana Barros, and Gil-Alana, 2011). Hence, understanding this behavior is essential for policy formulation as when a destination takes a longer time to recover, more aggressive strategies might be needed to revert back to previous level of performance. In addition, understanding how direct competitors respond to shocks in the industry may also assist low performing destinations devise more appropriate recovery strategies (Gil-Alana, 2005).

Research has already analyzed the persistence of different aspects of the tourism industry such as tourism arrivals or tourism receipts (e.g. Maloney & Montes Rojas, 2005; Narayan, 2005); however, the persistence analysis of technical efficiency has been completely ignored. The main challenge in using