UNIVERSIDAD CARLOS III DE MADRID
working papers

UC3M Working Papers
Statistics and Econometrics
16-13
ISSN 2387-0303
Noviembre 2016

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EFFICIENCY EVALUATION OF SPANISH HOTEL CHAINS

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Abstract

The tourism industry and in particular the hotel sector, is a highly competitive market. In this context, it is important that an hotel chain operates efficiently if it wants to maintain its market position. The objective of this work is to compare the relative efficiency of some of the largest hotel chains operating in Spain. To do this, we have designed a stochastic frontier model to measure revenue efficiency as a function of various different inputs such as total staff or number of rooms. Given that some chains are much bigger than others, both inputs and outputs are normalized by a measure of size. In contrast to previous works, we account for heterogeneity in hotel chains by introducing relevant inputs, such as the proportion of hotels in the chain with three stars or fewer, into the efficiency term of the stochastic frontier model. Our results suggest that in the Spanish case, in the period of the economic crisis, it was better in terms of revenue efficiency, for hotel chains to invest in hotels of three or fewer stars than in higher star rated hotels. Finally, we could find no clear evidence of a relationship between size and efficiency.

Keywords: Bayesian inference; Efficiency; Heterogeneity; Revenue function; Stochastic frontier analysis

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Acknowledgements: The authors acknowledge financial support from the Spanish Ministry of Economy and Competitiveness, research projects ECO2015-70331-C2-2-R and ECO2015-65701-P.

1. Introduction

The high level of competition in the tourism market, especially the hospitality industry, makes the formulation of a marketing strategy, strengthening hotel operations and improving the quality of service essential, not only for the profitability, but also for the survival of both individual hotels and hotel chains (see Hwang and Chang, 2003). All the factors mentioned previously, directly or indirectly depend on the efficient management of hotel chains. In addition, due to its characteristic of an oligopolistic market, Barros (2004) and Phillips (1999) indicate that the level of competition in the hospitality sector requires efficiency (see also Teague and Eilon, 1973).

In the 20th century, many efficiency studies in the tourism industry focused on measuring efficiency via accounting based measures (Baker and Riley, 1994; Phillips and Louvieris, 2005). However, modern approaches to efficiency measurement have been based on the idea of an efficient frontier function representing the output which may be achieved by an efficient company. The two most popular of these are data envelopment analysis (DEA), which assumes a deterministic frontier that can be estimated using optimization techniques, and stochastic frontier analysis (SFA), where a composite error term, composed of a random component and a component measuring inefficiency, is introduced to the frontier and statistical estimation techniques can be applied, see e.g. Coelli (2005) and Behr (2015) for good overviews of both DEA and SFA. Two of the first studies using the concept of the efficient frontier in the hospitality sector are Johns et al. (1997) and Anderson et al. (1999). The first of these uses data envelopment analysis (DEA) to measure hotel productivity, while the second applies SFA.

In most studies of efficiency using SFA, it is assumed that the inefficiency term is homogeneous. However, in many situations, inefficiency may be related to characteristics of a company that do not affect the frontier. For example, characteristics such as the star status or location of a hotel might be considered as belonging to this category. Heterogeneity in terms of such characteristics can lead to inaccurate inefficiency measurement, see e.g. (Reifschneider and Stevenson, 1991; Caudill and Ford, 1993; Caudill et al., 1995). Nevertheless, there are relatively few works that explore this issue. Some examples are Greene (2005) and Galán et al. (2014).

In the hotel sector, for example, Khrueathai et al. (2011) use a unique hotel-level dataset to examine operational efficiency and technology gap in Thailand's hotels. This paper classifies the hotels in Thailand into five groups with distinctive levels of operational technologies. The results show that, the hotels in the five groups differ in the use they make of input operational efficiency. Secondly, Oliveira et al. (2013) discuss the efficiency of hotel companies in the Algarve (Portugal). Their analysis is based on the parametric method of stochastic frontier approach using a revenue function. The results also point out the important role of the operational environment, particularly the location of the hotel and the existence of golf facilities. Star rating and owning multiple hotels do not seem to be so relevant. Finally, a more recent study that also considers heterogeneity is that by Bernini and Guizzardi (2015) where a metafrontier approach is applied to 2,705 hotels operating in Emilia-Romagna (Italy). They consider size, star rating and seasonality as environmental features affecting technology sets of a large variety of accommodations structures operating in an area of high tourism, where different accommodation alternatives coexist. Furthermore, they measure the bias in efficiency resulting from a failure to control for these sources of heterogeneity.

Although the majority of works on SFA are based on the use of frequentist statistical

approaches, stemming from van den Broeck et al. (1994b) and more recently Griffin and Steel (2007), who showed how to implement the Bayesian approach in a straightforward way using the freely available software package `WinBUGS`, there has been recent interest in applying Bayesian statistical methods. In particular, Bayesian approaches have been applied in the hospitality industry in Assaf (2012), Assaf and Magnini (2012) and Assaf and Barros (2013).

Most studies of efficiency in the hotel sector focus on comparing the efficiencies of individual hotels or of companies owning small numbers of hotels. For a very good, recent survey of the literature on efficiency in the hospitality sector, see Assaf and Josiassen (2016). However, a major contribution of our paper is the study of the relative efficiency of large hotel chains. Obviously, the selection of inputs for hotel chains cannot be carried out in exactly the same way as for individual establishments. For example, typically the price of a room varies within different hotels in the same chain so that if we wish to consider room price as an input, then we need to use an average price measure. Furthermore, in the case of the large Spanish hotel chains studied in this article, total revenue is typically almost directly related to chain size. Therefore, when modeling using SFA, in contrast to Oliveira et al. (2013) who suggested including a dummy variable in the frontier function to account for the ownership of multiple hotels, here we prefer to normalize revenue by an appropriate measure of chain size.

In this paper, we use both frequentist and Bayesian approaches to compare the revenue efficiencies of different Spanish hotel chains using SFA under the assumption of homoscedastic efficiency terms. There is evidence that the estimated efficiencies are correlated with exogeneous factors such as the proportion of hotels of three or fewer stars or the proportion of beach hotels in the chain, which suggests that these factors should be incorporated in the inefficiency model. In order to do this, we use a Bayesian statistical approach which is implemented in the free software `R` via the `R2OpenBUGS` package.

The rest of this paper is organized as follows. In Section 2 we introduce the SFA model and its inference through both frequentist and Bayesian techniques. In Section 3, we describe the data covering Spanish hotel chains and the relevant variables as inputs. We also analyze the data through SFA with heterogeneity using Bayesian inference. Finally, in Section 4 we provide some conclusions and consider some possible extensions of our approach.

2. Methodology

In this section, we present the stochastic frontier model motivated by the idea that deviations from the efficient frontier are not always entirely under the control of the firm.

2.1. Efficiency and the frontier function

According to Koopmans (1951), a company is technically efficient if it is able to use inputs efficiently. In other words, the company can produce the maximum output given a certain amount of inputs. Thus, technical efficiency is associated with the physical use of resources in the production process, and is not linked to any economic objective.

Assuming that the aim is to maximize output (in our case this will be revenue), besides being technically efficient, a firm needs to obtain an allocation of inputs that generates as much output as possible. If the firm is able to achieve this allocation, it is (revenue) efficient.

The frontier function, $I(x_i;\beta)$, representing the maximum output depends on the inputs employed, say x_n, for $n = 1,...,N$. The actual output of firm i, E_i, satisfies

$$E_i \leq I(x_i;\beta) \qquad \text{for} \quad i = 1,...,K. \tag{1}$$

The output efficiency of firm i, say $OE_i \leq 1$, is defined as

$$OE_i = \frac{E_i}{I(x_i;\beta)} \tag{2}$$

and is equal to one only if the firm is 100% efficient.

Various specifications for the frontier function $I(x_i;\beta)$ are possible. In this paper, we use a log-linear Cobb-Douglas function whose specification is given by:

$$\log I(x_i,\beta) = \beta_0 + \sum_n \beta_n \, ln \, x_{ni}. \tag{3}$$

2.2. The stochastic frontier

Inefficiency can be due to both firm inefficiency and factors that are beyond an individual firm's control. Therefore, it is reasonable to consider the possibility of a stochastic frontier function by including an error in the definition of the frontier, $I(x_i;\beta)$, so that, taking logarithms, we have:

$$\log I(x_i,\beta) = \beta_0 + \sum_n \beta_n \, ln \, x_{ni} + v_i, \tag{4}$$

where v_i represents the idiosyncratic error component which is often assumed to be normally distributed. Taking logarithms in (2), now gives the SFA equation

$$\log E_i = \beta_0 + \sum_n \beta_n \, ln \, x_{ni} + v_i - u_i. \tag{5}$$

where $u_i = -\log OE_i \geq 0$.

2.3. Inference for SFA models

In order to undertake inference for the SFA model, we need either to use a nonparametric approach, see e.g. Kumbhakar et al. (2007) or otherwise to specify distributional forms for the error terms v_i and u_i in equation (5). Here, we assume throughout that the idiosyncratic errors, v_i, for $i = 1,2,...$, are independent and identically distributed normal variables with a common variance term, $v_i \sim N(0,\sigma_v^2)$. For the inefficiency term, many parametric forms have been proposed in the literature, see e.g. Greene (2008). In this article, we shall generally assume one of the most standard functional forms, that is a half-normal distribution model $u_i \sim N^+(0,\sigma_{ui}^2)$ where in this case, when we allow for efficiency heterogeneity, the scale parameter may depend on individual hotel chain characteristics.

Two of the most common approaches to fitting SFA models use classical or frequentist and Bayesian statistical techniques respectively. This subsection summarizes the characteristics of these two methods.

2.3.1. Classical approach

The most popular approach to parameter estimation for SFA models is via maximum likelihood estimation that is, given the data sample, the optimal set of parameters is that which maximizes the likelihood function. Given the error distributions commented previously, the likelihood function can be calculated explicitly and then likelihood maximization can be carried out directly. A number of software packages are available for parameter estimation and in this case we use the `frontier` package (Coelli and Henningsen, 2013) within `R` for implementation.

In the models we analyze, there are quite a large number (twelve) of possible explanatory variables which could be included in the frontier function as well as others which might affect the inefficiency term. Therefore, it is important to decide which of these are relevant. In order to do this, we propose to use standard model selection criteria to choose between different fitted models. The two most popular of these within the classical framework are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

2.3.2. Bayesian approach

In contrast to classical methods, a Bayesian approach begins by assuming that, given a model M, there is a prior distribution, $f(\boldsymbol{\theta}|M)$, available for the unknown model parameters $\boldsymbol{\theta}$. Given the data $\mathbf{y}$, the prior distribution can then be updated to a posterior distribution, $f(\boldsymbol{\theta}|\mathbf{y}, M)$ via Bayes theorem:

$$f(\boldsymbol{\theta}|\mathbf{y}, M) \propto f(\boldsymbol{\theta}|M) f(\mathbf{y}|\boldsymbol{\theta}, M). \tag{6}$$

van den Broeck et al. (1994a) present several advantages of Bayesian inference as opposed to the classical approach. In particular, a posterior distribution for the inefficiency term, u_i, of firm i can be obtained as:

$$f(u_i|\mathbf{y}, M) = \int f(u_i|\mathbf{y}, \boldsymbol{\theta}, M) f(\boldsymbol{\theta}|\mathbf{y}, M)\, d\boldsymbol{\theta},$$

which permits interval estimation of the inefficiencies instead of just point estimation.

Unfortunately, for most of the models analyzed here, the exact calculation of posterior distributions is impossible. Therefore, we must apply simulation methods which allow us to simulate a sample from the posterior parameter distribution such as Markov chain Monte Carlo approaches, (see Robert and Casella, 2013). Fortunately, Griffin and Steel (2007) showed that these methods can be implemented for SFA models via the `WinBUGS` statistical package. We proceed in a similar way and use the more recent package `OpenBUGS` via `R2OpenBUGS` in `R` to carry out the fitting of Bayesian models.

To select models under the Bayesian approach, we consider a version of the deviance criterion (deviance information criterion or DIC) of Spiegelhalter et al. (2002), which is something like a Bayesian version of the AIC. A major advantage of this approach is that it makes DIC to be very easy to calculate through the output of OpenBUGS. One problem is that in models with latent variables (as in our case, the inefficiencies), the original criterion may give inaccurate results. Celeux et al. (2006) present several variants of the DIC and particularly recommend the use of DIC3 criterion, which we use in this paper. The interpretation is the same as that of the DIC: the lowest value of DIC3 indicates the best model.

3. Spanish hotel chains: a case study

The data that we analyze in this article correspond to the year 2014 and have been collected from the SABI (System for Library Automation) database[1]. The sample consists of forty four of the largest Spanish hotel chains, each with at least one thousand one hundred and eighty rooms in total.

Combining the hotels in all of the chains studied, there are seven hundred and eighty seven individual hotels. Of these, there are four one-star hotels, twenty two-star hotel, two hundred and forty three-star hotels, four hundred and sixty five four-star hotels and fifty six five-star hotels.

As well as the information available from SABI, we also used other sources, such as HOSTELTUR[2] in order to find the average number of rooms available in each hotel chain, and the individual website of each hotel chain in order to calculate the average room prices of the different chains and `Booking.com`[3] to find the proportion of hotels with golf facilities and the proportion of beach hotels in each chain. Finally, the proportion of hotels close to airports was calculated using google maps[4].

3.1. Variable selection

Table 1 shows a bried summary of the variables that have been used in some of the most important empirical papers in the efficiency literature on hotels.

Table 1: SFA studies in the hotel sector

Author	Methodology	Sample	Outputs	Inputs	Exogenous variables
Anderson et al. (1999)	SFA/translog	48 hotels, USA	(1) Total revenue	(1) N° rooms; (2) N° employees (3) Total gaming-ralated expenses (4) Total food ande beverage expenses (5) Other expenses.	
Barros (2004)	SFA/Cobb Douglas	42 hotels, Portugal	(1) Sales (2) N° occupied nights	(1) Price of work (2) Operational cost (3) Price of food (4) Price of capital	(1) Region
Rodríguez et al. (2007)	SFA/Translog	44 hotels, Spain	(1) Sales	(1) Annual operational expenses (2) Price of work (3) Ratio (Annual labor costs /number of full-time equivalent employees) (4) Ratio (Annual assets depreciation /fix assets at current prices) (5) Ratio (Annual financial expenses/debts)	(1) Work productivity
Thang (2007)	SFA/ Cobb Douglas y Translog	474 hotels, Vietnam	(1) Total revenue	(1) Labor costs (2) Net assets (3) Other operational costs	(1) N° employees (2) Ownership structure (3) Location
Chen(2007)	SFA/Cobb Douglas	55 hotels, Taiwan	(1) Total revenue (2) Room occupancy rate (3) Production value of unit catering space	(1) Price of labor (2) Price of F&B (3) Price of materials (4) Total operating costs	(1) Operation Type (2) Location (3) Scale
Khrueathai et al. (2011)	SFA/Cobb Douglas	1799 hotels, Thailandia	(1) Sales	(1) N° rooms (2) N° employees (3) Operational expenses (4) Assets (5) Room rate per night	(1) Ratio of workers per room (2) Ratio of foreign guest (3) Period of operation
Oliveira et.al (2013)	SFA/translog	28 hotels, Portugal	(1) Total revenue (2) Price of rooms (3) Price of F&B	(1) N° rooms (2) N° employees (3) N° seats (4) Other costs (5) Capex (CAPEX)	(1) N° Star (2) Regions (3) Golf (4) Number: 1 if exits more than 1 hotel, 0 otherwise
Assaf et.al. (2011)	SFA/ Translog/Bayesian	13 hotels, Angola	(1) Revenue per available room (2) Occupation rate	(1) Operational expenses (2) Price of labour (3) Price of capital	(1) Belonging to a group or not
Assaf (2012)	SFA/DEA/Bayesian	192 hotels, Asia-Pacific	(1) Total revenue	(1) N° rooms (2) N° employees (3) Other operational expenses	

In our case, similar to many of the studies cited in Table 1, we also propose to use the total operating revenue of each chain (O.R) as the basic output variable. The available input

[1] This database is published by the Bureau van Dijk Electronic Publishing and can be accessed from http://www.bvdinfo.com/en-gb/our-products/company-information/national-products/sabi.

[2] http://www.hosteltur.com/.

[3] http://www.booking.com/.

[4] https://www.google.es/maps/.

variables to the frontier are average room price (P.R), the average price of food price (P.F), the total number of rooms (N.R), total assets (T.A), material expenses (M.E), employee expenses (EM.E), number of employees (N.EM), financial expenses (F.E), funds (F), cash flow (C.F), operating expenditure (O.E) and number of establishments (N.ES).

As can be seen from Table 1, a variety of different variables have been considered as possibly influencing hotel efficiency in the literature. Here, we follow Oliveira et al. (2013) and consider factors that reflect the operating environment as potential exogenous variables. In particular, we consider the proportion of hotels with three stars or less within each chain (Star123), the proportion of beach hotels (Beach), the proportion of golf hotels (Golf) and the proportional of hotels that are ten kilometres or less from an airport (Airport) as possible heterogeneous variables.

3.2. Exploratory data analysis

Before formally defining the SFA models that we consider in this paper, we first perform some simple data analyses in order to illustrate some of the specific problems we face in applying SFA to hotel chains as opposed to individual hotels.

Firstly, in Table 2, we report the correlations between the different input and output variables.

Table 2: Correlation among variables

	O.R.	N.R	T.A	M.E	EM.E	N.EM	F.E	C.F	O.E	N.ES	O.F	P.R	P.F
O.R.	1.00	0.96	0.94	0.93	0.99	0.98	0.89	0.72	1.00	0.89	0.93	0.41	0.26
N.R	0.96	1.00	0.92	0.84	0.97	0.95	0.89	0.67	0.96	0.93	0.88	0.37	0.21
T.A	0.94	0.92	1.00	0.85	0.95	0.87	0.99	0.81	0.93	0.76	0.95	0.33	0.23
M.E	0.93	0.84	0.85	1.00	0.91	0.91	0.79	0.70	0.92	0.77	0.88	0.29	0.17
EM.E	0.99	0.97	0.95	0.91	1.00	0.97	0.92	0.72	0.99	0.89	0.92	0.37	0.22
N.EM	0.98	0.95	0.87	0.91	0.97	1.00	0.81	0.63	0.98	0.94	0.87	0.38	0.22
F.E	0.89	0.89	0.99	0.79	0.92	0.81	1.00	0.80	0.88	0.70	0.91	0.29	0.18
C.F	0.72	0.67	0.81	0.70	0.72	0.63	0.80	1.00	0.70	0.50	0.84	0.27	0.41
O.E	1.00	0.96	0.93	0.92	0.99	0.98	0.88	0.70	1.00	0.91	0.91	0.41	0.25
N.ES	0.89	0.93	0.76	0.77	0.89	0.94	0.70	0.50	0.91	1.00	0.76	0.36	0.18
O.F	0.93	0.88	0.95	0.88	0.92	0.87	0.91	0.84	0.91	0.76	1.00	0.32	0.26
P.R	0.41	0.37	0.33	0.29	0.37	0.38	0.29	0.27	0.41	0.36	0.32	1.00	0.78
P.F	0.26	0.21	0.23	0.17	0.22	0.22	0.18	0.41	0.25	0.18	0.26	0.78	1.00

It can be observed that there is a very high, positive correlations between the dependent variable, O.R, and the independent variables, number of rooms (N.R), number of employees (N.EM) and number of establishments (N.ES). Indeed, all of the variables excepting room price and food price are highly correlated. Figure 1 backs this up by showing regression plots of operating revenue against these variables, which suggest a close to linear relationship in each case, especially in the case of the number of employees.

The underlying explanation is that all of these variables are influenced by the size of the hotel chain. We would not only expect a larger chain to have higher total revenues but also to employ more staff, have more rooms in total, have more hotels, etc.

As hotel chains vary considerably in size, if we wish to compare them in terms of revenue, it is therefore necessary to normalize both revenue and size dependent inputs via some size measure. We choose to normalize revenue and (non-price) inputs either by the number of rooms, the number of employees or the number of establishments. Obviously, when

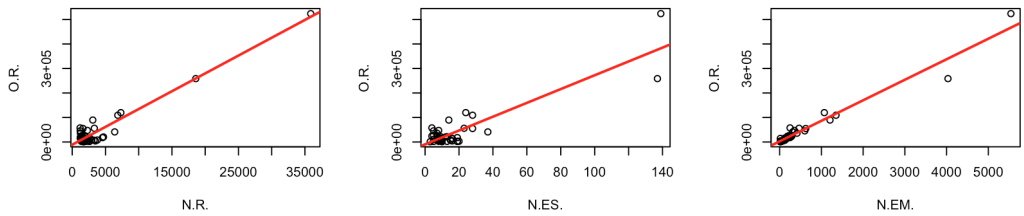

Figure 1: Relationship between total operating revenue and number of employees.

these variables are used to normalize the other input and output variables, they are not then included in the resulting SFA model.

3.3. *A revenue stochastic frontier model for hotel chains*

According to e.g. Kumbhakar and Lovell (2003), a change in prices should not cause a change in efficiency of a firm. Therefore, revenue efficiency just depends on relative output prices. This implies that for the frontier to satisfy this restriction, both the output and the price input terms should be normalized. Following Oliveira et al. (2013),we normalize by dividing operational revenue and room price by food price. This leads to the following SFA model for hotel chain revenues:

$$\log \frac{O.R_i}{s_i P.F_i} = \beta_0 + \sum_n \beta_n \, ln \frac{x_{ni}}{s_i} + \beta_{n+1} \frac{P.R_i}{P.F_i} + v_i - u_i, \tag{7}$$

where $s_i \in \{N.R_i, N.EM_i, N.ES_i\}$, is the size correction and $\mathbf{x}_i$ represents the input variables related to size for chain i.

3.4. *Model and variable selection*

To fully specify our models we need to choose a distribution for the inefficiency component and to select the input variables. We consider both the half-normal distribution and the truncated-normal distribution for the inefficiency component. Note that for a given inefficiency distribution and size normalization, we have ten potential independent variables, and consequently, $2^{10} = 1024$ possible models.

As Bayesian analysis of all models is somewhat more time consuming than the classical approach, in this case we fitted all possible model specifications via maximum likelihood using the R `frontier` package.

Table 3 reports the rankings of the optimal models selected by the AIC and BIC. It can be observed that the AIC and BIC values are very similar under both the half-normal and truncated-normal inefficiency distributions although slightly preferring the simpler, half-normal model. To discriminate between the two, we also performed a likelihood ratio test whose statistic is:

$$\tau = -2 \, ln \frac{L(\beta_{HN})}{L(\beta_{NT})} \sim \chi^2_1.$$

The values of the τ statistic are shown in the last column of Table 3. In all cases, the value of τ is less than the 95th percentile of the χ^2_1, which implies that there is no evidence to reject

the half-normal distribution. Therefore, in all future analyses in this paper, we shall assume that the efficiency term is modeled with a half-normal distribution throughout.

Table 3: Model selection using AIC and BIC

	Model number	Half-normal			Truncated Normal			Test
		Ranking by AIC	AIC	BIC	Ranking by AIC	AIC	BIC	τ
Normalized by N.R	751	1	38.965	56.807	1	40.861	60.027	0.104
	744	2	39.866	57.708	2	41.866	60.487	0.000
	759	3	39.930	57.772	3	41.930	60.914	0.000
Normalized by N.ES	717	1	36.000	50.273	1	38.000	54.057	0.000
	733	2	36.973	53.031	2	38.862	55.345	0.111
	973	3	37.894	53.952	3	39.894	56.565	0.000
Normalized by N.EM	749	1	36.973	53.031	1	38.862	56.704	0.111
	765	2	38.343	56.185	3	40.186	58.220	0.157
	751	3	38.355	56.197	2	40.150	57.537	0.205

Table 4 shows the independent variables that are included in the top three models under each size normalization, together with the signs of the coefficients that are associated with each variable. The results are fairly consistent in terms of the selected variables: the selection criterion always chooses those models that include as input variables material expenses (M.E), employee expenses (EM.E), cash flow (C.F), operating expenses (O.E) and price of room divided by price of food (P.R/P.F) as independent variables.

It is interesting to observe that (when it is not used as a normalizing factor), the number of establishments appears with a negative coefficient in the frontier function of the top models. This suggests that it is better for a hotel chain to invest in fewer large hotels than in more small hotels, when maintaining the total number of rooms or the total number of staff. As expected, the coefficient of the price per room and price for food ratio is positive, that is, if price per room increases relatively more than the food price, then so does revenue.

Table 4: Top models under different size normalizations

	Model number	Ranking by AIC	N.R	T.A	M.E	EM.E	N.EM	F.E	C.F	O.E	N.ES	O.F	P.R/P.F	AIC	BIC
Normalized by N.R	751	1			+	+	-		+	+	-		+	38.96525	56.80715
	744	2		+	+	+			+	+	-		+	39.86648	57.70838
	759	3			+	+		+	+	+	-		+	39.93027	57.77217
Normalized by N.ES	717	1			+	+			+	+			+	35.9997	50.27321
	733	2			+	+	-		+	+			+	36.97315	53.03086
	973	3			+	+			+	+		+	+	37.89447	53.95217
Normalized by N.EM	749	1			+	+			+	+	-		+	36.97315	53.03086
	765	2			+	+		+	+	+	-		+	38.34349	56.18539
	751	3		+	+	+			+	+	-		+	38.35516	56.19705

3.5. *SFA with heterogeneity*

In the previous analysis, we have not included any of the exogenous variables commented at the end of Section 3.1 in the SFA models specified in (7).

In their analyses, Oliveira et al. (2013) include these exogenous variables in the frontier function. However, following e.g. Greene (2008) and Coelli (2005) it is an open question whether it is better to include these variables in the frontier or in the inefficiency parameters. In this article, we shall take the second approach. Including these variables in the

scale parameter of a half-normal inefficiency distribution as we do here implies that inefficiency possesses the scaling property, see e.g. Wang and Schmidt (2002). This property has a number of modeling advantages, such as the fact that firm heterogeneity simply inflates or deflates the efficiency distribution without changing its shape, as outlined in e.g. Greene (2008).

In order to select the relevant exogenous variables, Figure 2 shows scatter plots of the efficiency estimates of the different firms against the possible heterogeneity factors using number of rooms as the size normalization. It can be seen that there is a slight positive relationship between the proportion of hotels in the three star or lower category and the efficiency rankings and possibly, although to a much lesser extent if at all, in the case of the proportion of beach hotels. There is no real evidence of a relationship between estimated efficiency and the proportions of hotels with golf or hotels close to the airport. Therefore, we consider models that include either the proportion of beach hotels or the proportion of hotels of three or fewer stars as variables influencing the inefficiency term.

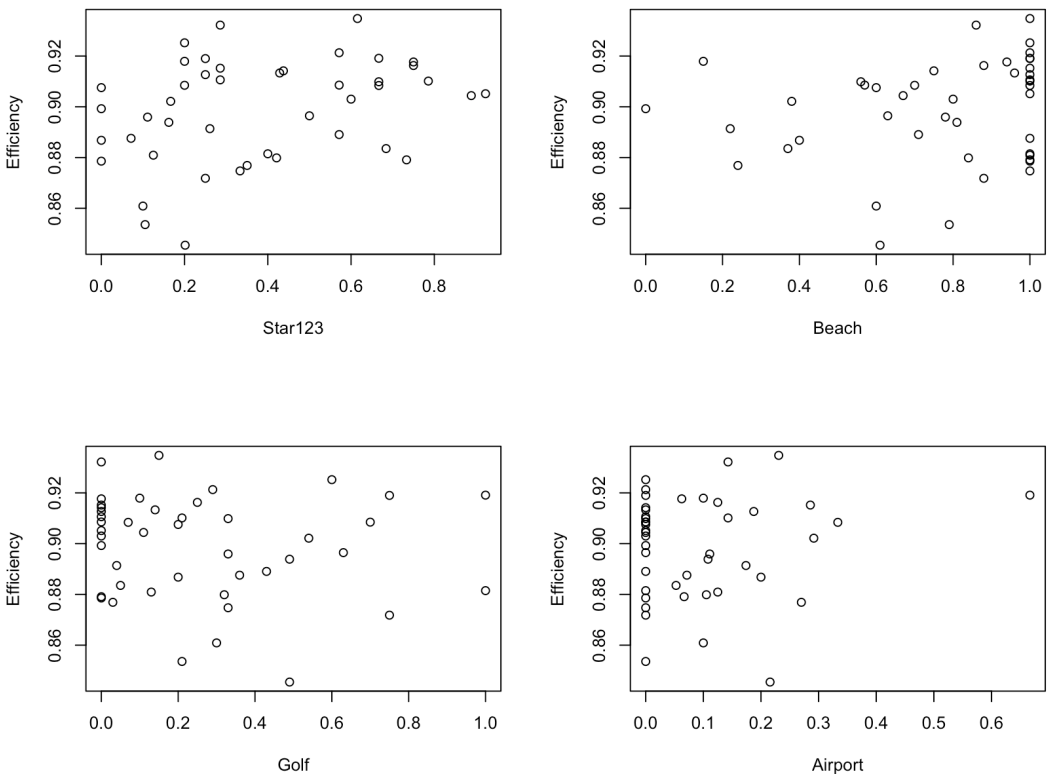

Figure 2: Scatter plots showing the relation between the estimated efficiency and exogenous variables.

In order to include heterogeneity in the SFA model of (7), we now introduce a log-linear

model for the scale parameter of the inefficiency as follows:

$$\begin{aligned} u_i &\sim N^+\left(0, \sigma^2_{ui}\right) \\ \log \sigma^2{}_{ui} &= \gamma_0 + \gamma_1 Beach_i + \gamma_2 Star123_i. \end{aligned} \tag{8}$$

We also consider all different possible sub-models of this complete specification. For example, the basic model of (7) corresponds to the case $\gamma_1 = \gamma_2 = 0$ and the sub-model containing just the proportion of beach hotels as a heterogeneity variable corresponds to $\gamma_2 = 0$.

3.5.1. Bayesian estimation

Unfortunately, it is not straightforward to fit the SFA model including heterogeneity using the classical approach and therefore, we adopt a Bayesian framework in this section.

In order to compare the Bayesian approach with the classical results, we first ran the top three models under the half-normal inefficiency specification as illustrated in Table 3 without considering heterogeneity, but now using Bayesian inference. In all cases, relatively weak, normal priors were used for the regression coefficients, an inverse gamma prior was applied for the variance of the idiosyncratic error and an inverse gamma prior was used for the inefficiency scale parameter. In this last case, the prior was designed so that the prior mean efficiency estimate was close to the estimated average efficiency under the classical approach.

Under this specification, the results of the Bayesian analysis were very similar to those of the classical analysis. For example, Kendall's rank correlation measure was used to compare the Bayesian mean efficiency rankings and classical efficiency rankings of the different chains. Rank correlations of at least 0.9 were achieved in all models and in the majority of cases, there was an almost linear relationship between the estimated efficiency rankings.

We also fitted the models including heterogeneity, again with normal priors for the coefficients $\gamma_0, \gamma_1, \gamma_2$.

Table 5 shows the value of the DIC3 criterion for the best three models of Table 3, but now also including the different combinations of exogenous variables in the inefficiency as in (8).

Table 5: Comparing DIC3 under different size normalizations

	Model number	Ranking AIC	Exogenous variables	DIC3	Ranking DIC3		Model number	Ranking AIC	Exogenous variables	DIC3	Ranking DIC3		Model number	Ranking AIC	Exogenous variables	DIC3	Ranking DIC3
Normalized by N.R	751	1	Both factors	83.0324	5	Normalized by N.ES	717	1	Both factors	81.5644	5	Normalized by N.EM	749	1	Both factors	82.1886	4
			Star123	81.7669	1				Star123	81.0300	2				Star123	80.3991	1
			Beach	82.6710	3				Beach	81.2040	3				Beach	82.3284	5
			Without factor	82.9677	4				Without factor	81.2367	4				Without factor	81.8743	3
	744	2	Both factors	84.4288	11		733	2	Both factors	82.8526	11		765	2	Both factors	85.8080	11
			Star123	82.5417	2				Star123	80.0405	1				Star123	82.4448	6
			Beach	83.3069	6				Beach	82.7235	9				Beach	86.6276	12
			Without factor	83.4305	7				Without factor	82.1156	6				Without factor	85.2321	10
	759	3	Both factors	84.6053	12		973	3	Both factors	82.9188	12		751	3	Both factors	82.6560	7
			Star123	83.8011	8				Star123	82.2893	7				Star123	80.8058	2
			Beach	84.2521	10				Beach	82.7439	10				Beach	84.5361	9
			Without factor	84.2224	9				Without factor	82.5983	8				Without factor	83.5665	8

We can see that, excepting the case of normalization via $N.EM$, when the orders of the second and third models are reversed, the rankings selected by the AIC and DIC3 for the models without heterogeneity are consistent. This consistency in model selection does not appear to be altered by the inclusion of heterogeneity variables. Thus, in the case of nor-

malization by number of rooms, model 751 is more popular than model 744 or model 759, whichever set of exogenous variables are included.

Furthermore, under each basic model, the DIC3 of the sub-model considering the percentage of hotels of three or fewer stars always outperforms the other models. This suggests that this is an important influencing factor in hotel chain efficiency. We can also see that including the proportion of beach hotels does not appear to improve upon the basic model as the DIC3 values in this case are virtually identical.

Table 6 shows the posterior mean parameter estimates under the best models under each normalization, selected using the DIC3 criterion. These models are model 751 when normalizing by number of rooms, model 733 when normalizing by number of establishments and model 749 when normalizing by number of employees. In each case we have used the proportion of hotels with three or fewer stars as the heterogeneity variable. It can be observed that the signs of the estimated coefficients are the same as in Table 4 under all normalizations which suggests that the results are fairly robust to the inclusion of the heterogeneity variable. Thus, for example, we can see that as previously suggested, for a fixed number of staff or a fixed number of rooms, relative revenue increases when a hotel chain invests in a small number of larger hotels as opposed to a larger number of small hotels. Secondly, it is interesting to observe the negative coefficient for the proportion of hotels of three or fewer stars. This suggests that in terms of revenue efficiency, it is not worth spending high quantities of money to obtain higher star ratings for the hotels in a chain as this does not appear to increase revenue with respect to chain size. This result contrasts a little with the findings of Oliveira et al. (2013) who found that for the Algarve region, revenue was higher for five star hotels than for four star hotels in general. However, in this paper, these variables were included in the frontier and not in the inefficiency. Observe also that the great majority of the hotels in the Spanish chains considered in our analysis belong to the three and four star categories. Note also that our analysis considers the year 2012 at the height of the Spanish and European economic crisis, when it may be that customers prefer to pay less for a three star hotel experience than invest more in a four star hotel.

Table 6: Estimation results of the best models under different normalizations

	Normalized by N.R		Normalized by N.ES		Normalized by N.EM	
	Estimate	SD	Estimate	SD	Estimate	SD
$\hat{\beta}_0$	-3.867	1.285	-3.833	1.153	-3.807	1.163
$\hat{\beta}_1$ (M.E)	0.200	0.074	0.201	0.073	0.200	0.073
$\hat{\beta}_2$ (EM.E)	0.535	0.306	0.570	0.294	0.564	0.293
$\hat{\beta}_3$ (N.EM)	-0.278	0.279	-0.304	0.271	-	-
$\hat{\beta}_4$ (C.F)	0.077	0.036	0.074	0.037	0.075	0.036
$\hat{\beta}_5$ (O.E)	0.366	0.170	0.367	0.169	0.366	0.172
$\hat{\beta}_6$ (N.ES)	-1.001	0.201	-	-	-0.973	0.148
$\hat{\beta}_7$ (PR/PF)	1.072	0.127	1.066	0.128	1.068	0.129
$\hat{\gamma}_0$	-10.742	9.075	-10.839	9.021	-10.975	9.211
$\hat{\gamma}_2$ (Star123)	-15.831	9.968	-11.013	5.680	-12.461	6.754

It is also interesting to explore whether including exogenous variables in the inefficiency term changes the relative rankings of the different hotel chains. In Table 7 we show the rank correlations of the efficiencies under the top three models previously selected by the AIC

criterion and analyzed under all combinations of factors when normalizing by the number of employees. We observe a high correlation between rankings obtained with models with both factors and the model with the percentage of hotels with three or fewer stars. The rankings without including this factor and rankings including Star123 are much lower correlated, indicating that the inclusion of this variable does provoke a substantial change in efficiency rankings.

Table 7: Kendall correlations for efficiency rankings under size normalization N.EM

Normalized by N.EM		Both factors	Star123	Beach	Without factor
1	Both factors	1.0000	0.8943	0.3214	0.3277
	Star123	0.8943	1.0000	0.2368	0.3277
	Beach	0.3214	0.2368	1.0000	0.4524
	Without factor	0.3277	0.3277	0.4524	1.0000
2	Both factors	1.0000	0.8140	0.4059	0.3404
	Star123	0.8140	1.0000	0.2537	0.3573
	Beach	0.4059	0.2537	1.0000	0.4144
	Without factor	0.3404	0.3573	0.4144	1.0000
3	Both factors	1.0000	0.8520	0.3890	0.3615
	Star123	0.8520	1.0000	0.2579	0.3404
	Beach	0.3890	0.2579	1.0000	0.4524
	Without factor	0.3615	0.3404	0.4524	1.0000

This is further illustrated in Table 8 which gives the top ten ranked chains under each model specification. Columns “1”, “2”, “3” correspond to the best three models classified by the AIC criterion. The green cells indicate the chains that remain in the top ten rankings whether or not the proportion of three or fewer star hotels is included in the analysis. The orange cells indicate the hotels that are high ranked when the exogenous variable is not included in the efficiency term, but are lower ranked when it is. Blue cells show the chains that hold the position under two proposals. Roughly, the rankings of the two SFA models without considering the heterogeneity are almost the same, while the ranking of the SFA including stars as factor varies greatly. Few of the best chains under the basic model maintain their positions when taking into account the exogenous variable.

3.5.2. The (lack of) relationship between efficiency and hotel chain size

In analyses of individual hotel efficiencies, a number of works have encountered a relationship between hotel size and efficiency. For example, Davutyan (2007) and Poldrugovac et al. (2016) observed an increasing relationship between the size of individual hotels and their efficiency in the case of Anatolian and Croatian hotels respectively. In the case of chains, it might be expected that larger chains can take advantage of economies of scale to reduce overall costs. On the contrary, it may be that smaller chains can only survive in a competitive market if they are efficient, whereas larger chains can continue to operate at lower efficiency levels due to having higher reserves, easier access to financial credit etc.

Figure 3 shows the posterior mean efficiency levels under the Bayesian model including the percentage of hotels of three or fewer stars as an exogenous variable, versus the size of hotel chains when revenues are normalized by number of employees as a size measure.

There is no obvious relationship between size and efficiency, but this could be a consequence of the fact that two of the hotel chains are over twice as big (in terms of number of

Table 8: Rankings of the top ten most efficient hotel chains under the three best models and different size normalizations

	Ranking	1			2			3		
		Bayesian		Clasical	Bayesian		Clasical	Bayesian		Clasical
		Star123	Without factor	MLE	Star123	Without factor	MLE	Star123	Without factor	MLE
Normalized by N.R	1	CHAIN21	CHAIN16	CHAIN16	CHAIN40	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN16
	2	CHAIN40	CHAIN41	CHAIN41	CHAIN21	CHAIN41	CHAIN41	CHAIN40	CHAIN41	CHAIN41
	3	CHAIN15	CHAIN25	CHAIN25	CHAIN8	CHAIN25	CHAIN25	CHAIN8	CHAIN25	CHAIN25
	4	CHAIN8	CHAIN24	CHAIN24	CHAIN15	CHAIN12	CHAIN12	CHAIN15	CHAIN12	CHAIN12
	5	CHAIN39	CHAIN15	CHAIN32	CHAIN16	CHAIN22	CHAIN24	CHAIN39	CHAIN24	CHAIN24
	6	CHAIN16	CHAIN38	CHAIN38	CHAIN39	CHAIN24	CHAIN38	CHAIN16	CHAIN22	CHAIN38
	7	CHAIN32	CHAIN32	CHAIN26	CHAIN32	CHAIN17	CHAIN26	CHAIN32	CHAIN26	CHAIN26
	8	CHAIN35	CHAIN39	CHAIN15	CHAIN11	CHAIN38	CHAIN17	CHAIN35	CHAIN38	CHAIN17
	9	CHAIN9	CHAIN22	CHAIN39	CHAIN35	CHAIN26	CHAIN22	CHAIN11	CHAIN17	CHAIN22
	10	CHAIN11	CHAIN26	CHAIN22	CHAIN9	CHAIN15	CHAIN15	CHAIN29	CHAIN32	CHAIN15
Normalized by N.ES	1	CHAIN21	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN16
	2	CHAIN15	CHAIN41	CHAIN41	CHAIN40	CHAIN41	CHAIN41	CHAIN40	CHAIN25	CHAIN41
	3	CHAIN8	CHAIN25	CHAIN25	CHAIN8	CHAIN25	CHAIN25	CHAIN8	CHAIN41	CHAIN25
	4	CHAIN16	CHAIN12	CHAIN12	CHAIN39	CHAIN24	CHAIN24	CHAIN39	CHAIN12	CHAIN12
	5	CHAIN40	CHAIN15	CHAIN38	CHAIN15	CHAIN38	CHAIN32	CHAIN32	CHAIN32	CHAIN24
	6	CHAIN39	CHAIN24	CHAIN24	CHAIN32	CHAIN32	CHAIN38	CHAIN16	CHAIN24	CHAIN38
	7	CHAIN32	CHAIN17	CHAIN22	CHAIN16	CHAIN39	CHAIN26	CHAIN15	CHAIN38	CHAIN17
	8	CHAIN11	CHAIN22	CHAIN17	CHAIN11	CHAIN15	CHAIN15	CHAIN24	CHAIN22	CHAIN32
	9	CHAIN35	CHAIN32	CHAIN32	CHAIN35	CHAIN26	CHAIN39	CHAIN11	CHAIN17	CHAIN22
	10	CHAIN9	CHAIN38	CHAIN26	CHAIN9	CHAIN22	CHAIN22	CHAIN35	CHAIN26	CHAIN15
Normalized by N.EM	1	CHAIN21	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN16
	2	CHAIN40	CHAIN41	CHAIN41	CHAIN40	CHAIN41	CHAIN41	CHAIN40	CHAIN41	CHAIN41
	3	CHAIN8	CHAIN25	CHAIN25	CHAIN8	CHAIN25	CHAIN25	CHAIN15	CHAIN25	CHAIN25
	4	CHAIN39	CHAIN24	CHAIN24	CHAIN15	CHAIN24	CHAIN24	CHAIN8	CHAIN24	CHAIN24
	5	CHAIN15	CHAIN32	CHAIN32	CHAIN39	CHAIN15	CHAIN15	CHAIN39	CHAIN15	CHAIN15
	6	CHAIN16	CHAIN38	CHAIN38	CHAIN32	CHAIN38	CHAIN32	CHAIN16	CHAIN32	CHAIN32
	7	CHAIN32	CHAIN15	CHAIN26	CHAIN16	CHAIN32	CHAIN38	CHAIN32	CHAIN39	CHAIN26
	8	CHAIN35	CHAIN39	CHAIN15	CHAIN11	CHAIN39	CHAIN12	CHAIN11	CHAIN38	CHAIN12
	9	CHAIN11	CHAIN26	CHAIN39	CHAIN35	CHAIN26	CHAIN26	CHAIN9	CHAIN26	CHAIN38
	10	CHAIN9	CHAIN22	CHAIN22	CHAIN9	CHAIN22	CHAIN17	CHAIN35	CHAIN12	CHAIN39

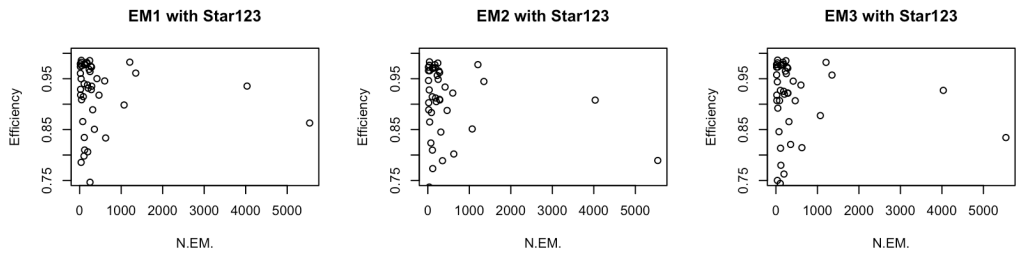

Figure 3: Relationship between efficiency and number of employees.

employees) than the rest of the chains in the study. Thus, it could be that these chains behave differently in terms of their efficiencies than chains of more similar sizes. Therefore, it is interesting to exclude these two chains from the analysis in order to explore the relationship between size and efficiency more clearly.

Table 9, shows the top ten ranked chains under a Bayesian analysis both with and without the inclusion of the proportion of hotels of three and fewer stars as a heterogeneity factor and under different normalizations in the same way as Table 8. The top ranked chains remain approximately the same as in Table 8 in both cases. This suggests that the inclusion of the two largest chains does not overly influence the results of the analysis. There is no clear evidence of a relation between chain size and efficiency here.

Table 9: Rankings of the top ten most efficient hotel chains under the three best models and different size normalizations when the two largest chains are excluded

		1		2		3	
	Ranking	Star123	Without factor	Star123	Without factor	Star123	Without factor
Normalized by N.R	1	CHAIN16	CHAIN16	CHAIN21	CHAIN16	CHAIN21	CHAIN41
	2	CHAIN15	CHAIN41	CHAIN40	CHAIN41	CHAIN40	CHAIN16
	3	CHAIN32	CHAIN25	CHAIN15	CHAIN25	CHAIN15	CHAIN25
	4	CHAIN8	CHAIN12	CHAIN8	CHAIN24	CHAIN8	CHAIN24
	5	CHAIN39	CHAIN38	CHAIN39	CHAIN15	CHAIN39	CHAIN38
	6	CHAIN21	CHAIN32	CHAIN9	CHAIN39	CHAIN11	CHAIN15
	7	CHAIN11	CHAIN22	CHAIN11	CHAIN38	CHAIN9	CHAIN39
	8	CHAIN35	CHAIN39	CHAIN16	CHAIN11	CHAIN16	CHAIN32
	9	CHAIN40	CHAIN17	CHAIN32	CHAIN32	CHAIN35	CHAIN11
	10	CHAIN24	CHAIN3	CHAIN35	CHAIN17	CHAIN32	CHAIN17
Normalized by N.ES	1	CHAIN15	CHAIN16	CHAIN21	CHAIN16	CHAIN16	CHAIN17
	2	CHAIN21	CHAIN25	CHAIN40	CHAIN41	CHAIN32	CHAIN16
	3	CHAIN16	CHAIN41	CHAIN15	CHAIN25	CHAIN24	CHAIN41
	4	CHAIN39	CHAIN12	CHAIN39	CHAIN24	CHAIN39	CHAIN26
	5	CHAIN8	CHAIN22	CHAIN8	CHAIN39	CHAIN15	CHAIN25
	6	CHAIN40	CHAIN17	CHAIN16	CHAIN15	CHAIN17	CHAIN38
	7	CHAIN32	CHAIN32	CHAIN35	CHAIN38	CHAIN8	CHAIN32
	8	CHAIN35	CHAIN15	CHAIN11	CHAIN32	CHAIN11	CHAIN12
	9	CHAIN11	CHAIN24	CHAIN32	CHAIN17	CHAIN35	CHAIN22
	10	CHAIN24	CHAIN39	CHAIN9	CHAIN22	CHAIN40	CHAIN24
Normalized by N.EM	1	CHAIN21	CHAIN16	CHAIN21	CHAIN41	CHAIN16	CHAIN16
	2	CHAIN40	CHAIN41	CHAIN40	CHAIN16	CHAIN15	CHAIN12
	3	CHAIN15	CHAIN25	CHAIN15	CHAIN25	CHAIN39	CHAIN25
	4	CHAIN8	CHAIN24	CHAIN8	CHAIN32	CHAIN21	CHAIN22
	5	CHAIN39	CHAIN15	CHAIN39	CHAIN24	CHAIN40	CHAIN41
	6	CHAIN16	CHAIN39	CHAIN32	CHAIN15	CHAIN8	CHAIN38
	7	CHAIN32	CHAIN38	CHAIN9	CHAIN29	CHAIN32	CHAIN24
	8	CHAIN35	CHAIN22	CHAIN35	CHAIN17	CHAIN35	CHAIN20
	9	CHAIN11	CHAIN32	CHAIN16	CHAIN36	CHAIN24	CHAIN15
	10	CHAIN9	CHAIN17	CHAIN11	CHAIN21	CHAIN11	CHAIN36

4. Conclusions and extensions

In this paper, we have measured the revenue efficiency of some of the largest hotel chains in Spain in the year 2012. In order to compare chains of very different sizes, we have proposed to use a normalization by either number of hotels, number of rooms or number of employees.

Using both classical and Bayesian analyses, our results suggest that in terms of revenue efficiency, it is preferable for chains to invest in fewer, larger hotels than in more smaller hotels. Also, it appears that revenue is higher for chains with a higher proportion of hotels in the three and fewer stars category than in higher star categories. Given that this result may be due to external factors such as the economic crisis, one interesting extension of this work would be to look at how hotel chain efficiencies change over time, as the effects of the crisis lessen. For examples of Bayesian approaches to time varying efficiency, see e.g. Tsionas (2006) or Galán et al. (2015).

We have also shown that it is important to take exogenous information into account when this is available as this can be very influential in efficiency estimates. In the case of Spanish hotel chains, the rankings of the most efficient chains change substantially when the proportion of lower star rated hotels is included as an exogenous variable in the efficiency. Other factors such as the proportion of beach hotels appear to be less influential. In many cases, there may also be unobserved exogenous factors influencing efficiency. Therefore, it would

be interesting to include, via a random effect, such factors in the efficiency model as commented in Greene (2008) under a classical framework or Galán et al. (2014) using a Bayesian approach. It would also be interesting to explore in more detail the question of where to include exogeneous variables; in the efficiency term as here or in the frontier as in Oliveira et al. (2013). In principle, using Bayesian analysis, the DIC3 criterion could be used to select the best of the two options.

Finally, in contrast to the results of Davutyan (2007) or Poldrugovac et al. (2016) for individual hotels, when hotel chains are considered, there appears to be little relationship between size and efficiency.

Acknowledgements. *The authors acknowledge financial support from the Spanish Ministry of Economy and Competitiveness, research projects ECO2015-70331-C2-2-R and ECO2015-65701-P.*

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