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The estimation and decomposition of tourism productivity

A. George Assaf [a, *, 1], Mike Tsionas [b, c, 1]

[a] Isenberg School of Management, University of Massachusetts-Amherst, 90 Campus Center Way, 209A Flint Lab, Amherst, MA 01003, USA
[b] Lancaster University Management School, LA1 4YX, UK
[c] Athens University of Economics and Business, Greece

HIGHLIGHTS

- We measure the performance of international tourism destinations.
- We account for heterogeneity between multiple tourism destinations as well as the potential endogeneity in inputs.
- We provide both short-term and long-term productivity measures.
- We decompose productivity into several interesting components.
- We rank tourism destinations based on their productivity and discuss the implications of the findings.

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ABSTRACT

This paper estimates a total factor productivity index that allows for a rich decomposition of productivity in the tourism industry. We account for two important characteristics: First, the heterogeneity between multiple tourism destinations, and second, the potential endogeneity in inputs. Importantly we develop our index at the macro level, focusing on cross-country comparisons. Using the Bayesian approach, we test the performance of the model across various priors. We rank tourism destinations based on their tourism productivity and discuss the main sources of productivity growth. We also provide long-run productivity measures and discuss the importance of distinguishing between short-run and long-run productivity measures for future performance improvement strategies.

1. Introduction

> "Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker" (Krugman, 1994, p.9).

Despite being a high priority on the World Tourism Organization (UNWTO) research agenda, the productivity analysis of the tourism industry has not received much attention in the tourism literature. There is a continuous effort at most tourism destinations to strengthen the productivity of their tourism industry (Cvelbar, Dwyer, Koman, & Mihalič, 2016). As stated by Assaf and Dwyer (2013, p.1234), with the tourism industry often perceived as a low productivity industry, productivity analysis is "crucial to evaluating tourism sustainability and reshaping tourism activities. There is a direct link between productivity and profitability, as when productivity increases, the tourism industry's competitiveness in labour, capital and real estate markets also increase".

The tourism competitiveness literature also highlights the important link between competitiveness and productivity. Dwyer, Forsyth, & Rao (2000, p. 9), for instance, view competitiveness as "a general concept that encompasses price deferential coupled with exchange rate movements, productivity levels of various components of the tourist industry and qualitative factors affecting the attractiveness or otherwise of a destination". Echoing this, Crouch and Ritchie (1999, p.149) have emphasized that ensuring higher destination productivity an effectiveness necessitates from each destination management organization (DMO) "the responsibility to disseminate key market and performance information to its

* Corresponding author.
E-mail addresses: assaf@isenberg.umass.edu (A.G. Assaf), m.tsionas@lancaster.ac.uk (M. Tsionas).
[1] Both authors have contributed equally to the paper.

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members on a timely basis". Even competitiveness at the firm level can be enhanced through productivity improvements (Dwyer & Kim, 2003). While some research evaluated competiveness from the perspective of productivity, the two are often viewed as separate but related components (Assaf & Josiassen, 2012). The concept of "competitiveness" should not also be used to reflect the productivity of the tourism industry (Assaf & Josiassen, 2012) - productivity is a major driver of "competitiveness", and not "competitiveness" itself (Cvelbar et al., 2016).

Often misleading is the definition of productivity in the tourism industry. The various league tables providing productivity indicators of the tourism industry "neither takes explicit account of productivity in tourism" (Blake, Sinclair, & Soria, 2006, p. 1100). Productivity is a complex phenomenon and involves several components; hence using simple metrics to reflect the overall tourism productivity can be misleading for policy implications (Barros, Botti, Peypoch, Robinot, & Solonandrasana, 2011). Over the last decade, there has been an increasing focus on analysing the performance of the tourism industry using the concept of "technical efficiency" (Assaf & Josiassen, 2012; Barros et al., 2011; Peypoch & Solonandrasana, 2006). However, while technical efficiency is a comprehensive measure of performance, it is only one component of productivity-productivity growth is not driven by technical efficiency alone, but by other factors such as "innovation" and "output growth" (Coelli, Rao, O'Donnell, & Battese, 2005).

In their recent paper, Assaf and Dwyer (2013) emphasized that the highly popular "Travel & Tourism Competiveness Index" published by the World Economic Forum and widely used by tourism destinations does not rank destinations based on their tourism productivity (Cvelbar et al., 2016). There is clearly a need to complement such index with a robust productivity index that takes into consideration the unique multiple input and output characteristics of the tourism industry (Assaf & Josiassen, 2012). The Malmquist productivity index, for example, recently used in the literature to measure tourism productivity (Barros, 2005; Cracolici, Nijkamp, & Rietveld, 2008; Peypoch & Solonandrasana, 2008) is an important step in the right direction; it is a comprehensive index that takes into account multiple inputs and outputs in the measurement of tourism productivity, and can be decomposed into measures of efficiency growth and technical growth.

Motivated by the above, the aim of this paper is to extend the current literature on tourism productivity, addressing several important gaps in the literature. We use a total factor productivity index that allows for a rich decomposition of the sources of productivity growth in the tourism industry. We use the Bayesian approach based on Sequential Monte Carlo/Particle Filtering (SMC/PF) to perform the computations.

Importantly, we introduce four important innovations to the tourism literature. First, we account for heterogeneity between multiple tourism destinations, something that has been completely ignored in related studies. As it is well known that considerable heterogeneity exists between tourism destinations, a failure to account for this can result in biased conclusions (Assaf & Tsionas, 2015). Second, we account for potential endogeneity in inputs using a reduced form equation that also takes into account the fact that productivity and inputs cannot be independent of each other. Third, we develop our index at the macro and not at the micro level, as is the case with most studies in the tourism literature. As stated by Assaf and Dwyer (2013, p. 1235) "for productivity measures to be even more useful and relevant to public policy and regulation, they need to relate to the overall tourism industry, and not just to particular sectors of the industry". Fourth and finally, we focus on cross-country comparisons; our aim is to provide each destination with a more accurate assessment of the international standing of their tourism industry.

The paper will proceed as follow. The next section provides a background of productivity and highlights some of the competing methods. Section 3 reviews the current literature on tourism productivity and highlights some of the existing gaps. Section 4 presents the model. Section 5 and 6 present the data and results and finally section 7 concludes.

2. Benchmarking and productivity

Interest in productivity has revived in econometrics through the work of Olley and Pakes (1996) and Levinsohn and Petrin (2003). Across many industries, productivity remains one of most comprehensive and reliable benchmark (Coelli et al., 2005). While in tourism, studies have benchmarked tourism destinations with respect to several performance indicators such as customer satisfaction (Milman & Pizam, 1995), competitiveness (Kozak & Rimmington, 1999), and market share (Dwyer & Kim, 2003), the use of productivity remains largely limited. For tourism policy makers "all these issues are important, but the problem is that they lead to subjectivity in selecting the true benchmarking parameters" (Assaf & Dwyer, 2013, p. 1235).

A more obvious and established benchmark is productivity (Jones, 2007). Usually measured based on multiple inputs and outputs, productivity provides a more comprehensive benchmark and reduces the subjectivity in comparing between different industry leaders (Barros et al., 2011). To define productivity, we start with a production function of this form:

$$Y_{it} = \lambda_{it} f(X_{it}) \tag{1}$$

where Y_{it} refers to the output, X_{it} is a vector of inputs, and λ refers to "how much output a given input is able to produce from a certain amount of inputs, given the technological level" (Del Gatto, Di Liberto, & Petraglia, 2011, p.952). The total factor productivity index (TFP) at a time period "t" is the ratio of produced output and total inputs used (Del Gatto et al., 2011):

$$TFP_{it} \equiv \lambda_{it} = \frac{Y_{it}}{f(X_{it})} \tag{2}$$

As simple as it looks, the estimation of productivity in (2) is not that straightforward, particularly when there are multiple and outputs, where finding the appropriate weights becomes challenging. There is an array of methodologies, and the distinction between them is not just in terms of whether they use a deterministic vs. a parametric approach, but also in terms of whether they adapt a micro (i.e. firm) vs. a macro level approach (industry/country, etc.).

The early literature on the measurement of aggregate productivity growth started with "the Solow growth theory (1957), in which the pattern of productivity growth essentially mirrors that of the so-called technologies progress (i.e. Solow residual)" (Del Gatto et al., 2011, p.954). Such approach is also known as "growth accounting", and despite the limitations, is still a very popular methodology. Recent extension of this method also includes the "level accounting" decomposition (Caselli, 2005), which has the advantage of providing not only growth measures but also estimates of productivity levels, and the so called "growth regressions" where productivity is not estimated as a residual (like "growth accounting"), and is not dependent on a specific functional form (Islam, 2003). This method has also the advantage of not requiring data on physical capital, which are usually characterized by high measurement errors (For a more detailed review of these methods refer to Del Gatto et al., 2011).

In tourism and other related industries, frontier methods have been the most popular for measuring both aggregate and firm level productivity. In contrast to non-frontier methods they provide two unique advantages. First, they do not assume that producers always use their full existing technology. Frontier methods have also a high flexible capability in disentangling the source of productivity change into technical efficiency change and technological change.

To fully understand the difference between frontier and non-frontier methods (Del Gatto et al., 2011), one can rewrite equation (1) with relative to the frontier function $Y^*_{it} = \lambda^*_{it} f^*(X_{it})$:

$$\frac{Y_{it}}{Y^*_{it}} = \lambda_{it} \frac{f(X_{it})}{f^*(X_{it})} \tag{3}$$

where the difference between the observed output and the frontier in (3) is due to either a lack of ability to improve outputs given a input and the technology λ_{it}, or due to a lack of technical efficiency with respect to the frontier $\frac{f(X_{it})}{f^*(X_{it})}$.

The two popular methodologies for estimating productivity using the frontier methodology are the Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Generally, DEA is a non-parametric frontier which envelops the input/output combination of the data and then uses the closest approximation possible of the best-practice frontier to obtain measures of productivity change, technological change and efficiency change. The main strengths of the method are that it: 1- does not require functional form for the technology, 2- does not impose any assumption on the market structure and does not impose the hypothesis that markets are perfect (Gatto et al., 2001), and 3- is highly flexible in terms of allowing for multiple outputs in the estimation of productivity (Assaf, Deery, & Jago, 2011).

SFA also has the same strengths as DEA but has an additional advantage of accommodating for random error that is beyond the control of a firm. Several approaches for estimating productivity using SFA have also been proposed in the literature (Kumbhakar, Denny, & Fuss, 2000; Orea, 2002). In this paper, we build on this SFA literature and provide some important extensions that are of high relevance to the tourism industry. In contexts like ours, where the sample involves comparing between international and heterogeneous tourism destinations, using DEA may be even more sensitive to measurement error. With SFA being an econometric approach, one can also impose some more advanced assumptions on the model.

3. Current gaps in the literature

Before discussing the current gaps in the literature, it is important to emphasize that this review focuses mainly on productivity studies within the tourism literature. While there are many DEA and SFA studies in tourism, these are mainly “efficiency” studies and not productivity studies (for a detailed review of these studies refer to Assaf & Josiassen, 2015). To clearly highlight the current gaps, Table 1 lists the existing studies based on several criteria, including the methodology and the sample used, the extent of productivity decomposition, as well as assumptions made on the model.

Several trends can be identified from Table 1:

- First, most studies use the non-parametric approach to estimate productivity, adopting well established indices such as the Malmquist index and the Luenberger productivity indicator. None of these studies, however, use the SFA approach, which in contexts like ours (comparing between international destinations), where the data is usually plagued by measurement error, has a clear advantage.
- Second, most existing studies focus on one tourism destination, or multiple destinations within one specific geographic region. Only one study has compared between international tourism destinations.
- Third, none of these studies provide both short-run and long-run productivity estimates. For policy implications both these measures become important as while a destination might be performing well in the short-run, its long-run estimate may show otherwise.
- Fourth, with the exception of one study, none of the existing studies has accounted for heterogeneity in modeling tourism productivity. It would be hard to believe that the technology used to produce “tourism” in different tourism destinations is the same. If it differs the “frontier technology of best practices”, simply does not exist. The fact that the recent literature uses one destination (or different regions of a same destination) is not also enough to convince that there is no problem of heterogeneity in the production technology and - consequently - a bias in the evaluation of destination performance.
- Fifth, most of the existing studies have focused only on two types of productivity decomposition: efficiency change and technological change. We believe that providing a richer decomposition can help identify the sources of productivity growth in the tourism industry.
- Sixth, and finally, none of these studies has used the Bayesian approach. In complicated models like ours where we impose a dynamic assumption on the model and account for heterogeneity, the Bayesian approach provides higher flexibility than traditional estimation methods such as the Maximum Likelihood.

The present paper aims to address all the above limitations. We take up the idea that productivity is a dynamic process, and develop appropriate methods of estimation in the context of multiple-input, multiple-output production which is, typically, the characteristic of the tourism industry. An input distance function is used to describe the technology. We address the problem of unobserved heterogeneity that is not simple and cannot be captured using fixed-effects formulations. Full heterogeneity requires that the parameters of the input distance function change across individuals and over time. This shift of the frontier also generates growth that is different from productivity growth and can be identified. We address the classical endogeneity problem in inputs by posing a reduced form for inputs, taking the assumption that inputs are not necessarily uncorrelated with productivity or the random error term in the input distance function. We use the Bayesian approach to perform the computation, using highly advanced Sequential Monte Carlo/Particle Filtering (SMC/PF) techniques.

We use a rich decomposition of the providing index, deriving measures such as input growth, output growth, efficiency growth, and frontier growth. We also derive short-term and long-term measures of productivity growth. Our sample is unique in that we compare between 101 international tourism destinations, providing hence better complement to other international statistical releases published by organizations such the United Nations World Tourism Organization (UNWTO) or the World Travel and Tourism Council (WTTC).

4. The model

As stated, we use here the frontier approach. Suppose $X \in \mathbb{R}^K$ is a vector of inputs, $Y \in \mathbb{R}^M$ is a vector of outputs and $Z \in \mathbb{R}^{d_z}$ is a vector of contextual or environmental variables. Our starting point is an input-oriented distance function of the form

Table 1
Review of productivity studies in the tourism literature.

Study	Methodology	Sample	Heterogeneity	Long-Term Productivity Measures
Barros (2005)	Malmquist DEA Index	42 Portuguese Hotels	No	No
Cracolici et al. (2007)	Malmquist DEA Index	103 Italian Regions	No	No
Peypoch and Solonandrasana (2008)	Luenberger productivity indicator (non-parametric)	10 French Hotels	No	No
Barros, Peypoch, and Solonandrasana (2009)	Luenberger productivity indicator (non-parametric)	15 Portuguese Hotels	No	No
Assaf and Dwyer (2013)	Metafrontier DEA approach	97 International Tourism Destinations	Yes	No
Goncalves (2013)	Luenberger productivity indicator (non-parametric)	64 French Ski Resorts	No	No
Barros and Alves (2004)	Malmquist DEA Index	42 Portuguese Hotels	No	No
Peypoch and Sbai (2011)	Luenberger productivity indicator (non-parametric)	15 Moroccan Hotels	No	No
Peypoch (2007)	Luenberger productivity indicator (non-parametric)	22 French Destinations	No	No
Chen and Soo (2007)	Stochastic Cost Frontier	47 Taiwanese Hotels	No	No
Sun, Zhang, Zhang, Ma, and Zhang (2015)	Malmquist DEA Index	31 Chinese Provinces	No	No

$$D(X,Y,Z;\beta)=1, \tag{4}$$

where $\beta\in\mathbb{R}^p$ is a vector of parameters. After imposing homogeneity of degree one with respect to input and using lower-case letters to denote logs and $x_1=\log X_1,\ x_2=\log\left(\frac{X_2}{X_1}\right),\dots,x_K=\log\left(\frac{X_K}{X_1}\right)$ we have:

$$x_1=f\left(x_2,\dots,x_K,y_1,\dots,y_M,z_1,\dots,z_{d_z};\beta\right)+v_1+u\equiv f\left(x_{(-1)},y,z;\beta\right)+v_1+u, \tag{5}$$

where v_1 is a usual econometric error term, and $u\geq 0$ represents technical inefficiency (in the form of radial input over-utilization). If we denote $w=[x'_{(-1)},y',z']'\in\mathbb{R}^{d_w}$ so that the distance function takes the form:

$$x_1=f(w)+v_1+u, \tag{6}$$

We can use the translog functional form:

$$f(w)=a_o+a'w+\frac{1}{2}w'\Gamma w= a_o+\sum_{j=1}^{d_w}a_jw_j+\frac{1}{2}\sum_{j=1}^{d_w}\sum_{h=1}^{d_w}\gamma_{jh}w_jw_h. \tag{7}$$

The parameter vector β consists of the parameters in the above expression, viz. a_o, a and Γ. From these expressions we have the inputs distance function in the form:

$$x_1=a_o+a'w+\frac{1}{2}w'\Gamma w+v_1+u\Rightarrow x_1=a_o+\sum_{j=1}^{d_w}a_jw_j+\frac{1}{2}\sum_{j=1}^{d_w}\sum_{h=1}^{d_w}\gamma_{jh}w_jw_h+v_1+u. \tag{8}$$

Assuming the availability of panel data we can write the equation as follows:

$$x_{1,it}=a_{o,it}+a'w_{it}+\frac{1}{2}w_{it}'\Gamma w_{it}+v_{1,it}-u_{it}\Rightarrow x_{1,it}=a_{o,it}+\sum_{j=1}^{d_w}a_jw_{j,it}+\frac{1}{2}\sum_{j=1}^{d_w}\sum_{h=1}^{d_w}\gamma_{jh}w_{j,it}w_{h,it}+v_{1,it}+u_{it}, \tag{9}$$

where $a_{o,it}$ captures firm and time effects, $i=1,\dots,n,\ t=1,\dots,T$. Our interest here focuses on productivity growth (PG) and its decomposition.

Two problems arise which we can solve them at the same time. First, $x_{(-1),it}$ in (9) is endogenously determined. Second, productivity cannot be independent of the inputs used. To proceed we use the following reduced form equation for $x_{(-1),it}$ in (10):

$$x_{(-1),it}=\Pi z_{it}+V_{(-1),it}, \tag{10}$$

where Π is a $(K-1)\times d_z$ matrix of reduced form coefficients and $V_{(-1),it}$ is a $K\times 1$ error term. We assume the following error structure:

$$\left[v_{1,it},V_{(-1),it}\right]'\sim N_K(0,\Sigma). \tag{11}$$

In this way endogeneity of $x_{(-1),it}$ is taken into account.

Another problem that empirical researchers often face, and which is of high importance when comparing between tourism destinations, is unobserved heterogeneity. The challenge is that unobserved heterogeneity cannot be captured using fixed-effects formulation as in (9). For this reason we assume that the parameters of the frontier are country-specific and time-specific, as follows:

$$x_{1,it}=a_{o,it}+a_{it}'w_{it}+\frac{1}{2}w_{it}'\Gamma_{it}w_{it}+v_{1,it}+u_{it}\Rightarrow a_{o,it}+\sum_{j=1}^{d_w}a_{j,it}w_{j,it}+\frac{1}{2}\sum_{j=1}^{d_w}\sum_{h=1}^{d_w}\gamma_{jh,it}w_{j,it}w_{h,it}+v_{1,it}+u_{it}. \tag{12}$$

For details on how we model heterogeneity, see Appendix A. In this study, we use Sequential Monte Carlo/Particle Filtering (SMC/PF) to perform the computations, see Appendix C and Tsionas (2016) for more details. We use 10^6 particles per iteration for 15,000 iterations the first 5000 of which are discarded to mitigate possible start-up effects. Our results remained the same when we used an additional 10,000 iterations with 10^7 particles per iteration. Convergence was monitored using the standard diagnostics (Geweke, 1991) and was obtained within the first 5000 iterations which we discarded. To ensure convergence further we use random initial conditions from the prior and run 100 different SMC chains for the baseline prior. We impose monotonicity and concavity restrictions in the translog functional form using rejection sampling.

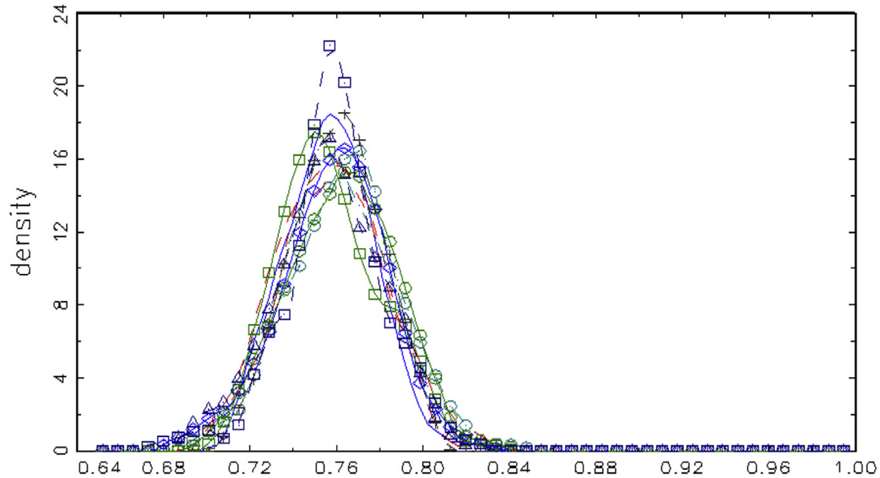

Fig. 1. Distribution of persistence parameter across various priors.

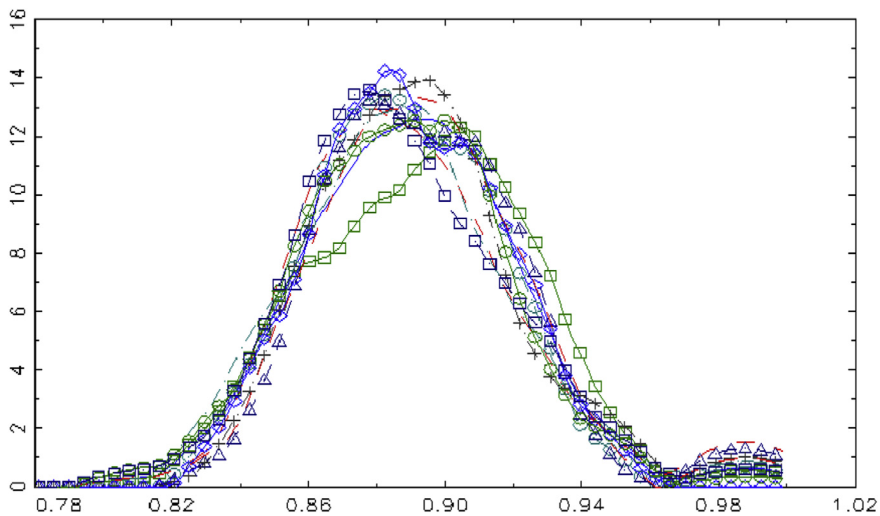

Fig. 2. Distribution of technical efficiency across various priors.

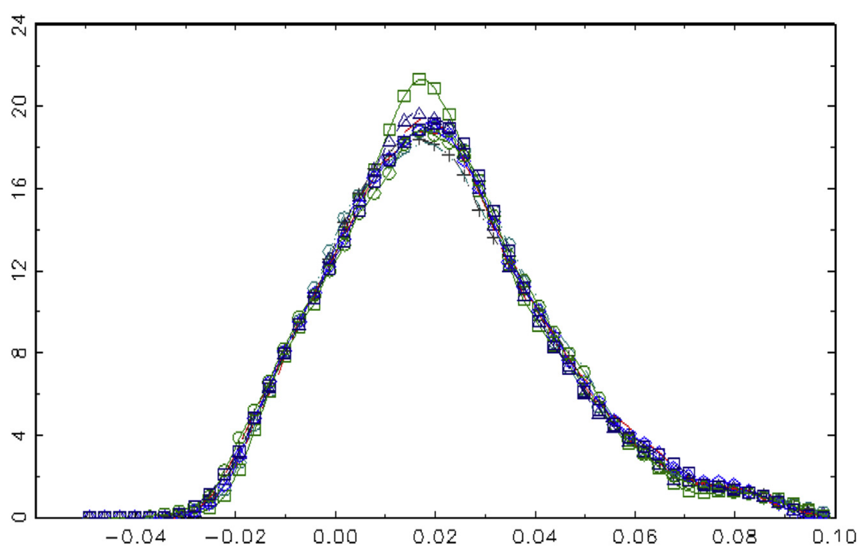

Fig. 3. Distribution of productivity change across various priors.

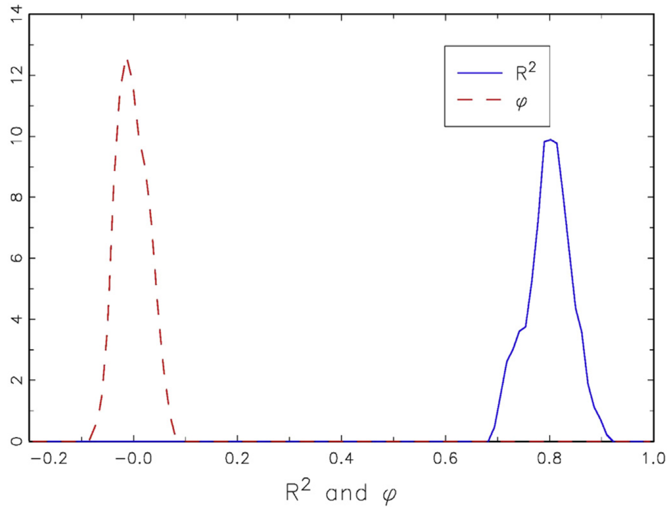

Fig. 4. Posterior distribution of R^2 and ϕ.

Specifically, we first impose these restrictions at the means of the data say $\bar{\mathbf{d}}$. Then we impose the same conditions at $\bar{\mathbf{d}}\pm h\mathbf{s}$ for $h = 0.1,\ 0.2,\ 0.3, \ldots, \bar{h}$. At $\bar{h} = 1.5$ led to acceptance of the constraints at almost every observed point (more than 95% of all observations).

4.1. Decomposition

In order to better understand the sources of total factor productivity (TFP) growth we decompose TFP into various interesting components (see Appendix B). This should enable tourism destinations to assess more clearly the sources of productivity changes in their destinations, and hence tailor their strategies more intensively toward less performing components.

Sometimes it is also important to estimate long-run productivity growth and make projections. Conditionally on $\tilde{z}_{it}$s from (A.5) we assume:

$$tfpg_{it} = a_i + \rho_i tfpg_{i,t-1} + \tilde{z}'_{i,t-1}\delta_i + \zeta_{it},$$

where ρ_i is an autoregressive coefficient, δ_i is a vector of parameters and ζ_{it} is an error term. If we use a two-step procedure it is well known that estimates will be inconsistent. Instead we view the above equation as *auxiliary*, that is as a forecasting model. For each MCMC iteration, we fit the above model using the draw for *tfpg*, we assume normality of the error term ζ_{it}, and we estimate the above model, assuming the same priors for its coefficients and its specification for the prior hyperparameters. In turn long-run productivity growth is

$$tfpg_i^* = (1-\rho_i)^{-1}\left(\tilde{z}_i^{*\prime}\delta_i\right),$$

where $\tilde{z}_i^*$ is an estimate of the long run value of $\tilde{z}_{it}$ which we take to be their last observed values, and $tfpg_i^*$ is the country-specific long-run value of TFP growth. Here, the draws for $tfpg_i^*$ can be used to estimate its posterior mean and posterior standard deviation or its entire posterior distribution for each country.

4.2. The problem of instruments

When using instruments like z_{it} in (10) two econometric questions arise. First, whether the instruments are strong enough, viz. whether they are correlated with $x_{(-1),it}$. Second, whether the instruments are proper in the sense that they are uncorrelated with the error term $v_{1,it}$. The first problem can be dealt with by looking at the pseudo-R^2 between $x_{(-1),it}$ and z_{it} which can be computed from the reduced form as:

$$R^2 = 1 - \frac{L_U}{L_U}, \tag{13}$$

where L_U corresponds to a (multivariate normal approximation) to the likelihood function of the reduced form in (10) when are coefficient except for the intercept are set to zero, and L_U denotes the corresponding unrestricted likelihood function, again from a multivariate normal approximation for simplicity.

The second problem is more fundamental. To resolve it we can append to the reduced form in (10) the following equations:

$$z_{it} = \Psi\tilde{z}_{i,t-1} + V_{it}^z. \tag{14}$$

where the $\tilde{z}_{i,t-1}$ are compressed in BCR fashion as in (A.5). Then we modify (11) as follows:

$$\left[v_{1,it}, V'_{(-1),it}, V_{it}^{z\prime}, \varepsilon_{it}\right]' \sim N_{K+d_z+1}(0, \Sigma). \tag{15}$$

Then, the question is whether *the maximum absolute correlation between* V_{it}^z say φ, and $v_{1,it}$ *is zero*, in which case we have valid instruments. The correlation coefficients can be computed from the appropriate elements of Σ in (15). There is a variety of Bayesian ways to test for this, the most meaningful being probably to present the marginal posterior distribution of the maximum absolute correlation between V_{it}^z and $v_{1,it}$.

5. Data

To estimate the frontier model in (2) we need first to define the inputs (x_{it}), outputs (y_{it}), as well as the vector of environmental variables (z_{it}). Following the majority of studies in the literature (Barros et al., 2011; Cracolici, Nijkamp, & Cuffaro, 2007), we select the following inputs: the number employees working in the tourism industry, capital investments made on the tourism industry, and number of rooms in accommodation properties, and outputs: the number of international tourism arrivals, receipts from domestic tourism, receipts from international tourism, and average length of stay of international tourists. For the environmental variables z_{it}, we follow closely Assaf and Tsionas (2015) and define twenty one variables that may affect the production process in the tourism industry. These include variables reflecting the “infrastructure quality”, “human resource quality” and “natural and environmental quality” of a tourism destination. The study by Assaf and Tsionas (2015) has shown that all the variables play “a critical role in attracting tourism outputs and hence ignoring them represent an important shortcoming that might bias the benchmarking outcomes”. The idea of including them in the reduced form of the input equation in (10) can be also theoretically justified as higher tourism quality is usually associated with more investments in inputs (Assaf & Tsionas, 2015). We test below whether these instruments are strong enough and proper as discussed in Section 4.2.

We refer the reader to Assaf and Tsionas (2015) for a more detailed breakdown of these quality variables, and for the descriptive statistics of all variables included in the model. We used several sources to collect our data including the United Nations World Tourism Organization, Euromonitor database, tourism satellite accounts of some countries, as well as Eurostat database. Most

Table 2
Input change (IC), output change (OC), frontier change (FC) and Total productivity growth (PG).

Country	IC (%)	OC (%)	FC (%)	TFP %
Australia	0.1220	−1.4750	−0.2916	−1.6450
New Zealand	−0.3698	0.6451	−1.3160	−1.0410
Russia	−0.4142	0.8447	−1.4090	−0.9782
Sri Lanka	−0.2829	0.5202	−1.1350	−0.8979
Bahrain	0.3733	−1.4850	0.2319	−0.8798
Argentina	0.2818	−1.1700	0.0413	−0.8468
Morocco	−0.4531	1.1110	−1.4900	−0.8322
Barbados	0.0272	−0.3131	−0.4892	−0.7752
India	−0.5130	1.3590	−1.6150	−0.7685
Jordan	−0.3494	1.0150	−1.2740	−0.6080
Ukraine	0.3903	−1.1820	0.2674	−0.5242
Mauritius	−0.2153	0.7058	−0.9944	−0.5039
Nepal	0.6647	−1.9680	0.8389	−0.4643
Portugal	−0.4865	1.5960	−1.5590	−0.4494
Hong Kong	0.0785	0.0598	−0.3824	−0.2441
Ireland	0.4891	−1.1640	0.4730	−0.2018
Guatemala	0.1293	0.1046	−0.2765	−0.0425
Cameroon	−0.4368	1.9660	−1.4560	0.0733
Sweden	0.2984	−0.2600	0.0758	0.1142
Slovenia	0.5493	−0.8414	0.5986	0.3066
Iceland	0.0268	0.7936	−0.4901	0.3302
Lithuania	0.0752	0.6844	−0.3891	0.3705
Kenya	0.0773	0.7486	−0.3848	0.4411
Peru	−0.0769	1.2730	−0.7060	0.4897
Paraguay	0.0902	0.7699	−0.3579	0.5022
Oman	0.6190	−0.6892	0.7437	0.6735
Albania	−0.0527	1.5090	−0.6555	0.8013
Moldova	0.0197	1.3890	−0.5047	0.9037
Mexico	0.2004	0.8624	−0.1283	0.9345
Pakistan	−0.1789	2.0480	−0.9185	0.9512
Switzerland	0.2515	0.8429	−0.0220	1.0720
Libya	0.6925	−0.4195	0.8969	1.1700
Hungary	0.8251	−0.7835	1.1730	1.2150
Cyprus	−0.1521	2.2470	−0.8628	1.2320
Qatar	0.6618	−0.2499	0.8330	1.2450
Kuwait	−0.1151	2.1680	−0.7857	1.2670
China	0.7841	−0.5113	1.0880	1.3600
Bolivia	0.8451	−0.6716	1.2150	1.3880
Greece	0.5242	0.3548	0.5462	1.4250
Panama	0.3350	0.9681	0.1521	1.4550
Italy	0.3575	0.9056	0.1989	1.4620
Azerbaijan	0.4303	0.7052	0.3505	1.4860
Slovak Republic	0.9039	−0.7535	1.3370	1.4880
Austria	0.6371	0.0844	0.7814	1.5030
Indonesia	0.1193	1.7450	−0.2973	1.5670
Cambodia	0.9650	−0.8594	1.4650	1.5700
Belgium	0.6073	0.3583	0.7194	1.6850
Chile	0.3967	1.0380	0.2806	1.7150
Tanzania	0.4594	0.9137	0.4113	1.7840
Nicaragua	0.2683	1.5760	0.0131	1.8570
Saudi Arabia	0.2125	1.7740	−0.1032	1.8830
Honduras	0.8065	−0.0319	1.1340	1.9090
Poland	0.4579	1.0710	0.4081	1.9370
Latvia	0.8543	−0.1471	1.2340	1.9410
Zambia	0.4083	1.2870	0.3048	2.0000
Romania	0.6840	0.6328	0.8792	2.1960
Finland	0.9296	−0.0944	1.3910	2.2260
Mozambique	1.4290	−1.6150	2.4310	2.2450
Singapore	0.5291	1.1980	0.5565	2.2830
Chad	0.8973	0.0930	1.3240	2.3140
Costa Rica	1.0010	−0.1952	1.5390	2.3450
Bulgaria	0.0064	2.9100	−0.5325	2.3840
Senegal	0.9054	0.3149	1.3400	2.5610
Tunisia	0.9588	0.1981	1.4520	2.6090
Spain	0.3057	2.2390	0.0910	2.6360
Madagascar	0.8497	0.7094	1.2240	2.7830
Gambia	0.8852	0.7031	1.2980	2.8860
Croatia	0.5475	1.7590	0.5948	2.9010
Uruguay	0.6033	1.5910	0.7110	2.9060
Serbia	1.3000	−0.5118	2.1630	2.9510
Israel	1.0040	0.4213	1.5460	2.9720
Georgia	0.4417	2.2010	0.3744	3.0170
Malta	1.2090	−0.0169	1.9740	3.1660
Dominican Republic	0.9615	0.8113	1.4570	3.2300
Bangladesh	0.7742	1.4460	1.0670	3.2870
Thailand	0.7156	1.7920	0.9451	3.4530
Jamaica	1.0280	0.8848	1.5970	3.5100
Turkey	1.0190	0.9290	1.5760	3.5240
Korea, Rep.	1.4320	−0.3348	2.4380	3.5350
Colombia	1.2310	0.4266	2.0190	3.6770
El Salvador	0.7901	1.7900	1.1000	3.6800
Japan	1.4310	−0.1207	2.4360	3.7460
Taiwan	0.6562	2.4130	0.8213	3.8900
United Kingdom	−4.1670	3.5570	4.5580	3.9470
France	1.6110	−0.2515	2.8110	4.1710
Germany	0.8922	1.9660	1.3130	4.1710
Syria	1.2230	1.1050	2.0020	4.3300
Malaysia	1.1840	1.2950	1.9210	4.4000
Puerto Rico	1.3430	0.8399	2.2520	4.4350
United States	−4.2880	3.9470	5.2550	4.9140
Vietnam	1.3500	1.3190	2.2660	4.9350
Venezuela	1.2500	2.0460	2.0590	5.3550
Denmark	1.5080	1.3130	2.5960	5.4170
Estonia	1.6000	1.0760	2.7880	5.4650
Egypt	1.9280	0.2454	3.4720	5.6450
Netherlands	2.0340	−0.0394	3.6910	5.6850
Armenia	1.7650	0.9119	3.1300	5.8070
Kazakhstan	1.7840	1.4390	3.1710	6.3940
Czech Republic	2.1600	1.2320	3.9540	7.3460
Philippines	2.1570	1.8530	3.9470	7.9570
Luxembourg	2.8100	0.1313	5.3090	8.2500
Average	0.5534	0.6894	0.8894	2.1321

of the quality variables were collected from the World Economic Forum, Executive Opinion Survey. The final sample included 101 tourism destinations over 4 years of data (2008–2012).

6. Results

Before presenting the results, we will elaborate here on some robustness checks we conducted to ensure the convergence of our model. For instance, one of the key criteria of Bayesian estimation is to ensure that the model is robust across various prior selections.

To perform sensitivity analysis we consider here 100 different priors resulting from random different values of h_A and h_B uniformly distributed in the interval [1, 20]. We present in Figs. 1–4 some of these findings. In Fig. 1, we examine the stability of the system via the maximal modulus eigenvalue of $\overline{A}_i$, the prior mean of the coefficients of A_i, see Appendix A. If this is unity then we have a random walk, otherwise if the maximal modulus eigenvalue of $\overline{A}_i$ is less than one the system is stable. This measure can be used to check whether popular specifications where $\overline{A}_i = I$ might be close to being valid in our specification. The results show they are stable and not a unit root as much of the literature assumes.

In Figs. 2–3 we show the sensitivity analysis for technical efficiency, and productivity change. We reproduced each of these figures using ten random sample distributions resulting from the final posterior distributions of the model. Both these figures clearly show high persistence of the results across various priors. As discussed above, we also test whether the instruments (z_{it}) we selected for the reduced form of the input equation in (10) are strong enough and proper. For instance, we report in Fig. 4 the pseudo-R^2. These results were averaged across all draws to account for parameter uncertainty, and while we consider 100 different priors, we show the average results here. We can see a highly consistent pseudo-R^2, indicating that the instruments we selected are strong enough. In the same figure we also report the maximum absolute correlation φ, which as shown is close to zero indicating again that the instruments are valid.

Table 3
Long-run productivity growth (PG).

Country	Long-run PG (%)
Australia	−1.6600
New Zealand	−1.0390
Russian Federation	−0.9759
Sri Lanka	−0.9035
Bahrain	−0.8747
Argentina	−0.8549
Morocco	−0.8039
Barbados	−0.7927
India	−0.7747
Jordan	−0.6042
Ukraine	−0.5251
Mauritius	−0.5082
Portugal	−0.4652
Nepal	−0.4633
Hong Kong	−0.2417
Ireland	−0.2008
Guatemala	−0.0437
Cameroon	0.0713
Sweden	0.1103
Slovenia	0.2956
Iceland	0.3302
Lithuania	0.3654
Kenya	0.4341
Peru	0.4899
Paraguay	0.5155
Oman	0.6684
Albania	0.7933
Mexico	0.9106
Moldova	0.9237
Pakistan	0.9420
Switzerland	1.0700
Libya	1.1380
Hungary	1.2030
Cyprus	1.2070
Kuwait	1.2300
Qatar	1.2630
China	1.3770
Greece	1.4230
Bolivia	1.4280
Panama	1.4320
Italy	1.4700
Austria	1.5030
Slovak Republic	1.5060
Azerbaijan	1.5120
Cambodia	1.5530
Indonesia	1.5910
Belgium	1.6600
Chile	1.6700
Tanzania	1.7830
Honduras	1.8380
Saudi Arabia	1.8510
Nicaragua	1.8600
Latvia	1.8740
Poland	1.9040
Zambia	1.9750
Romania	2.1370
Mozambique	2.2230
Finland	2.2380
Singapore	2.2440
Chad	2.2690
Costa Rica	2.3110
Bulgaria	2.4100
Senegal	2.5180
Tunisia	2.5770
Spain	2.7120
Madagascar	2.7220
Gambia	2.8670
Serbia	2.8670
Croatia	2.9590
Israel	2.9610
Georgia	2.9630
Uruguay	2.9630
Dominican Republic	3.1080
Malta	3.1490
Bangladesh	3.2170
Jamaica	3.4060
Turkey	3.4480
Korea, Rep.	3.5270
Colombia	3.6070
Thailand	3.6710
Taiwan, China	3.7060
El Salvador	3.7640
Japan	3.8080
Germany	4.1520
France	4.2670
Puerto Rico	4.2690
Malaysia	4.3160
Syria	4.4610
Vietnam	4.8660
Venezuela	5.3330
Estonia	5.4230
Denmark	5.4600
Netherlands	5.6010
Armenia	5.6020
Egypt	5.6950
Kazakhstan	6.3070
United Kingdom	6.5230
Czech Republic	7.2320
United States	7.6750
Philippines	7.9040
Luxembourg	8.2890
Average	2.1700

Having checked all the above, we present in Table 2 our productivity results along with the various components: input change, output change and frontier change. We rank all 101 destinations from lowest to highest according to their rate of productivity growth.[1] Of the three components of productivity "frontier change" seems to be driving most of this growth. Out of all destinations, 28 destinations have experienced a negative output growth, while 73 destinations have experienced output growth. Some destinations with the highest output decline include Nepal, Mozambique, and Bahrain, while countries with the highest output growth include Bulgaria, the UK and the US. In terms of input growth, we can see that only 16 destinations experienced negative input growth, while all the remaining 85 destinations experienced positive input growth. Destinations with the highest negative input growth include the US, the UK, and India, while destinations with the highest input growth include Philippines, Czech Republic and Luxembourg. In total, 43 destinations experienced negative correlation between input and output growth, while all remaining destinations experienced both input and output growth.

As mentioned, on average frontier growth seem to have contributed the most to productivity growth at most destinations-around 42% of total productivity growth was driven by frontier growth, while around 32% came from output growth and the rest from input growth. In total, only 23 destinations in our sample experienced negative frontier growth: Countries with the most negative frontier growth include India, Portugal and Morocco, while countries with the highest frontier growth include the US, the UK and Luxembourg. In other words, these countries seem to have achieved the highest progress in terms of "innovation". The interesting finding is that only 17 destinations in our sample experienced a productivity decline while all the remaining others experienced productivity growth. Destinations with the strongest productivity decline include countries such as Australia, New Zealand, Russia and Sri Lanka, while destinations with the strongest productivity growth include countries such as Czech Republic, Philippines and Luxembourg.

While it might appear surprising that countries such as Australia and New Zealand rank the worst in terms of productivity growth, a

Table 4
Efficiency change (EC) and average efficiency.

Country	EC %	Country	Efficiency
Iceland	−0.2454	India	0.8152
Russian Federation	−0.2244	Nicaragua	0.8375
Lithuania	−0.1888	Jamaica	0.8392
Panama	−0.1848	Hong Kong	0.8397
Honduras	−0.1576	Nepal	0.8406
Zambia	−0.1179	Greece	0.8440
Austria	−0.1173	Kazakhstan	0.8449
Uruguay	−0.1145	Switzerland	0.8487
Nepal	−0.1058	Mexico	0.8496
Malta	−0.0971	Chad	0.8535
Serbia	−0.0883	New Zealand	0.8556
Argentina	−0.0646	Italy	0.8569
Singapore	−0.0589	Moldova	0.8577
Syria	−0.0510	Poland	0.8593
Albania	−0.0490	Cambodia	0.8599
Netherlands	−0.0335	Bangladesh	0.8605
Italy	−0.0307	Barbados	0.8605
Thailand	−0.0216	Bulgaria	0.8614
China	−0.0215	Cyprus	0.8637
Cyprus	−0.0184	Bolivia	0.8638
Saudi Arabia	−0.0156	Paraguay	0.8639
Sweden	−0.0051	Finland	0.8669
Slovak Republic	−0.0042	Estonia	0.8672
Moldova	0.0004	Morocco	0.8680
Gambia	0.0062	Slovenia	0.8691
Czech Republic	0.0105	Austria	0.8721
Belgium	0.0125	Libya	0.8721
Jamaica	0.0183	Czech Republic	0.8725
Colombia	0.0195	Albania	0.8734
Romania	0.0214	Taiwan, China	0.8736
Bulgaria	0.0244	Puerto Rico	0.8741
Sri Lanka	0.0289	El Salvador	0.8746
Finland	0.0327	Netherlands	0.8763
Ireland	0.0372	China	0.8769
Chile	0.0378	Serbia	0.8781
Paraguay	0.0393	Singapore	0.8781
Venezuela	0.0552	Croatia	0.8790
Tunisia	0.0605	Bahrain	0.8804
Kazakhstan	0.0725	Turkey	0.8811
Puerto Rico	0.0751	Senegal	0.8814
Pakistan	0.0874	Costa Rica	0.8816
Luxembourg	0.0911	Belgium	0.8817
Korea, Rep.	0.0934	Malaysia	0.8820
Estonia	0.1000	Georgia	0.8822
Slovenia	0.1003	Hungary	0.8847
Armenia	0.1023	Philippines	0.8862
Hong Kong	0.1032	Saudi Arabia	0.8880
Libya	0.1040	Panama	0.8887
Madagascar	0.1102	Pakistan	0.8906
Morocco	0.1152	Australia	0.8907
Tanzania	0.1248	Tanzania	0.8921
Egypt	0.1252	Uruguay	0.8928
Hungary	0.1312	Egypt	0.8937
Peru	0.1328	Germany	0.8937
Israel	0.1341	Guatemala	0.8941
Mauritius	0.1361	Armenia	0.8943
Bolivia	0.1372	Cameroon	0.8947
Azerbaijan	0.1416	Jordan	0.8953
Malaysia	0.1419	Zambia	0.8962
Denmark	0.1422	Chile	0.8964
New Zealand	0.1531	Iceland	0.8974
Spain	0.1587	Oman	0.8986
Cameroon	0.1714	Japan	0.8991
Australia	0.1729	Lithuania	0.9000
Chad	0.1783	Mauritius	0.9000
Latvia	0.1798	Thailand	0.9007
Vietnam	0.1824	Honduras	0.9031
Nicaragua	0.1851	Madagascar	0.9033
Qatar	0.1860	Tunisia	0.9044
Portugal	0.1890	Argentina	0.9047
Kuwait	0.1891	Ireland	0.9047
Mexico	0.1908	Peru	0.9075
El Salvador	0.1911	Kuwait	0.9086
Greece	0.2010	Qatar	0.9087
Dominican Republic	0.2054	Gambia	0.9090

Table 4 (*continued*)

Country	EC %	Country	Efficiency
Bangladesh	0.2126	Slovak Republic	0.9104
Cambodia	0.2163	Portugal	0.9107
Bahrain	0.2220	Spain	0.9110
India	0.2381	Syria	0.9118
Barbados	0.2435	France	0.9127
Croatia	0.2483	Colombia	0.9134
Kenya	0.2525	Ukraine	0.9162
Costa Rica	0.2548	Azerbaijan	0.9164
Mozambique	0.2637	Korea, Rep.	0.9165
Georgia	0.2650	Latvia	0.9170
Oman	0.2699	Romania	0.9177
Ukraine	0.2742	Israel	0.9182
Germany	0.2774	Dominican Republic	0.9183
Taiwan, China	0.2892	Luxembourg	0.9203
Philippines	0.2936	Venezuela	0.9223
Turkey	0.2994	Russian Federation	0.9259
Jordan	0.2998	Sri Lanka	0.9271
Senegal	0.3083	Denmark	0.9288
France	0.3084	Mozambique	0.9359
Switzerland	0.3155	Sweden	0.9364
Indonesia	0.3188	Malta	0.9383
Guatemala	0.3459	Kenya	0.9387
Japan	0.3851	Indonesia	0.9452
Poland	0.4036	Vietnam	0.9461
United Kingdom	1.4360	United States	0.9877
United States	1.6790	United Kingdom	0.9886
Average	0.1341	*Average*	0.8908

deeper investigation of these results may reveal some of the reasons. For example, within the context of Australia, where the main source of negative productivity is the decline of output growth, one can justify the findings in terms of some recent industry trends. For example, "Australia's market share of total international visitors declined from 0.7 per cent in 2000 to 0.6 per cent in 2013. The number of visitors from Japan has significantly declined in recent times, and growth in visitor numbers has slowed or declined for some other historically important source countries, including the United States, the United Kingdom, and New Zealand" (Australian Productivity Commission,p.3).

For New Zealand, where the main source of productivity decline is the lack of input and frontier growth, one can also link the findings to some recent industry trends. The Chief executive of the "Tourism Industry Association" of New Zealand, recently stated that the main challenge facing the industry is finding quality staff, and generating sufficient capital investments to cope with the growing numbers of travellers: "We still have a challenge of getting sufficient investment into the tourism industry and we don't have a great pool of capital in New Zealand, so it is often a matter of looking offshore to see what money may come into New Zealand."

Of course, there might be other reasons affecting the results, but this would require a more detailed case analysis of these destinations. Luxembourg which has the highest productivity growth in our sample has experienced a significant increase in the number of international tourist arrivals and visitor spending (WTTC, 2015). The country also ranks high on the tourism competitiveness report and has invested significantly in the tourism industry over recent years (WTTC, 2015). Similar characteristics can also be said about other highly related destinations such as Czech Republic and Philippine where tourism has also expanded significantly. For example, in 2012, the number of tourism arrivals to Philippines grew to a record 4.27 million visitors compared to 3.5 million visitors in 2010.

Importantly, in Table 3, we present our long-run productivity results-the future expectation of productivity growth in these destinations. These measures may lead to important policy implications as they highlight the difference between short and long-run productivity measures of some destinations. For example, the

United States and the United Kingdom rank very well in the long-run, indicating that current tourism policies in these destinations seem to be moving the industry in the right direction. Importantly, some destinations seem to be performing poorly in both the short-run and long-run (e.g. Australia and New Zealand), suggesting that more aggressive strategies are needed to generate future growth in these tourism industries.

Finally, we report in Table 4 the efficiency results and the change in efficiency of all destinations over the sample period. Again, we rank destinations in order from the least performing to the best performing, where it is clear that destinations such the US and the UK dominate the ranking in both efficiency growth and average efficiency. In total there are 23 destinations with negative efficiency growth, with the most being Iceland, Russia and Lithuania. In terms of average efficiency alone, low efficient destinations include countries such as India, Nicaragua, Jamaica, Nepal and Hong Kong, while along with the US and the UK; other high performing destinations include France, Sweden, Indonesia, Vietnam and Luxembourg. Our results do not necessarily fully converge with other efficiency studies on tourism destinations (e.g. Assaf and Dwyer, 2013; Tsionas & Assaf, 2014). This is probably due to the difference in methodologies and model assumptions we adopt in this paper.

7. Concluding remarks

We introduced in this paper several important contributions to the tourism literature. First, we estimated a more robust productivity index that accounts for unobserved heterogeneity as well as the classical endogeneity problem in the estimation of input distance functions. Second, we provided a richer decomposition of productivity growth into three important components (input change, output change and frontier change). Third, we derived both short term and long-term productivity measures, providing hence some richer information for policy formulation in the tourism industry. Fourth, we provided measures of efficiency for each tourism destination, and applied the new methods to a rich of sample of leading tourism destinations and provided aggregate and individual country results. As mentioned, most existing studies in the area have focused only on one destination, or specific regions within one specific destination. Fifth, and finally, we measured productivity for the first time in this area using the Bayesian approach. The advanced assumption we impose on our model gives rise to a complicated statistical estimation problem which can be addressed successfully via Bayesian methods based on Sequential Monte Carlo/Particle Filtering (SMC/PF). We tested the performance of the model across various priors and also tested whether the instruments we selected for the reduced form are strong enough and proper.

Within all these contributions, this study aims to set the stage for more robust estimation of tourism productivity. Destination managers have an interest in tourism benchmarking as it is integral to the development of a systematic approach to tourism policy (Bosetti, Cassinelli, & Lanza, 2007; Kozak & Rimmington, 1999). Benchmarking also helps countries understand where they have strengths and weaknesses. Through comparison with other destinations, they can determine what and how much improvement can be achieved. Unfortunately, benchmarking is made more difficult given that the statistics published by tourism authorities or statistical agencies in some of the countries involved are limited to a narrow set of indicators and do not have an international or regional focus. We expect the results from this study to benefit directly the countries involved, especially, as most of the available tourism benchmarking methodologies are based on simplistic assumptions. The results of this study can also provide a genuine advance in our knowledge of productivity and destination competitiveness-a somehow neglected research topic. By accounting for heterogeneity, assessing the relationship between competitiveness and productivity becomes more meaningful as the technology used to produce "tourism" in different tourism destinations is not the same. Finally, with none of the existing studies providing short-run and long-run productivity estimates, we encourage more differentiation between these two measures. Future investment purposes, for instance, may become more effective if the relationship between productivity and competiveness is assessed from both short term and long term perspectives.

APPENDIX A

Modeling Heterogeneity

Let us denote $\beta_{it} = [a_{o,it}, a'_{it}, vec(\Gamma_{it})]' \in \mathbb{R}^{d_\beta}$, to model unobserved heterogeneity, we use a dynamic stochastic time-varying parameters framework:

$$\beta_{it} = b_i + A_i\beta_{i,t-1} + \Lambda z_{it} + e_{it},\ e_{it} \sim N_{d_\beta}(0, \Omega),\ i = 1, ..., n, t = 1, ..., T, \tag{A.1}$$

where b_i is a $d_\beta \times 1$ vector, A is a $d_\beta \times d_\beta$ matrix, Ω is the $d_\beta \times d_\beta$ covariance matrix of the error term and Λ is a $d_\beta \times d_z$ matrix of coefficients. In (A.1) we allow for stochastic time-varying parameters of the distance function where the dynamics of the parameter vector are country-specific through b_i and A_i. The model is quite general but we need shrinkage prior in order to estimate the parameters with accuracy. Our hierarchical prior for this model is:

$$\begin{aligned} & b_i \sim N_{d_\beta}\left(\overline{b},\ \overline{\Sigma}_b\right), \quad i = 1, ..., n, \\ & a_i \equiv vec(A_i) \sim N_{d_\beta^2}(\overline{a},\ \overline{\Sigma}_A), \quad i = 1, ..., n. \end{aligned} \tag{A.2}$$

The prior covariance matrices $\overline{\Sigma}_b$ and $\overline{\Sigma}_A$ control the degree of shrinkage. Our prior is that the z_{it}s are adequate in modeling the evolution of parameters so we would like to have $A_i = O_{d_\beta^2}$, viz. the zero matrix. Therefore, we set all elements of $\overline{a}$ equal to zero depending and we set $\overline{\Sigma}_A = h_A^2 I_{d_\beta^2}$ where h_A is a shrinkage parameter. We set $h_A = 10$ as we do not wish to place too much confidence in our prior belief about A_i being a zero matrix. We also try a model without instruments in which case our prior for A_i is that it is an identity matrix, viz. $I_{d_\beta^2}$.

For vector b_i we do not have much prior information so we set $\overline{b} = 0$, $\overline{\Sigma}_b = h_b^2 I_{d_\beta}$ and we set, again, $h_b = 10$ as we do not wish to place much confidence in our prior belief.

When the number of exogenous variables is large or when the basic exogenous variables are few but we have to consider squares and cross-products, we need some way of controlling the proliferation of parameters. In this study, we adopt the procedure of Bayesian Compressed Regression (BCR) of Guhaniyogi and Dunson (2015). Specifically we replace the model in (12) and (A.1) by the following:

$$x_{(-1),it} = \Pi \tilde{z}_{it} + V_{(-1),it}, \tag{A.3}$$

$$\beta_{it} = b_i + A_i\beta_{i,t-1} + \Lambda\tilde{z}_{it} + e_{it},\ e_{it} \sim N_{d_\beta}(0,\ \Omega),\ i = 1,\dots,n, t = 1,\dots,T, \tag{A.4}$$

where

$$\tilde{z}_{it} = \Psi z_{it}, \tag{A.5}$$

is an $r \times 1$ vector of compressed variables resulting from z_{it} through the application of a linear transformation using the $r \times d_z$ matrix Ψ. Here, r is the rank (dimensionality) of the compressed regressors. Guhaniyogi and Dunson (2015) avoid estimation of $\Psi = [\Psi_{ij}]$ altogether by drawing its elements randomly as follows:

$$\begin{aligned} &P(\Psi_{ij} = \psi) = \psi^2,\\ &P(\Psi_{ij} = 0) = 2\psi(1-\psi),\\ &P(\Psi_{ij} = -\psi) = (1-\psi)^2, \end{aligned} \tag{A.6}$$

where ψ is a parameter randomly drawn from (0.1, 1] —the lower bound is 0.1 instead of 0 for numerical stability. We search over different random draws, the rank r and the parameter ψ for $R = 10^6$ times. We select the appropriate matrix Ψ, the rank r and the parameter ψ by maximizing the marginal likelihood of the model which is a natural byproduct of our Sequential Monte Carlo/Particle-Filtering techniques.

In our application we have 21 z's including a time trend. Taking squares of non-categorical variables and their interactions we have almost 230 exogenous variables that cannot possibly be used in conjunction with (12) and (A.5). In our empirical application we find that $r = 12$ so we have huge dimensionality reduction in effect. The optimal parameter ψ turned out to be 0.31 based on maximizing the marginal likelihood of the model.

APPENDIX B

Decomposition

To start, suppose we have the following distance function:

$$D(x, y; \beta) = u + v, \tag{A.7}$$

where β is a parameter vector, u is inefficiency and, v is the error term. A la Olley and Pakes (1996), we have:

$$\sum_{k=1}^{K} \frac{\partial D}{\partial x_k}\frac{\partial x_k}{\partial t} + \sum_{m=1}^{M} \frac{\partial D}{\partial y_m}\frac{\partial y_m}{\partial t} + \sum_{j=1}^{p} \frac{\partial D}{\partial \beta_j}\frac{\partial \beta_j}{\partial t} = \frac{\partial u}{\partial t} + tfpg \tag{A.8}$$

where $tfpg$ is a "modified Solow residual" or TFP growth. Also $\frac{\partial D}{\partial x_i} = e_{x_i}$ is an input elasticity, $\frac{\partial D}{\partial y_j} = e_{y_j}$ is an output elasticity, $\frac{\partial x_i}{\partial t} = \dot{x}_i$, $\frac{\partial y_i}{\partial t} = \dot{y}_i$, and $\frac{\partial u}{\partial t} = \dot{u}$ are relative rates of change as our expressions are in log terms. So we end up with

$$tfpg = \sum_{k=1}^{K} e_{x_k}\dot{x}_k + \sum_{m=1}^{M} e_{y_m}\dot{y}_m + \sum_{j=1}^{p} e_{\beta_j}\dot{\beta}_j, \tag{A.9}$$

where, as usually, we omit efficiency change. However, we do not omit the last term in (A.8) which is:

$$\sum_{k=1}^{K} \frac{\partial D}{\partial \beta_k}\frac{\partial \beta_k}{\partial t} = \sum_{k=1}^{K} \frac{\partial D}{\partial \beta_k}\frac{\partial \beta_k}{\partial t}\left(\frac{1}{\beta_k}\right)\beta_k = \sum_{k=1}^{K} e_{\beta_k}\dot{\beta}_k. \tag{A.10}$$

Growth can be decomposed to the following components in (A.9). The first component corresponds to change in the inputs. The second component corresponds to change in the outputs. The third component corresponds to a change in the frontier due to parameter changes.

To summarize, first, we have an input change component which measures the percentage change in input investment over time:

$$IC_{it} = \sum_{k=1}^{K} e_{x_k}\dot{x}_k \tag{A.11}$$

where β_{it}^x contains the appropriate elements of β_{it}. An $IC_{it} > 0$ indicates a positive change, while $IC_{it} < 0$ indicates the opposite.

Second, an output change component which measures the percentage change in outputs over time:

$$OC_{it} = \sum_{m=1}^{M} e_{y_m}\dot{y}_m \tag{A.12}$$

where β_{it}^y contains the appropriate elements of β_{it} from (A.1). An $OC_{it} > 0$ indicates a positive change while $OC_{it} < 0$ indicates the opposite.

Third, a frontier change component:

$$FC_{it} = \sum_{j=1}^{p} e_{\beta_j}\dot{\beta}_j. \tag{A.13}$$

which measures the difference between the maximum productivity possible using the period "t" technology and the maximum productivity possible using the period "s" technology. A frontier growth is usually a reflection on technical progress or "innovation".

Of course, apart from these, we have an efficiency change component:

$$EC_{it} = \frac{u_{i,t+1} - u_{it}}{u_{it}} \simeq \Delta \log u_{i,t+1}. \tag{A.14}$$

which measures the difference in technical efficiency between the base period "s" and the period "t"

Appendix C

Particle filtering

The particle filter methodology can be applied to state space models of the general form:

$$y_T \sim p(y_t|x_t),\ \ s_t \sim p(s_t|s_{t-1}), \tag{A.15}$$

where s_t is a state variable. For general introductions see Gordon (1997), Gordon, Salmond, and Smith (1993), Doucet, De Freitas, and Gordon (2001) and Ristic, Arulampalam, and Gordon (2004).

Given the data Y_t the posterior distribution $p(s_t|Y_t)$ can be approximated by a set of (auxiliary) particles $\{s_t^{(i)}, i = 1, \dots, .N\}$ with probability weights $\{w_t^{(i)}, i = 1, \dots, N\}$ where $\sum_N^{i=1} w_t^{(i)} = 1$. The predictive density can be approximated by:

$$p(s_{t+1}|Y_t) = \int p(s_{t+1}|s_t)p(s_t|Y_t)ds_t \simeq \sum_{i=1}^{N} p\left(s_{t+1}\middle|s_t^{(i)}\right)w_t^{(i)}, \tag{A.16}$$

and the final approximation for the filtering density is:

$$p(s_{t+1}|Y_t) \propto p(y_{t+1}|s_{t+1})p(s_{t+1}|Y_t) \simeq p(y_{t+1}|s_{t+1}) \times \sum_{i=1}^{N} p\left(s_{t+1}\middle|s_t^{(i)}\right)w_t^{(i)}. \tag{A.17}$$

For more technical details and discussion refer to Tsionas (2016).

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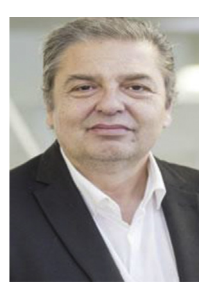
A. George Assaf is an Associate Professor at the Isenberg School of Management, University of Massachusetts-Amherst. His work has appeared in several tourism, management and economic journals, such as Tourism Management, Journal of Travel Research, Annals of Tourism Research, and Journal of Retailing.



Mike Tsionas is a Professor of Econometrics at Lancaster University and the Athens University of Economics and Business. He serves as an Associate Editor of the Journal of Productivity Analysis. His work has appeared in leading statistics and econometric journals such as the Journal of the American Statistical Association (JASA), Journal of Econometrics, and Journal of Applied Econometrics, among others.