The impact of ownership and size heterogeneity on hotel industry efficiency in the Canary Islands (Spain)

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Abstract: This study was conducted to analyse the influence of technological differences on hotel efficiency in the Canary Islands (Spain), with particular regard to the heterogeneity observed in hotel ownership and size. A metafrontier approach, based on non-parametric deterministic efficiency methods (DEA and FDH) and robust non-parametric estimators (order-α), is used. This empirical analysis considered a panel data sample selection model of Canary Islands hotels for the period 2002-2015. The results obtained show that the frontiers against which the hotels are compared (metafrontier or group) and the consideration or otherwise of outliers are factors of crucial importance. We find that efficiency depends on hotel size (large hotels are more efficient than small ones), but not on the type of ownership. The results also show that the impact of the global financial crisis on the average technical efficiency of these hotels was slight or non-existent. Finally, the technological gap narrowed over time, especially in large hotels and those with no majority shareholder.

Keywords: Metafrontier, technological gap, lodging industry, DEA, FDH, order-α.

JEL codes: D61, L83, Z30, Z31.

1. **Introduction**

The resource-based theory focuses on the internal analysis of differences in firm resources and explains how these differences can be a source of sustained competitive advantage (Wernerfelt, 1984; Peteraf, 1993; Barney, 1991; see Arbelo et al. (2020b) for an excellent overview of the theoretical background). As pointed out by Assaf et al. (2010), following this theory, hotels are heterogeneous in terms of the resources and capabilities employed in their managerial practices. For example, hotels differ greatly in their production (cost) technologies and this heterogeneity can distort efficiency levels in terms of their response to uncontrollable environmental factors such as size, location, type of ownership (chain vs. independent, and international vs. non-international) and quality classification (Assaf et al., 2010). In consequence, the hotels in one group may have very different production technologies from those in another.

Battese and Rao (2002), Battese et al. (2004) and O'Donnell et al. (2008), among others, address questions of efficiency, heterogeneity and technological differences among firms using the metafrontier approach, i.e., distinguishing between the metafrontier and the groups of firms. The (pooled) sample size is the main difference between the meta-concept and the group-concepts. With respect to the lodging industry, several empirical studies have analysed the differences between international and non-international hotels, or between hotel chains and independently-operated establishments (see, for example, Assaf et al., 2010; Huang et al., 2013; Huang et al., 2014; Yu and Chen, 2016; Cho and Wang, 2018). These researchers have highlighted the need to identify and measure the environmental factors which create inter-hotel heterogeneity, composed of diverse groups of firms with comparable technologies.

To estimate the metafrontiers and the group technologies of hotels and to analyse the technological differences between them, the above researchers mainly used non-parametric deterministic methods such as data envelopment analysis (DEA) or Malmquist-DEA (Assaf et al., 2010; Yu and Chen, 2016), with particular reference to the hotel industry in Taiwan. More recently, the free-disposal hull (FDH, a non-convex variant of DEA which is less restrictive than DEA) has also been used (Huang et al., 2013; Cho and Wang, 2018). In addition, some authors have analysed heterogeneity among hotels using stochastic frontier (SF) models (Huang et al. 2014; Bernini and Guizzardi, 2015).

Non-parametric estimators such as DEA, FDH and partial frontier estimators are appealing because they rely on very few assumptions about the shape of the frontier (like free disposability and, perhaps, concavity).[1] However, this flexibility and generality has certain drawbacks. Although Krüger (2012) showed DEA methods to be fairly robust, in Monte Carlo experiments designed to study nonparametric deterministic and stochastic methods, nonparametric approaches such as DEA and FDH have been criticised by econometricians as being mainly deterministic and lacking the parameters needed for economic interpretation, as well as being extremely vulnerable to outliers and measurement errors. However, robust frontiers such as order-*m* efficiency (Cazals et al., 2002) and order-*α* efficiency (Aragon et al., 2005) can overcome some of the drawbacks of traditional nonparametric technology.

Partial frontier approaches such as order-*m* and order-*α* efficiency generalise the FDH model by allowing some observations to be located beyond the estimated production-possibility frontier (Aragon et al., 2005). In the literature, such observations are termed 'superefficient'. Although the concept of superefficiency is also used in DEA,[2] in the present paper it is fundamentally taken as a means of dealing with outliers and with the measurement errors incurred in partial frontier approaches. These recently-developed nonparametric methods use only part of the sample to compute efficiency scores, thereby reducing the influence of outliers and extreme observations, while maintaining the same rate of convergence of parametric estimators, which in practical terms means that the "curse of dimensionality" (the need to obtain thousands of observations in order to avoid unacceptable statistical imprecision) can be overcome. Furthermore, the economic interpretation of order-*m* and order-α measures of efficiency is both interesting and useful (Daraio and Simar, 2007).

Our paper contributes to the empirical literature on hotel efficiency in two ways. First, in line with the earlier analysis by De Witte and Marques (2009) of the drinking water sector in various countries, we consider the possibility that some (or many) of the hotels which are fully efficient might be outliers, in our assessment of the technological heterogeneity arising from factors such as size and ownership. In this approach, we compare various non-parametric techniques used to estimate convex frontiers (e.g., DEA) and non-convex ones (e.g., FDH and robust nonparametric methods) by a metafrontier approach. In this analysis, we use the order-α estimator because it does not require re-sampling and so is less time consuming than order-*m*

[1] One of the main drawbacks of frontier models (DEA/FDH based) is the influence of outliers. This is a consequence of the fact that the efficient frontier is determined by sample observations which are extreme points. Simar (1996) pointed out the need to identify and eliminate outliers when using non-parametric models, and observed that if they could not be identified, then stochastic frontier models should be used.

[2] In the literature, the concept of super-efficiency is mainly addressed in the context of using partial frontier approaches to deal with outliers and measurement error. However, Lovell and Rouse (2003) also defined an equivalent standard DEA model to provide super-efficiency scores in the context of full frontier approaches.

(Cazals et al., 2002). In the DEA, we also study scale efficiency, i.e. the distance between constant returns to scale (CRS) and variable returns to scale (VRS); the scale efficiency score thus obtained indicates whether or not a hotel is operating at its most productive size.

The second major contribution of the present study is its focus on possible technological differences in the hotel industry of the Canary Islands (a major Spanish sun-and-sand tourist destination). Such differences could make a significant impact on hotel efficiency and are an important consideration for policymakers. The hotels in our study sample are differentiated by size and type of ownership, for the following reasons. On the one hand, empirical studies of firm-level productivity largely concur that size is a major source of heterogeneity in business performance (Halkos and Tzeremes, 2007). For example, large firms might be more efficient in their production methods due to the use of more specialised inputs or to the better coordination of their resources. In addition, it has been hypothesised that the economies of scale associated with large hotels enable them to quickly expand their operations and achieve operational savings. However, small firms might be more efficient because they have flexible, non-hierarchical structures, and do not usually suffer from agency problems (Halkos and Tzeremes, 2007). On the other hand, membership of a hotel chain (as opposed to independent operation) might enhance management capabilities, facilitate access to new technologies and enable these hotels to raise capital at a lower cost.

The rest of this paper is organised as follows. Section 2 describes the lodging industry in the Canary Islands. Section 3 then reviews the main literature in this field. The metafrontier approach is discussed in Section 4, after which the sample data configuration is described and the empirical results obtained. Finally, the main conclusions drawn are summarised in Section 6.

2. **The lodging industry in the Canary Islands**

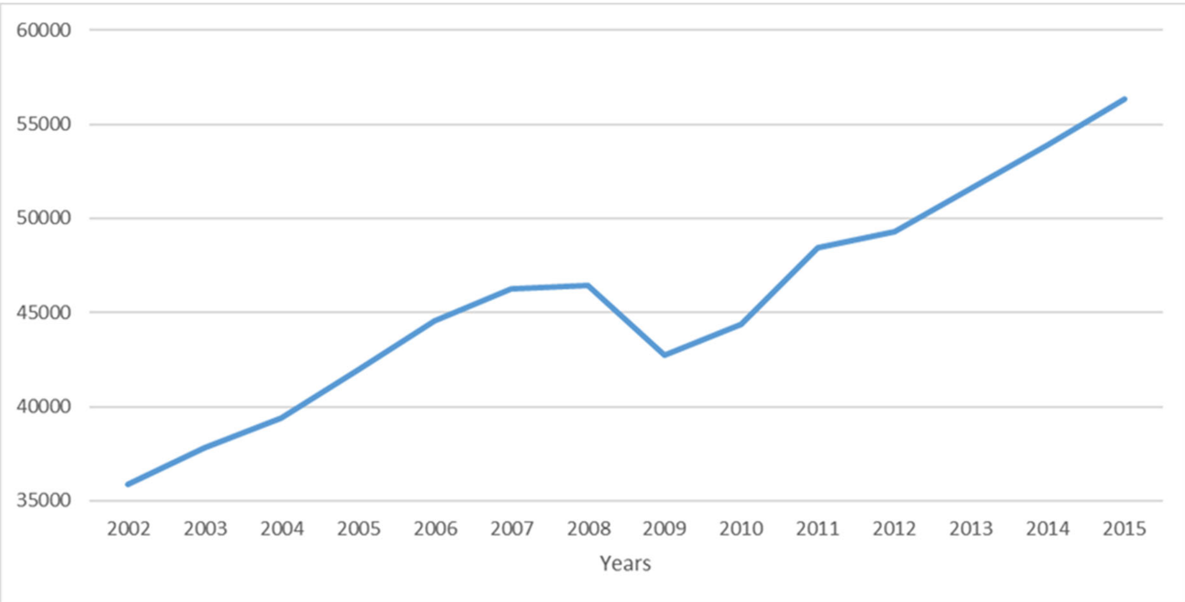
The Canary Islands, an archipelago of seven islands is one of the most important tourist destinations in Spain, thanks to its beaches, natural beauty, sports facilities and other cultural and recreational attractions.

According to the Canary Institute of Statistics (ISTAC), in 2017, the islands received 14.2 million international tourist arrivals. In terms of tourism, the most important islands are Tenerife, Gran Canaria, Lanzarote and Fuerteventura, and the majority of visitors are European (Germans, Britons, mainland Spanish and Swedish, among many others). The Canary Islands are crowded; most of the coastline is built up and there are more roads per km^2 than in any other European island group (Moreno-Gil, 2003).

The Canary Islands archipelago is characterised by its mild climate, with average temperatures ranging from 18 ºC in winter to 25 ºC in summer, and it receives tourists all year round. Apart from the beaches, the islands have tourist attractions such as 300 endemic plant species and four National Parks. Moreover, 40% of the surface area of the archipelago is officially protected (Santana-Jiménez and Hernéndez, 2011).

The tourism industry in the Canary Islands underpins economic growth by creating jobs, generating income, stimulating consumption and contributing to tax revenues, thus facilitating government expenditure. However, these jobs are generally poorly paid, with little prestige or future career prospects (Moreno-Gil, 2003). Private consumption and public spending both produce a multiplier effect on economic growth. Moreover, tourism is a major source of foreign exchange earnings and stimulates investment in both physical and human capital. Figure 1 shows the rising time-path for Spanish tourism revenue between 2002-2015, a trend that was only interrupted by the economic crisis period of 2008-2009.

Figure 1. Tourism revenues in Spain (millions of euros).



Source: DATATUR 2010 - *Subdirección General de Conocimiento y Estudios Turísticos* (www.iet.tourspain.es).

The tourism sector accounts for over 30% of GDP and employment in the islands, as well as 30% of tax revenues and around 8% of public spending (National Institute of Statistics, INE). Each year, overall tourist spending is around 16.6 billion euros and there are over 100 million overnight stays. Moreover, this demand is constantly increasing, allowing hoteliers to increase occupancy rates and tariffs.

In the Canary Islands, the lodging industry is relatively stable and highly professionalised. According to their location and circumstances, the individual elements of this industry are at different stages of the lifecycle, from development to stagnation. In general, however, the tourist industry in the Canary Islands presents infrastructural obsolescence, together with the degradation of the natural environment in some areas, especially in the islands of Gran Canaria and Tenerife (Santana-Jiménez and Hernández, 2011). The growth of lodging capacity in the Canary Islands has been limited since 2001, when a moratorium on new hotel construction was imposed, following previous excesses. The aim of this legislation was to curb the flood of new constructions attracted by the booming tourist industry. Subsequent laws have complemented (not replaced) the first moratorium, producing some confusion and uncertainty among investors. Inchausti-Sintes and Voltes-Dorta (2020) found evidence that these restrictions had a significant impact on the supply of 5-star hotels in the islands. Christie & Co (2016) list the changes introduced in this respect up to 2015.

Table 1 details the tourist accommodation resources of the Canary Islands in the period 2010-17 (Canary Institute of Statistics, ISTAC). This table distinguishes between hotel and apartment accommodation, showing that hotels are more important in terms of bed-spaces, average occupation rate, employment and the two key indicators of performance, average daily rate (ADR) and revenue per available room (RevPAR).

In general, the number and quality of establishments remained fairly constant during the above period. The largest hotel category was that of four-star establishments, followed by those with three stars. Investors in this field were predominantly of Spanish origin, although some investment from other European countries also took place. The islands attracted 28% of total hotel investment in Spain in 2015 and accounted for 33.2% of the hotel rooms available nationwide.

In this scenario, it is to be expected that the Canary Islands hotel industry will be extremely efficient, given the high level of competition in the sector and the marketing efforts of both the private and the public sectors.

Table 1. Canary Islands tourist accommodation capacity. Period 2010-2017.

Year	2010	2011	2012	2013	2014	2015	2016	2017
Panel A. Hotels								
Number of hotels	611	615	617	625	630	626	628	629
Number of 5-star hotels	40	40	41	42	43	44	44	47
Number of 4-star hotels	228	229	229	231	231	233	237	246
Number of 1-3 star hotels	343	346	347	352	356	349	347	336
Total hotel capacity (beds)	235,999	237,900	237,860	241,052	245,271	244,657	246,476	247,065
Average occupation 1-3 star hotels (%)	67.27	74.46	72.45	72.73	76.62	77.40	84.15	84.34
Average occupation 4-5 star hotels (%)	68.56	77.53	74.73	77.07	80.26	81.74	87.05	85.93
Average stay 1-3 star hotels (nights)	7.20	7.35	7.59	7.41	7.37	7.26	7.05	6.95
Average stay 4-5 star hotels (nights)	7.46	7.69	7.77	7.74	7.65	7.65	7.69	7.51
ADR 1-3 star hotels (€)	44.91	47.24	48.09	49.71	52.95	55.55	58.53	61.91
ADR 4-5 star hotels (€)	76.90	78.24	80.53	83.34	87.78	93.64	99.35	104.01
RevPAR 1-3 star hotels (€)	30.18	35.20	34.84	36.15	40.60	42.99	49.25	52.21
RevPAR 4-5 star hotels (€)	52.74	60.66	60.18	64.24	70.43	76.55	86.49	89.38
Employment	38,353	39,132	39,614	39,956	42,153	43,507	45,983[a]	47,539[a]
Panel B. Apartments								
Number of apartments	1,198	1,187	1,183	1,171	1,156	1,152	1,150	1,141
Number of 1-2 key apartments	996	992	988	981	969	963	964	954
Number of 3-key apartments	202	195	195	190	187	189	186	187
Total apt. capacity (beds)	195,598	193,300	194,549	186,719	180,267	171,998	169,634	168,222
Average occupation 1-2 key apts. (%)	55.63	61.08	57.39	61.08	63.32	63.39	71.20	73.01
Average occupation rate/stay 3-key apts. (%)	63.26	69.45	69.29	73.20	77.00	76.17	82.44	83.21
Average stay 1-2 key apts. (nights)	8.58	8.86	8.95	8.90	9.14	8.83	8.98	9.11
Average stay 3-key apts. (nights)	8.59	8.71	8.90	8.78	8.58	8.41	8.24	8.61
ADR 1-2 key apts. (€)	36.12	37.94	38.03	39.75	42.78	45.95	48.62	54.64
ADR stay 3-key apts. (€)	39.99	41.40	44.90	47.11	49.59	49.72	53.35	60.30
RevPAR 1-2 key apts. (€)	20.10	23.34	21.89	24.27	27.09	29.13	34.33	39.99
RevPAR stay 3-key apts. (€)	25.30	28.79	31.11	34.47	38.18	37.87	43.96	50.17
Employment	12,047	12,359	12,393	12,255	12,268	12,866	12,771[a]	13.705[a]

Notes: Data from Canary Islands surveys of tourist lodging (*Encuestas de Alojamiento Turístico (hotelero y extrahotelero)*, Canary Islands Institute of Statistics, ISTAC). Monthly series. 2009-2018 (2012-base methodology). [a] These values are forecasts. ADR: Average daily rate. RevPAR: Revenue per available room. ADR measures the performance of a hotel against its competitors, especially those of a similar size and in a similar location. RevPAR is a revenue management instrument that describes the degree to which hotel/apartment rooms are occupied, relative to their theoretical capacity.

3. **Literature review on metafrontier model of hotel efficiency**

Most previous studies of hotel efficiency did not address the question of technological differences (between small and large hotels, by type of ownership, etc.). Some used non-parametric methods, either deterministic (robust and/or non-robust) or stochastic, while others were parametric, based on stochastic frontier models. Tables A1.1 and A1.2, in Appendix 1, detail many of these studies, for the non-parametric and parametric techniques, respectively.

An alternative concept of efficiency measurement, based on a DEA metafrontier model, was developed by Rao et al. (2003). The metafrontier for firms/units operating under different technologies is an overarching function that incorporates all the components of the corresponding frontier production functions (Battese et al. 2004). Various studies have used the metafrontier concept to measure technical efficiency (TE) and the technological gap ratio (TGR). For example, Rao et al. (2003) used this approach to perform an inter-regional comparison of production technologies. Similarly, Battese et al. (2004) presented a metafrontier production function to measure the efficiency of garment firms in the five regions of Indonesia.

Metafrontier analysis has also been studied in the hotel industry, distinguishing between parametric and non-parametric estimators (see Table A1.3, Appendix 1). Regarding the nonparametric methods, convex (DEA) and non-convex (FDH) frontiers may be used.

The DEA metafrontier has been used to assess the efficiencies of units in groups operating under different technologies, i.e. it is a threshold concept for measuring inter-group efficiency differences. In this respect, Assaf et al. (2010) were pioneers in using the metafrontier framework to measure operative efficiency, in a study of 78 hotels in Taiwan. Their results clearly indicate that a hotel's size, ownership characteristics and quality classification are significantly related to its efficiency. In a related study, Yu and Chen (2016) studied the performance of 54 international tourist hotels in Taiwan, for the period 2008 to 2011, using the Malmquist productivity index as a metafrontier. This index satisfies the requirement of circularity, is immune to linear programming infeasibility, overcomes the problem of base period dependency and considers the presence of heterogeneity among hotels. To investigate sources of productivity change, this index can be further decomposed into within-group efficiency change, within-group technical change and technical leadership change. The empirical results obtained in this study show that the use of different technologies by hotels affects their productivity and that within-group efficiency and technical change are the main factors of productivity change. Chain hotels are usually technology leaders, while independent hotels tend to be followers. By identifying each competitor's productivity change, operators can reference appropriate best-practice hotels to improve their operational effectiveness.

With regard to the non-convex metafrontier, introduced by O'Donnell et al. (2008), Huang et al. (2013) proposed a specific modelling function and calculational operation for the non-convex metafrontier model and applied the model obtained to investigate possible technological gaps between the four types of international tourist hotels operating in Taiwan. The empirical findings reported show that of the four groups considered, management contract technology achieves the potential best practice, and that there exists a significant gap between this potential best practice and current performance in the domestic, franchise and chain-membership technologies. Cho and Wang (2018) introduced a novel way of calculating and analysing the cost metafrontier Malmquist productivity index model (CMMPI) under variable return to scale measurement and the FDH approach. The CMMPI, which reflects operational performance more comprehensively than alternative instruments and indicates how future competitiveness might be enhanced, not only estimates efficiency change but also decomposes the gap ratio, thus enabling the decision-making unit to differentiate the group frontier from the metafrontier within the broad definition of "catch-up." The empirical results obtained show that the CMMPI of international tourism hotels in Taiwan declined by 0.9% between 2002 and 2010, mainly because of the deterioration of meta-technical efficiency change, meta-allocative efficiency change, meta-cost scale efficiency change and the meta-input price effect change. Empirical results suggest that the completeness provided by the cost approach is useful for exploring the characteristics of the Taiwanese international tourism hotel industry. Moreover, international chain hotels significantly outperform independent establishments in terms of meta-cost efficiency, meta-technical efficiency and meta-allocative efficiency. Finally, these authors discuss various managerial insights and implications.

Regarding the parametric or stochastic metafrontier, the following papers are especially significant. Huang et al. (2014) proposed a two-step stochastic frontier approach to estimate technical efficiency scores for firms in different groups adopting distinct technologies. The estimators thus obtained have appropriate statistical properties and enable valuable statistical inferences to be drawn. While the within-group variation in firms' technical efficiencies is frequently assumed to be associated with firm-specific exogenous variables, the between-group variation in technological gaps can be specified as a function of certain exogenous variables, in order to take account of group-specific environmental differences. Two empirical applications are illustrated, one based on chain-operated hotels in Taiwan and the other on independently-operated establishments. The results derived from these applications support the use of the model proposed.

Finally, Bernini and Guizzardi (2015) used the metafrontier approach to identify different production processes and to measure technical efficiency scores, while heterogeneity was tackled using a Cobb-Douglas stochastic frontier production function. These authors based their analysis on a sample of 2705 hotels in the Italian region of Emilia-Romagna. The results obtained show that the star rating is the primary source of efficiency bias, followed by seasonality, while hotel size has a relatively minor impact.

To our knowledge, no previous studies have investigated the question of the metafrontier via comparisons of different nonparametric methods. The only papers published in this area, according to the literature review conducted, focus on DEA or FDH separately in their analyses of production, costs or productivity change, and limit their scope to the hotel industry in Taiwan.

4. **Metafrontier approach**

Taking into account earlier proposals by Battese and Rao (2002), Battese et al. (2004) and O'Donnell et al. (2008), we consider the operational environment in terms of groups.

Let n be the observations of hotels (or, in general, decision-making units, DMUs), $i = 1, 2, ..., n$. Let x_{ip} be the observed level of the p-th input at DMU i and let $x = (x_{i1}, ..., x_{iP}) \in \Re_+^P$ be the vector of P inputs for the i-th unit; y_{iq} is the observed level of the q-th output at DMU i, where $y = (y_{i1}, ..., y_{iQ}) \in \Re_+^Q$ is a vector of Q outputs.

Moreover, suppose K groups, each with n_k observations, $k = 1, 2, ..., K$. The technology and production sets and the distance function in the input-oriented case for the k-th group are then defined as:

$$\Psi^k = \{(y, x) : x_k \ can \ produce \ y_k\}, k = 1, ..., K$$
$$P^k(x) = \{y : (y, x) \in \Psi^k\}, x \in \Re_+^p$$
$$D_I^k(x, y) = \sup\{\mu : x/\mu \in L^k(y)\}$$

where $L^k(y) = \{x : (x, y) \in \Psi^k\}, y \in \Re_+^q$ is the input requirements set.

By pooling the observations of the K subgroups, the DMUs are evaluated with respect to the same standards. In this sense, the metafrontier represents an over-arching metatechnology where the technology set is defined by $\Psi^M = \{(x, y) \in \Re_+^{p+q} : x \ can \ produce \ y\}$ and the input requirements and output sets are defined as $L^M(y) = \{x : (x, y) \in \Psi^M\}, y \in \Re_+^q$ and $P^M(x) = \{y : (x, y) \in \Psi^M\}, x \in \Re_+^p$, respectively. The metadistance in the input-oriented case is defined by $D_I^M(x, y) = \sup\{\mu : x/\mu \in L^M(y)\}$. A combination (x, y) can be considered technically efficient regarding the metafrontier if and only if $D_I^M(x, y) = 1$.

The following rules characterise the behaviour of the input-output combinations, technology, distance and convexity.

1) If $(x, y) \in \Psi^k$ for all *j*, then $(x, y) \in \Psi^M$.
2) If $(x, y) \in \Psi^M$, then $(x, y) \in \Psi^k$ for each *k*.
3) $\Psi^M = \{\Psi^1 \cup \Psi^2 \cup ... \cup \Psi^K\}$.
4) $D_I^k(x, y) \le D_I^M(x, y), \forall k = 1, ..., K$.
5) The convexity of $P^M(x)$ does not imply that of $P^k(x)$, and vice versa.

Rules 1) to 4) imply that the production sets $P^k(x)$, $k = 1, ..., K$ are subsets of the unrestricted set $P^M(x)$.

The (pooled) sample size is the main difference between the meta-concept and the group concepts.

In this study, robust and non-robust non-parametric deterministic approaches for estimating the frontier are used, mainly based on data envelopment analysis (DEA), free disposal hull (FDH) and robust partial frontier approaches such as order-α.

Input-oriented models are used in this analysis under the assumption that hotel managers will attempt to increase efficiency by focusing on inputs, because the output (i.e., the amount of business available) depends largely on customer demand, a factor that is beyond the manager's control, at least in the short term. Logically, managers will focus on variables which can be modified, and so efficiency is measured by reference to those variables. This is the classical approach and has been used in several papers employing non-parametric methods.

Let θ be the radial efficiency score (a value between 0 and 1) and λ_i, the optimal weights of the referenced units for unit *i*. For a DMU located at $(x, y) \in \Re_+^{p+q}$ the input-oriented efficiency of the *k*-th group can be measured as $\theta^k(x,y)=\inf\{\theta|(\theta x,y)\in\Psi^k\}$. In the case of the metafrontier, $\theta^M(x,y)=\inf\{\theta|(\theta x,y)\in\Psi^M\}$.

4.1. **DEA efficiency estimates**

Following O'Donnell et al. (2008), a convex metafrontier can be constructed by applying the DEA method to all the observed inputs and outputs of the firms in all groups. For T periods, the VRS input-oriented DEA problem is defined as follows.

$$
\begin{aligned}
&\min_{\phi_{it},\lambda_{it}} \theta_{it}^{M,DEA}, i=1,\dots,n, t=1,\dots,T\\
&\textit{subject to}:\\
&\qquad -y_{it}+Y_{it}\lambda_{it}\geq 0\\
&\qquad \theta x_{it}-X_{it}\lambda_{it}\geq 0\\
&\qquad \sum_{i=1}^{n}\lambda_{it}=1,\forall t\\
&\qquad \lambda_{it}\geq 0,\forall it
\end{aligned}
\qquad [1]
$$

where $\theta_{it}^{M,DEA}$ is a scalar for the i-th hotel in the *t*-th period. This represents the technical efficiency for the metafrontier, where y_{it} is a $q\times 1$ vector of outputs, x_{it} is a $p\times 1$ vector of inputs, Y_{it} is a matrix of order $q\times n$, X_{it} is a matrix of inputs of order $p\times n$ and λ_{it} is a vector of weights $n\times 1$.

If group *k* consists of data on n_k hotels, the group frontiers can be estimated from the above model, considering only the observation for the *k*-th group. This procedure should be repeated *K* times. The efficiency of each group is expressed as $\hat{\theta}_{it}^{k,DEA}, k=1,\dots,K$.

4.2. **FDH efficiency**

The FDH estimator, proposed by Deprins et al. (1984), is a more general version of the DEA estimator which relies only on the free disposability assumption, and hence is not restricted to convex technologies. This seems an attractive property of FDH since it is frequently difficult to find a good theoretical or empirical justification for postulating convex production sets in efficiency analysis.

With this model, the integer constraint $\lambda_j \in \{0,1\}$ is added to [1], which then becomes an integer programming problem that can be solved using the numerical algorithm proposed by Tulkens (1993).

In practice, the FDH estimator is computed by a simple vector comparison procedure that amounts to a complete enumeration algorithm, as proposed by Tulkens (1993). Following Tauchmann (2012), and assuming an input-oriented approach, efficiency can be calculated by comparing each DMU (*i* = 1, . . . , *n*) with each of all other DMUs (*j* = 1,. . . , *n*), in the data that produce at least as much of any output as DMU *i*. The peer DMUs in the sample that satisfy the condition $y_{lj} \geq y_{li}, \forall l$ are denoted as B_i. Among the peer DMUs, the one that exhibits the minimum input consumption is taken as the reference to *i*, and the FDH estimator of the non-convex metafrontier, $\hat{\theta}_{it}^{M,FDH}$, is calculated as the relative input use, such that:

$$\hat{\theta}_{it}^{M,FDH} = \min_{j=1,\dots,n/y_{lj} \geq y_{li}, \forall l} \left\{ \max_{p=1,\dots,P} \left(\frac{x_{pj,t}}{x_{pi,t}} \right) \right\}$$

In this maximin procedure (for the input-oriented framework): the “max” part of the algorithm identifies the most dominant DMUs relative to which a given DMU is evaluated. Once these are identified, slacks are calculated from the “min” part of the algorithm.

Similarly, the non-convex *k*-th group frontiers can be estimated by the FDH method, considering only the observation for the *k*-th group. The FDH efficiency of each group is expressed as $\hat{\theta}_{it}^{k,FDH}, k = 1,\dots,K$.

4.3. **Order-*α* efficiency**

Both DEA and FDH analysis are highly sensitive to outliers and measurement errors. However, a partial-frontier analysis such as order-α generalises the FDH by allowing for superefficient observations located beyond the production-possibility frontier, enveloping just a subsample of observations, which makes it less sensitive to outliers. Moreover, the procedure used for detecting outliers can also be used to determine appropriate choices for α (see section 4.3.2).

4.3.1. **Estimation and interpretation**

As mentioned above, order-*α* also generalises FDH but rather than using minimum input consumption among the available peers as a benchmark, it considers the (100−α)-th percentile. Specifically, order-α determines the frontier by defining the probability $\left(1-\frac{\alpha}{100}\right)$ of points above the order-α frontier being observed.

With $0 \le \alpha \le 100$, this (100-α)-th percentile can be calculated as follows.

$$\hat{\theta}_{it}^{M,\alpha} = \underset{j=1,\ldots,n/y_{lj} \ge y_{li},\forall l}{P_{100-\alpha}} \left\{ \max_{p=1,\ldots,P} \left(\frac{x_{pj,t}}{x_{pi,t}} \right) \right\}$$

According to Daraio and Simar (2007), the order-α efficiency score provides useful information: for instance if $\hat{\theta}_{it}^{M,\alpha} = 1$, then the DMU is said to be efficient at the $\alpha\%$ level since it is dominated by firms producing more output than y with a probability $\left(1-\frac{\alpha}{100}\right)$. If $\hat{\theta}_{it}^{M,\alpha} < 1$ then the DMU has to reduce its input to the level $x\hat{\theta}_{it}^{M,\alpha}$ to reach the input efficient frontier of level $\alpha\%$. Moreover, $\hat{\theta}_{it}^{M,\alpha}$ can be greater than one. In this case, the DMU is considered to be superefficient with respect to the order-α frontier level. Another interesting interpretation of α was pointed out by Daraio and Simar (2007), who agreed with Aragon et al. (2003) and Daouia and Simar (2007) that α could be employed as an alternative measure of efficiency. Thus, the firm considered would be associated with an α value that makes the efficiency equal to 1. For a more detailed analysis of these questions, see Aragon et al. (2003) for the univariate case and Daouia and Simar (2007) for the multivariate extension.

When $\alpha \to 100$ the order-α frontier converges to the full frontier, and so the FDH model is a particular case of the order-α estimator when α=100, enveloping all the observations. When α<100, some DMUs may be classified as superefficient and hence would not be enveloped by the estimated production-possibility frontier. α can be regarded as a tuning parameter that determines the number of superefficient DMUs. From a computational standpoint, the main difference with respect to order-*m* is that order-α does not require resampling, and therefore the estimation is performed more quickly.

The *k*-th group frontiers can be estimated by the order-α method, considering only the observation for the *k*-th group. The efficiency of each group is then expressed as $\hat{\theta}_{it}^{k,\alpha}, k = 1,\ldots,K$.

4.3.2. **Partial frontier-based outlier detection**

Partial frontier analysis can be used to detect potential outliers in data subjected to nonparametric efficiency analysis by DEA or FDH (see Daraio and Simar, 2007). To perform this procedure, points of discontinuity in the presence of outliers must be obtained, since in the absence of outliers the proportion of super-efficient DMUs should decrease smoothly. Thus, the DMUs classified as superefficient for $\alpha \geq \alpha^{disc}$ (point of discontinuity) are the outliers or most likely outliers. With this information, such outliers can be excluded from the efficiency analysis in the application of FDH or DEA.

The approach suggested by Tauchmann (2012, following Daraio and Simar, 2007) is composed of the following steps, used to estimate the metafrontier and the groups: 1) perform a series of partial frontier analyses for different values of α; 2) plot the share of superefficient DMUs against α; 3) identify the discontinuities in the resulting curve. These discontinuities highlight the outlier DMUs that are classified as superefficient for the corresponding values of α. It is noteworthy that the STATA command *oaoutlier* implements order-α-based outlier detection and, from Daraio and Simar (2007), provides one global and two local rules for detecting discontinuities: a) the values of α for which the twice-differenced series takes a minimum value (following a non-negative one); b) the values of α for which negative values persist after repeatedly smoothing the twice-differenced series by running odd-spaced median smoothers; c) the values of α that minimise BIC after splitting the series into two parts and fitting linear (quadratic) functions to each one. Empirically, the choice of α is usually within the interval [90,99] when this parameter is obtained by an automatic selection procedure.

4.4. **Technological gap ratio**

Once the specific technical efficiencies of the group and those corresponding to the metafrontier have been obtained, the technological gap ratio can be calculated using the following expression:

$$TGR_{it}^{k,\Theta} = \frac{\hat{\theta}_{it}^{M,\Theta}}{\hat{\theta}_{it}^{k,\Theta}} \leq 1, k = 1,..., K$$

where $\Theta = \{DEA, FDH, order-\alpha\}$.

5. **Data**

5.1. **Inputs and outputs**

The data for the variables considered in this study were obtained from the Iberian Balance Sheets Analysis System (SABI) database provided by Bureau van Dijk (BvD), specifically from the annual reports from 2002 to 2015, containing information on inputs and outputs. From this database, companies meeting the following four conditions were initially selected: (1) They must be operating in the Canary Islands. (2) They must be classified in category 5510 of the National Classification of Businesses (CNAE-93, which covers the exploitation and management of hotels and similar). (3) They must have had an annual operating revenue of at least 500,000 euros for one year or more during the study period. (4) They must have had more than 10 employees in 2015. A total of 341 companies meeting these conditions are registered in the database. However, many of these companies were subsequently eliminated from the study because they managed not only hotels but also apartments. This circumstance was ascertained by consulting the firm's website. After performing this check, 127 companies remained in the group selected for analysis, providing a total of 1287 observations (the information was incomplete for certain years, and so the analysis is based on unbalanced panel data).

Inputs and outputs were selected for analysis according to data availability, using the SABI balance sheets. The inputs considered are labour, physical factors and operating costs. Labour factors are measured by the number of full-time equivalent employees and by labour costs (Jorge and Suárez, 2014; Parte-Esteban and Alberca-Oliver, 2015; among others). Physical costs (Barros and Santos, 2006; Fernández and Becerra, 2015; among others) are taken as capital costs (measured as annual amortisation). Operating costs (Shang et al., 2008; Barros et al., 2011; Jorge and Suárez, 2014; among others) are measured as material costs plus other operating costs. Output is measured by total operating revenue, following Tzeremes (2019, 2020), among others. All monetary values are presented in euros (CPI base 2016) and refer to the period 2002 to 2015. Table 2 shows the descriptive characteristics of the variables considered for 127 hotels, with information on their inputs and outputs. In the study sample, the average hotel had a total revenue of 10.4 million euros and employed 138 workers. There were more small and large hotels than medium-sized ones; the types of ownership differed widely and other characteristics were also heterogeneous.

Table 2. Characteristics of inputs and outputs in the period 2002-2015.

Variables	Mean	SD	Min	Max
Inputs				
Full-time employees	138	110	10	1158
Labour costs (€)	3938.765	2855.708	212.9476	12813.92
Capital costs (€)	1089.216	993.5723	55.29516	4884.476
Material costs (€)	1845.6	2312.495	0.0931966	22096.84
Other operating costs (€)	2786.697	3932.128	0.0394697	43883.57
Output				
Total revenue	10368.75	7793.846	518.5839	35410.55

Notes: SD, Standard deviation; Min, minimum value; Max, maximum value. All monetary values are expressed in thousands of euros, according to the CPI base 2016. Descriptive statistics are reported for the pooled sample.

As mentioned in the Introduction, partial frontier approaches such as order-m and order-α do not suffer from the 'curse of dimensionality', and so larger sample sizes are not required in order to avoid excessive bias and imprecise estimation. However, for the DEA/FDH estimator it might be necessary to increase the number of observations in order to avoid these problems. To determine the sample size when these models are used, certain empirical rules can be applied, relating the number of DMUs (sample size) to the number of inputs and outputs incorporated in the model estimation. Cooper et al. (2007) described a guide that encompassed most of the proposals made in this respect by authors such as Homburg (2001), Banker et al. (1989), Raab and Lichty (2002) and Dyson et al. (2001). Moreover, Cooper et al. (2007) observed that the number of DMUs should be the greater of the following values: $\max\left(P \times Q, 3\left(P+Q\right)\right)$, which in the present study are 5 and 18, respectively. These values are well below the sample size we use, both for the overall period and for each of the years into which it is divided (Table 4 shows the sample size for each year).

5.2. **Ownership and size heterogeneity**

To evaluate the heterogeneity present in the study sample, the hotels were classified by size and type of ownership, using the SABI definitions to characterise the companies' independence with regard to their shareholders. This indicator is assigned to each company according to categories A, B, C, D and U, with further qualifications. Category A is assigned to the company when no shareholders are known to control more than 25% of the company ownership. Category B is assigned when no shareholder controls over 50% (direct, total or calculated total), but one or more shareholders have more than 25%. Category C is assigned to the company when any one shareholder has a total or calculated total ownership exceeding 50%. The category C+ is assigned when the sum of direct ownership percentages (including all the above categories of shareholders) is 50.01% or greater. This means that the company cannot be classified as category D (since it cannot have an unknown direct shareholder with 50.01% or more of the ownership). The indicator C is also assigned when the company has an ultimate owner, although the percentage of ownership is unknown. Indicator D is assigned to any company that has a recorded shareholder with a direct ownership of over 50%. Category D is also assigned when the company is question is a branch or subsidiary of a foreign company. Finally, category U is assigned to companies that cannot be classed as A, B, C or D, i.e. the degree of independence is unknown[3]. The present study includes a dummy variable which takes the value 1 if the hotel is assigned category C, C+ or D, and 0 otherwise. Therefore, the hotels analysed are grouped into two classes, according to their type of ownership; those with a majority shareholder and those with no majority shareholder. Focusing on the first group (with a majority shareholder), none of the 127 hotels in the sample were classed as category C, seven were category C+ and 80 corresponded to category D. In the latter case, all these hotels were controlled by a corporation. The corporations controlling the hotels classed as C+ had an average of 70 firms, while those controlling the category D hotels had an average of 32 firms. The category D group, therefore, is entirely composed of hotels with a dependent management, which reports directly to the owners. We refer to these hotels as chain-operated. In contrast, independently-operated hotels and those with no majority shareholder are directly managed by their owners/investors, who take responsibility for all administrative decisions. According to the information obtained from the SABI data base, none of the independently-operated hotels belong to a corporate group.

Differing from Assaf et al. (2010) in this respect, and because no information was available on the number of rooms in each hotel, we defined large hotels as those obtaining an annual income greater than that of the 75th quantile in this respect. All others were classed as small to medium-sized.

6. **Empirical analysis**

In this section, we comment on the main results obtained from this study, conducted to analyse and compare various estimators of hotel efficiency, in terms of metafrontier, groups and the technological gap ratio (TGR). In addition, certain characteristics of scale efficiency

[3] Twenty-six hotels were assigned category U. These cases were not included in the analysis of independence.

are examined and discussed. Our analysis takes into account the heterogeneity of the sector, by hotel size and ownership, determines mean differences and also considers the effect of the global financial crisis on technical efficiency and the time path of the TGR for each estimator included in the analysis.

The main implication of applying both convex and non-convex technologies to the data is that with the first approach hotel efficiency is measured relative to non-existent convex combinations of peer hotels, while under non-convex technology, this efficiency is measured relative to existing peer hotels. The use of existing hotels as role models is a feature of the FDH and the order-α models and provides valuable information for managing hotels that are currently operating below their maximum efficiency level.

6.1. **Metafrontier, group and technological gap ratio estimates**

Table 3 shows the mean technical and scale efficiency estimates obtained, both those associated with the group (where different technologies are considered for each group) and those associated with metafrontier models (where the same technology is considered for all hotels). The table also shows the average technological gap ratio (TGR) obtained. These results were calculated by DEA with CRS and VRS models (applying the convexity assumption) and also by FDH and the robust order-α estimator (whereby the convexity assumption is relaxed). The last column of Table 3 shows the average technical efficiencies calculated for order-α when α is obtained using an automatic selection procedure (Tauchmann, 2012).[4] Table 4 shows the values of α obtained for each year and the corresponding sample size.

[4] The frontier is estimated for different fixed values of α (=25, 50, 75, 99). However, as α decreases the number of superefficient hotels increases considerably, and so the number of hotels with a technical efficiency score equal to or less than one decreases in the same proportion. In consequence, in many cases it is not viable to test the equality of technical efficiency scores between the different groups of hotels, due to the lack of degrees of freedom, unlike what happens when α is obtained automatically. Thus, for example, when α =75 the number of superefficient hotels is about 96%. These results depend on the data generating process. Similar results were reported by Aragon et al. (2005) for a nonconvex production set. These authors found that for α =70 about 95% of the observations were classified as superefficient (see Figures 3a and 4a of Example 2 of the above-mentioned paper). In the present case, when α=50 or 25 the results are even more extreme, making it impossible to implement any kind of test on the efficiency of hotel groups.

Table 3. Metafrontier, group and technological gap ratio (TGR) mean estimates for each efficiency estimator. Overall period.

Heterogeneity	DEA			FDH	Order-α
	CRS	**VRS**	**Scale**		**Automatic selection procedure for each year**
I. Metafrontier (same technology)					
A. ***Ownership***					
Independently-operated (n_1=160)	0.6971	0.7369	0.9428	0.9790	0.9893
Chain-operated (n_2=956)	0.7264	0.8091	0.8995	0.9878	0.9935
B. ***Size***					
Small and medium-sized hotels (n_1=1063)	0.7129	0.7169	0.9086	0.9853	0.9821
Large hotels (n_2=271)	0.7656	0.8260	0.8653	0.9961	0.9964
II. Groups (different technologies)					
A. ***Ownership***					
Independently-operated (n_1=160)	0.9225	0.9736	0.9471	0.9971	1.000
Chain-operated (n_2=956)	0.8248	0.8885	0.9284	0.9841	0.9964
B. ***Size***					
Small and medium-sized hotels (n_1=1063)	0.8073	0.8734	0.9241	0.9857	0.9873
Large hotels (n_2=271)	0.8803	0.9226	0.9536	0.9961	0.9989
III. TGR					
A. ***Ownership***					
Independently-operated (n_1=160)	0.7544**	0.7571**	0.9452	0.9818**	0.7045**
Chain-operated (n_2=956)	0.8722**	0.8990**	0.9298	0.9983**	0.9094**
B. ***Size***					
Small and medium-sized hotels (n_1=1063)	0.8689**	0.8872**	0.9382	0.9996*	0.9749**
Large hotels (n_2=271)	0.8413**	0.9373**	0.8827	1.0000	0.7703**

Notes: The programs were run year by year, and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different each year. Finally, the null hypothesis that TGR=1 was tested for the DEA, FDH and order-α (automatic selection) technologies. (*) and (**) The null hypothesis is rejected for significance levels of 5% and 1%, respectively.

Table 4. Values for order-α using the automatic selection procedure. Period 2002-2015.

Year	02	03	04	05	06	07	08	09	10	11	12	13	14	15	***Averaged***
N	65	72	79	92	90	92	91	102	99	99	103	105	103	95	92
α	92.4	91.88	92.5	94.6	93.4	93.6	94.6	96.1	96.0	94.0	95.2	94.3	96.2	95.8	94.3

The main characteristics of the efficiency estimators are as follows. On the one hand, let $\hat{\bar{\theta}}_{method}$ denote the mean technical efficiency estimator, according to the method applied, i.e. CRS, VRS, FDH and order-α, respectively, using the automatic selection procedure for each year. For the sake of brevity, the individual efficiency results of the hotels studied are not reported, but they are available from the authors on request. In general, the mean efficiencies obtained from robust estimators (order-α) are always higher than those derived from non-parametric deterministic estimators such as CRS, VRS and FDH, both for the metafrontier and for the group frontiers. For example, the mean efficiency estimates obtained are $\hat{\bar{\theta}}_{CRS}^{M} < \hat{\bar{\theta}}_{VRS}^{M} < \hat{\bar{\theta}}_{FDH}^{M} < \hat{\bar{\theta}}_{order-\alpha}^{M}$ for the metafrontier (even distinguishing between groups), but also for the *k*-th frontier group, $\hat{\bar{\theta}}_{CRS}^{k} < \hat{\bar{\theta}}_{VRS}^{k} < \hat{\bar{\theta}}_{FDH}^{k} < \hat{\bar{\theta}}_{order-\alpha}^{k}$. This result indicates that when outliers (superefficient hotels) are taken into account, efficiencies can be estimated more robustly using order-α than with traditional DEA and FDH methods.

Table 3 also shows the scale efficiency results obtained from the DEA estimates, distinguishing between metafrontier, group frontier and TGR. In managing hotel operations, the aim is not only to achieve technical efficiency (i.e., maximal output from a given set of inputs), as reflected in the CRS and VRS models, but to do so at an optimum scale, thus also achieving scale efficiency, such that any change in the hotel's size would render the unit less efficient. Scale efficiency reflects the distance between the constant and variable returns to scale (CRS and VRS) technologies at which a hotel may secure its output once any technical inefficiency of the unit has been eliminated.

As can be seen, scale inefficiencies exist in the hotels considered, and therefore hotel activity could exhibit VRS, which is less restrictive than CRS because not all hotels operate at their optimal scale.

However, the scale efficiencies are high for both types of heterogeneity (size and ownership), with values exceeding 85%. The average scale efficiencies for the group frontiers show that whether the hotel is independent or part of a chain, the level of scale efficiency is similar, but that large hotels are more efficient in this respect than small and medium-sized ones. This finding corroborates the hypothesis that the economies of scale associated with large hotels enable them to expand their operations rapidly, when necessary, thus achieving operational savings. However, this conclusion was not reached with respect to the metafrontier, where scale efficiencies are slightly greater for hotels with no majority shareholder and for small and medium-sized establishments.

Nevertheless, neither for the mean TGR results in particular nor for the overall findings was any clear trend, increasing or decreasing, observed.

6.2. **Testing the heterogeneity of hotels**

The impact of hotel ownership and size was tested, with two groups in each case. Student-*t* tests were performed on the equality of means among the efficiency results detailed in Table 3. Table 5 shows the results of these tests. As expected, the metafrontier mean estimates are always lower than the group estimates, which we ascribe to the fact that with the metafrontier estimates, the hotels are restricted to a common, homogeneous technology, and therefore the estimates are less accurate.

Table 5. Mean difference test by heterogeneity (ownership and size).

Heterogeneity	**DEA**			**FDH**	**Order-α**
	CRS	**VRS**	**Scale**		**Automatic selection procedure for each year**
I. Metafrontier (same technology)					
A. ***Ownership***	-2.054 [0.04]	-5.398 [0.00]	4.647 [0.00]	-1.956 [0.05]	-0.611 [0.54]
B. ***Size***	-7.143 [0.00]	-5.549 [0.00]	-4.424 [0.00]	-3.073 [0.00]	-2.508 [0.01]
II. Groups (different technologies)					
A. ***Ownership***	7.967 [0.00]	8.205 [0.00]	2.274 [0.02]	2.030 [0.04]	1.326 [0.19]
B. ***Size***	-7.143 [0.00]	-5.549 [0.00]	-4.424 [0.00]	-3.073 [0.00]	-2.508 [0.01]
III. TGR					
A. ***Ownership***	-11.71 [0.00]	-13.90 [0.00]	1.941 [0.05]	-7.100 [0.00]	-12.87 [0.00]
B. ***Size***	2.183 [0.03]	-6.715 [0.00]	8.513 [0.00]	-1.006 [0.31]	18.30 [0.00]

Note: The programs were run year by year, and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different each year. The mean difference test is the two-sample t-test (two-way) with equal variances for the mean differences between the first and second groups. The p-value is shown in parentheses.

6.2.1. **Differences by hotel ownership**

Summarising the results obtained for the different technologies considered, Table 5 shows that for the DEA and FDH models the average technical efficiency scores differ significantly according to the type of hotel ownership. Thus, independently-operated hotels are more efficient than chain-operated ones. For example, with the DEA-CRS model, for independently-operated hotels the average technical efficiency score is about 92%, while for chain-operated hotels the corresponding score is about 82%. The difference between these two values is significant, according to the mean difference test, also shown in Table 5. This result contrasts with the findings reported from related studies, most of which focus on differences between chain and independently-operated hotels. Thus, several studies of the hotel industry in Taiwan have reported that international chain hotels significantly outperform independent establishments, not only in terms of meta-technical efficiency (see, for example, Assaf et al., 2010; Yu and Chen, 2016), but also in terms of meta-cost efficiency, meta-technical efficiency and meta-allocative efficiency (Cho and Wang, 2018). As pointed out by Assaf et al. (2010), these prior findings might reflect advantages enjoyed by hotel chains, such as better marketing strategies, stronger management policies and stronger economies of scale (Wang et al., 2006). However, when a single technology forms the basis of analysis, the results obtained lead to the opposite conclusion being drawn, i.e., that chain-operated hotels obtain higher levels of efficiency than independently-operated ones. These results demonstrate the need to account for the existence of heterogeneity by applying procedures such as the metafrontier approach, thus ensuring that heterogeneous firms or groups are assessed according to their distance from a common and identical frontier.

Another reason why the above results may not be definitive is the possible existence of outliers, or "superefficient" hotels. Order-α is a robust procedure but highly sensitive to outliers. Table 5 shows, in contrast to the conclusions discussed above, that there are no significant differences between the average technical efficiencies of independently-operated hotels and those of chain-operated hotels when the order-α model is used. This is so both when a single technology (the metafrontier) is considered and when different ones (groups) are included in the analysis. Specifically, Table 5 shows that the average differences in technical efficiencies for the two types of ownership are -0.611 and 1.326, respectively. In neither case are these differences significant. Only the “order-α” model distinguishes between efficient hotels and those that are outliers, or superefficient, and it is precisely when this distinction is made that a result is obtained indicating the absence of difference between the two groups of technologies. This finding could mean that the difference in technologies detected by the DEA and FDH models is due to the existence of super-efficient hotels (outliers) that the latter models do not identify.

Another interesting aspect of these findings is the difference between the average technical efficiency scores obtained for the groups and the metafrontier models, according to TGR analysis. For example, the average DEA-CRS technical efficiency of the chain-operated hotels relative to the metatechnology is only 0.6971, which suggests that this group of hotels is much less efficient relative to the metafrontier. In fact, even if all the hotels in this group achieved best practices with respect to the technology observed in this group, their technology would still lag behind that for the 'overall hotels' group, with a technology gap ratio of 0.7544. For all models, the TGR of the chain-operated hotels is greater than for independently-operated establishments. However, these results are not as conclusive when the groups formed are analysed according to their size.

In all cases except that of large hotels in the FDH model, the hypothesis of a TGR equal to one is rejected (see the footnote to Table 5). However, chain-operated hotels have an average TGR that is closer to one than those with no majority shareholder (independently-operated hotels). As can be seen throughout the present study, the way in which outliers are addressed can have a decisive impact on the results obtained, and so careful attention should be paid to the order-α model. Table 5 shows that chain-operated hotels reach 90.94% of their potential output while the corresponding figure for independently-operated ones is only 70.45%. Similar differences can be seen when the sample is divided into small and medium-sized vs. large hotels. In the first group, the potential output is 77.03%, while in the second this figure rises to 97.49%. However, it should be noted that the TGR of the order-α model is calculated only when hotels have a technical efficiency score between zero and one. If the hotels are considered outliers with respect to the metafrontier and/or with respect to the group frontier then the TGR is not calculated.

6.2.2. **Differences by hotel size**

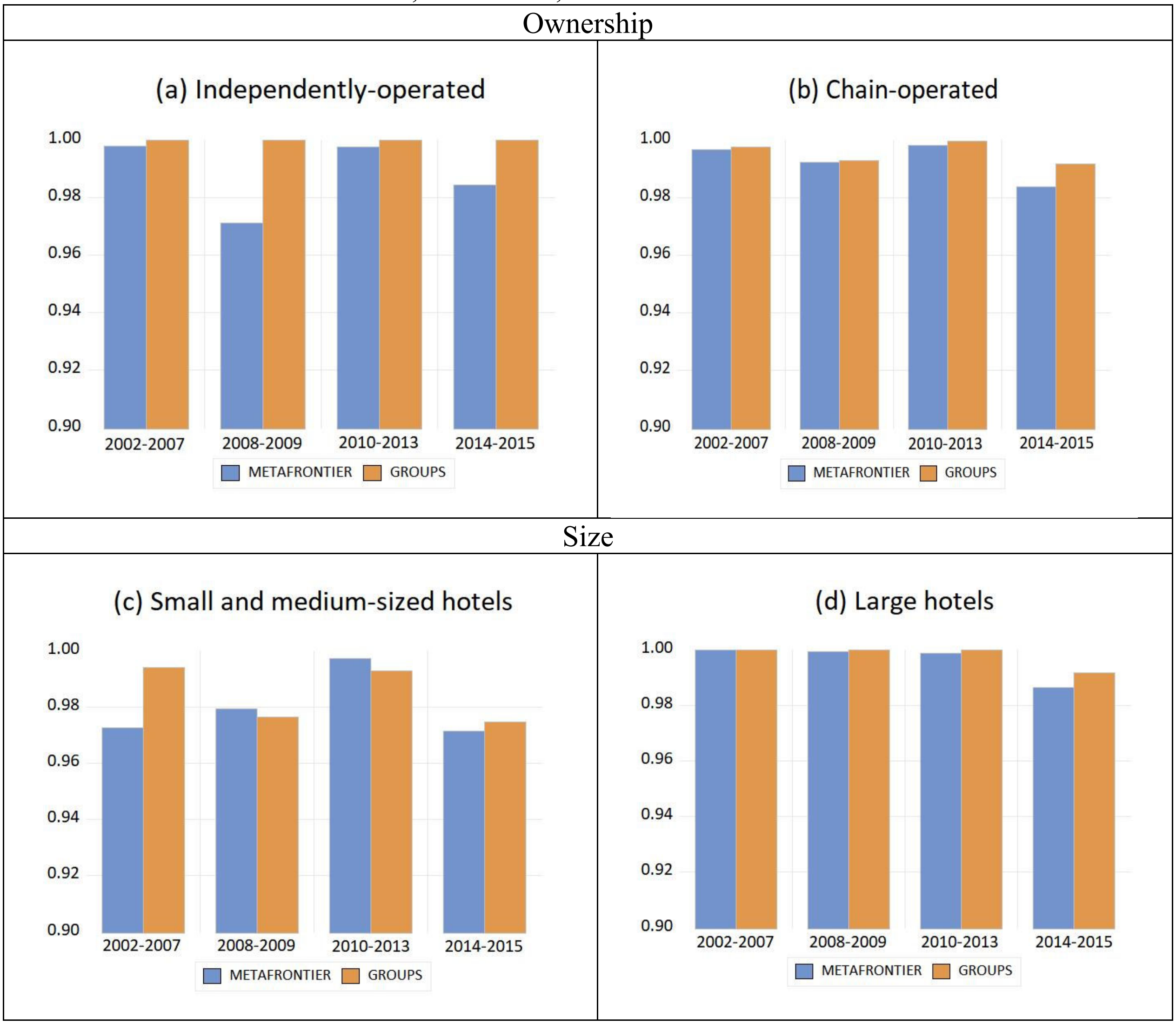
Presenting the different technologies considered, Table 5 shows that large hotels perform significantly better than small and medium-sized ones, both in the group estimates and with the metafrontier model (CRS, VRS, Scale, FDH and order-α). For example, in the order-α model, the average group efficiency for large hotels is about 98%, whereas for small and medium-sized ones it is about 99%. Despite the similarity of these values, the difference is statistically significant.

With respect to the TGR, large hotels achieve only 94% of their potential outputs, while for small and medium-sized hotels the corresponding figure is 89%. Finally, the results for size and ownership indicate that, regardless of the model used, large hotels perform better than small ones. On the other hand, when metafrontier analysis is applied and outliers are taken into account, there appears to be no difference between the technical efficiencies of independent and chain-operated hotels.

6.3. **The impact of the global financial crisis**

This section examines the impact of the global financial crisis on the technical efficiency of hotels in the Canary Islands, taking into account the type of ownership and hotel size. To do so, the sample period is divided into four sub-periods. A first pre-crisis sub-period from 2002 to 2007, a second sub-period mainly marked by the global financial crisis from 2008 to 2009, a third sub-period covering the sovereign debt crisis from 2010 to 2013, and finally, the post-crisis sub-period that covers 2014 and 2015. Estimates of the average technical efficiencies for each of these sub-periods are presented in Appendix 2, in Tables A2.1 to A2.4. Notably, several of the conclusions drawn for the overall period are similar for all sub-periods, such as the fact that large hotels outperform small and medium-sized ones, and that independently-operated hotels outperform chain-operated ones.

Figure 2. Average technical efficiencies estimated with the order-α model for the sub-periods 2002-2007, 2008-2009, 2010-2013 and 2014-2015.



For the sake of brevity, this section mainly considers the order-α model, in the view that the treatment of outliers must be taken into account, according to the results obtained for the models estimated, especially when the sample is divided by type of hotel ownership. Figure 2 shows the evolution of the average technical efficiency value (plotted on the y-axis) during each of the sub-periods into which the sample was divided (on the x-axis), considering hotel ownership and size. Each figure distinguishes between the efficiencies obtained from the estimation of the metafrontier and those obtained from estimating the frontier for each group.

Figure 2 shows that the global financial crisis did not produce a significant impact on the average technical efficiency of the hotels considered, possibly due to the rapid recovery of tourism revenue in Spain following the "Arab Spring". This trend is reflected in Figure 1, on tourism revenue in Spain, which rose during the sample period, fell in 2009 by approximately

8%, but quickly regained the previous level with the increases that took place in 2010 and 2011. In fact, the figure reached in 2011 was the highest to date. Moreover, this recovery in tourism revenues was fairly homogeneous among all the main tourist destinations in Spain. Another significant point is that the financial crisis did not have a particularly significant impact on inputs because it was not accompanied by any major inflationary effect, i.e. hotel costs remained fairly stable. In addition, new employment legislation increased the flexibility of the labour market. Summarising these effects, Figures 2(a) and 2(b) show that independently-operated hotels and small and medium-sized hotels underwent only a small decrease in technical efficiency in the sub-period 2008-2009, when this value was calculated from the metafrontier. This decrease was also apparent in the same sub-period when efficiencies were obtained from the group frontiers (Figure 2(b)). The evolving pattern of technical efficiency among chain-operated hotels and large hotels remained fairly stable throughout the sub-periods considered, regardless of whether it was measured from the metafrontier or from the group frontiers. These results are consistent with those obtained by Cordero and Tezeremes (2017), Tzeremes (2020) and Sellers-Rubio and Casado-Diaz (2018), which suggests that the hotel industry in the Canary Islands was resilient to the global financial crisis.

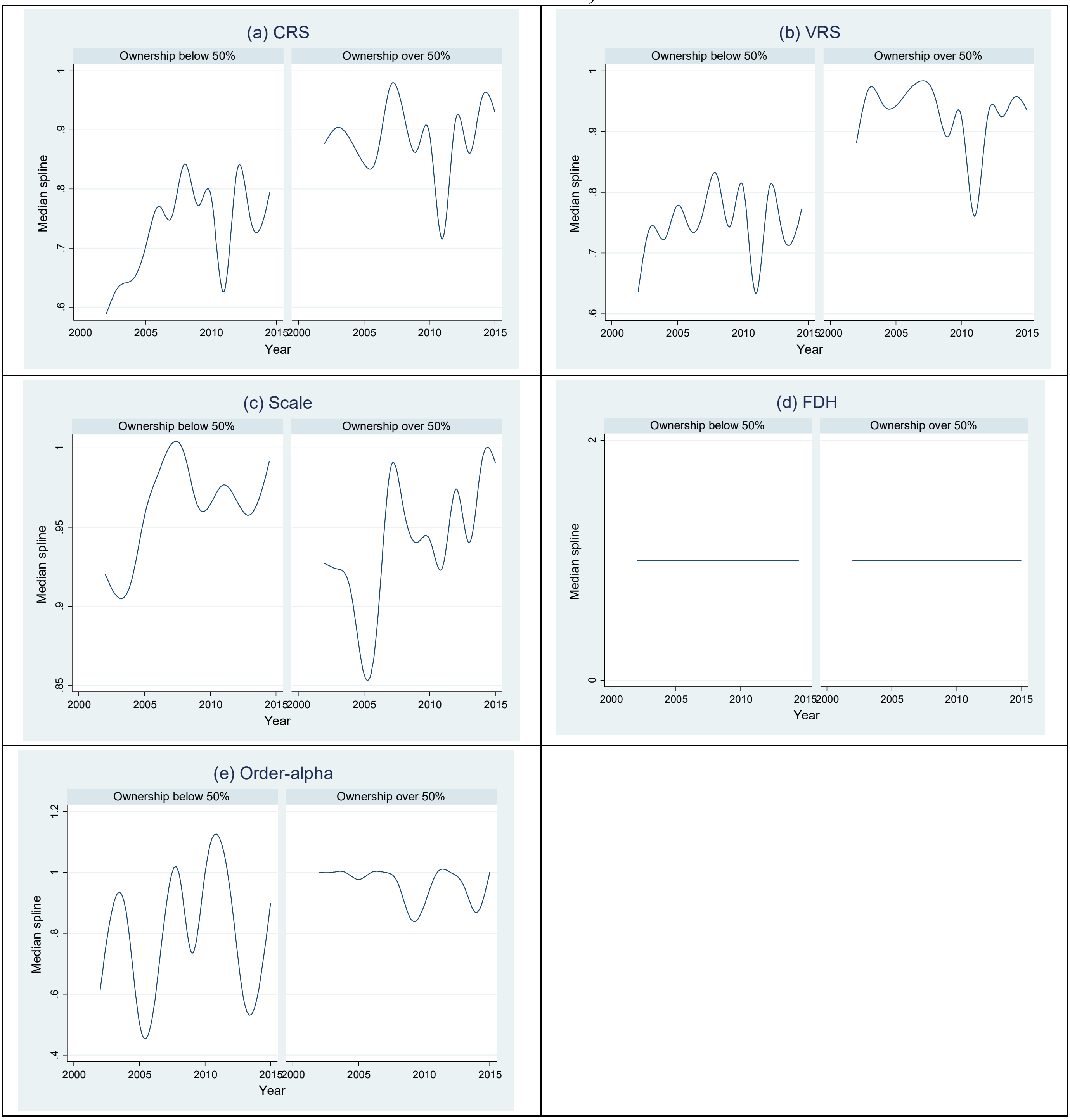
6.4. **Time path of the technological gap ratio**

In this sub-section, the trend of the technological gap ratio (TGR) for each type of hotel over time is examined. To reflect the evolving achievement of potential outputs, the time path of the TGR for each estimator is plotted in Figures 3 and 4, considering the type of hotel ownership and the degree of size heterogeneity, respectively.

Figure 3 distinguishes between two types of hotels: “ownership over 50%” (i.e. those with a majority shareholder or chain-operated hotels) and “ownership below 50%” (i.e. those with no majority shareholder or independently-operated hotels). The first type presents a stable pattern of TGR, at a median value of around one, which suggests that the hotels in this group outperformed those with no majority shareholder during the study period.

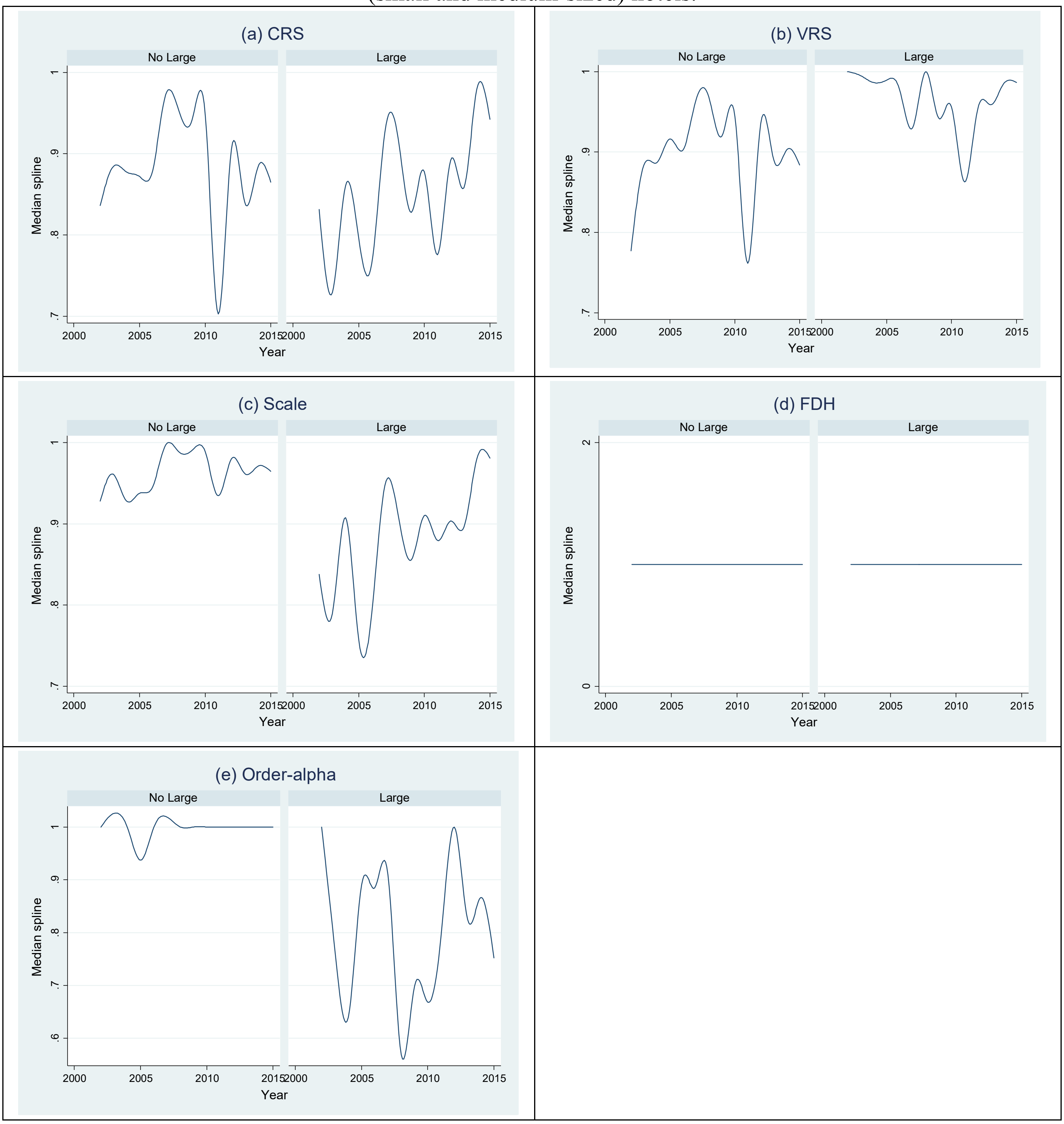
However, the performance of the independent hotels in the study sample tended to improve during the study period, i.e. their proportion of potential outputs in the Canary Islands hotel industry tended to rise. These results are coherent with those shown in Table 3, where the mean TGR scores for chain-operated hotels are higher than those for independently-operated establishments.

Figure 3. Technological gap ratio by type of ownership (hotels with or without a majority shareholder)



In Figure 4, the median results for TGR contrast with those shown in Figure 3, in the sense that small and medium-sized hotels present a stable pattern over time (with values around 1.0), while the results for larger establishments tend to rise over time, towards 1.0, with the exception of the FDH estimates, for which the TGR is always 1.0. These results seem contradictory to the idea of scale, because large hotels do not achieve their potential outputs.

Figure 4. Technological gap ratio for estimated efficiencies by size for large and non- large (small and medium-sized) hotels.



7. **Conclusions**

Most previous non-parametric efficiency studies of the hotel industry are based on the homogeneity hypothesis for technology. However, some have employed the metafrontier concept to address the differences among groups of hotels using different technologies and nonparametric estimators of the frontier (see, for example, Assaf et al., 2010; Yu and Chen, 2016; Huang et al., 2013; Cho and Wang, 2018) or SF models (i.e., Huang et al. 2014; Bernini and Guizzardi, 2015).

Going beyond other studies based on metafrontier analysis within a nonparametric framework, this paper makes two novel contributions to the empirical literature on hotel efficiency. First, technological heterogeneity is assessed using the metafrontier approach and comparing technology estimators based on the convex frontier (such as DEA) and on the non-convex frontier (such as FDH), together with robust nonparametric estimators (order-α, which account for outliers in the estimation of hotel efficiency), in line with De Witte and Marques (2009), who compared DEA, FDH and order-*m* estimates. The metafrontier is estimated by pooling the relevant data for each year, while the group frontier is obtained by considering only the hotels belonging to a particular group. Finally, once the estimates of both the metafrontier and the group have been determined, the technological gap ratio for each hotel is calculated. These individual results are then averaged by reference to the heterogeneous group analysed.

Second, in performing these comparisons, the hotels considered are assumed to be heterogeneous in terms of the resources and capabilities on which their managerial practices are based (as proposed by the resource-based theory). In brief, this study analyses the impact of certain environmental variables on hotel efficiency in the Canary Islands for the period 2002-2015, examining how two types of heterogeneity may affect hotel efficiency, and taking into account the type of ownership and the existence of different hotel sizes.

The main results obtained indicate two facts. On the one hand, there are measurable differences between the technology estimators considered. For example, order-α is preferred to DEA and FDH, indicating that outliers influence hotel efficiency. On the other hand, the hotel industry in the Canary Islands is characterised by heterogeneity in terms of hotel size and type of ownership. Both of these factors are strong determinants of hotel efficiency. These results partially converge, and suggest similar conclusions may be drawn regarding the impact of selected environmental variables on efficiency. In terms of hotel size, these results are in line with those reported in the empirical metafrontier literature, using non-parametric methods. Specifically, large establishments tend to outperform small ones. In this respect, moreover, Assaf et al. (2010) in their study of the hotel industry in Taiwan, concluded that hotel size was clearly associated with efficiency. They also found that large hotels achieved greater efficiency in terms of the group and the metafrontier models. The second major finding of the present study is that in the Canary Islands there is no significant difference in average technical efficiency between independently-operated and chain-operated hotels, and therefore one type of business organisation cannot be said to perform better than the other. This is the case both with the metafrontier and for different technologies. However, it should be noted that this result is obtained using a robust model such as order-α, which is sensitive to outliers and measurement errors. When no such robust model is used the results may vary, as can be seen in the Results section.

The technological gap ratio differs between these heterogeneity groups, although it tends to increase over time in hotels that are independently-operated and in large establishments. When there is a majority shareholder (chain-operated hotels), and in the case of small and medium-sized hotels, the ratio remains fairly constant. The results for large hotels are in line with those of Assaf et al. (2010), who found that large hotels had a larger TGR. However, in terms of ownership, there is a significant gap between the metafrontier and group technologies. In this respect, Huang et al. (2013) identified potential best practices and the current performance achieved with domestic, franchise and chain-membership technologies.

The policy implications of the study results obtained should be formulated mainly from the standpoint of hotel size and not so much from that of type of ownership. On the one hand, from the managerial perspective, the managers of small hotels and of chain-operated hotels should adopt strategies based on favouring best practices. On the other hand, the regional government of the islands should seek to implement strategies favouring the hospitality industry. For example, policies for small hotels will probably differ from those appropriate for large establishments, as the latter are subject to resource constraints and may need more help. Sometimes this help can be aimed at achieving a larger size. The hotel construction moratorium (mentioned in section 2) has led to a significant increase in the supply of 5-star accommodation in the Canary Islands (Inchausti-Sintes and Voltes-Dorta, 2020), often integrated within exceptional projects with complementary facilities (golf, water sports, etc).

The final conclusion drawn from the present study is that the global financial crisis had no significant impact on the average technical efficiency of hotels in the Canary Islands, possibly due to the transfer of tourists from other Mediterranean holiday destinations during and after the Arab Spring. Except for the 8% drop in tourism income in Spain in 2009, due to the financial crisis, revenue figures rose uninterruptedly throughout the study period.

Certain limitations to the present study should be acknowledged. On the one hand, hotel efficiency can be studied considering multi-production technology. Therefore, certain outputs that were not included in this study could be introduced, such as occupancy rates, or revenue could be subdivided into revenue from rooms, from meals and from other services. Unfortunately, the SABI database does not contain this type of information. Another problem is that it was not possible to study the effect produced by the hotel construction moratorium on the technical efficiency of the hotels because the moratorium legislation came into effect in 2001 and remains in force today. In future research, it would be of special interest to address these issues.

Finally, this paper compares several (radial) input-oriented estimators (DEA, FDH, order-α) in order to estimate hotel efficiency (under the assumption that managers control inputs but not outputs). However, a (non-radial) non-oriented approach could also be used if managers wish to control and improve both inputs and outputs, simultaneously. Therefore, in future research, the superefficiency slack-based measure (SBM) could also be used to assess hotel efficiency in the Canary Islands.

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Appendix 1. List of papers studying hotel efficiency.

. Non-parametric studies of hotel efficiency based on the non-metafrontier approach.

Method	Efficiency model	Inputs	Outputs
DEA	--	Salaries, energy costs, fixed market expenditure, room division expenditure, non-salary expenses with property, non-salary expenses with administrative work, non-salary expenses with variable advertising, payroll and related expenses for administrative work and salaries and related expenses with variable advertising.	Market share, rate of growth, total revenue and level of service provided
DEA	--	The number of rooms, the number of full-time equivalent workers, total gaming-related expenditure, total expenditure on food and beverages and various other expenditures	Total revenue and other revenue
DEA	--	Price, problems, service, upkeep, hotels, rooms	Satisfaction and value
DEA & Malmquist-DEA	--	Full-time employees, the number of guest rooms, the total dimension of the meal department and operating expenses	Room revenue, food and beverage revenue and other revenue
Malmquist-DEA	--	Full-time workers, cost of labour, book value of property, operating costs and external costs	Sales, number of guests, and nights spent in the hotel.
DEA	--	Hotel rooms, food and beverage capacity, number of employees and total hotel costs	Yielding index (revenue per available room), food and beverage revenue and remaining revenue (total revenue excluding food and beverage revenue and room revenue)
DEA	--	Full-time equivalent workers and salaries paid, physical capital (external costs, operating costs and book value of the property)	Sales, number of guests and nights spent
Malmquist DEA	Tobit regression	Full-time equivalent workers and salaries paid, physical capital (external costs, operating costs and book value of the property)	Sales, number of guests and nights spent
Cost DEA	Tobit regression	Full-time employees in room department. Number of rooms. Area of food and beverage department (m^2). Number of full-time employees in food and beverage department. Average wage rates of a full-time employee in the room department (US$). Average room rate (US$). Average price of food and beverage operations (US$). Average wage rate for a full-time employee in the food and beverages department (US$)	Revenues from room department for the year ending 2001(US$). Revenues from food and beverage department for the year ending 2001(US$). Revenues other than from rooms and food
DEA	--	Employees, physical capital [input prices: price of labour, price of physical capital]	Sales, added value and earnings
DEA	Stepwise multiple regression	Server wage, seats, square footage, units in the same State, and several other contextual variables as inputs	Sales, tips and turnover
Malmquist-	Simar & [illegible]	[illegible]	[illegible]

				environmental variables		from sources other than rooms and food and beverages)
Botti et al. (2009)	France	16 hotel chains	DEA	--	Costs, territorial coverage and length of existence of the chain.	Sales
Shang et al. (2010)	Taiwan	57 internatio nal tourist hotels	Stochastic DEA (SDEA)	Tobit regression	Guest rooms, food and beverage capacity, number of full-time employees and operating expenses	Room revenues, food and beverage revenues and miscellaneous revenues (revenue from sources other than the room and food and beverage revenues)
Barros et al. (2011)	Portugal	15 hotels	DEA	Simar & Wilson method	Full-time workers, book value of property and operational costs	Sales, number of guests
Devesa and Peñalver (2013)	Spain	297 hotels	DEA	--	Full-time employees, staff cost and number of rooms	Total operating revenue
Ashrafi et al. (2013)	Singapore	16 DMU (years)	SBM	--	Average room rate, total international visitor arrivals and GDP	Hotel room revenue, hotel food and beverage revenue, occupancy rate and gross lettings
Jorge and Suárez (2014)	Spain	303 hotels	Malmquist-DEA	Tobit panel data model	Employment, labour costs, number of rooms, operational costs	Sales, market share
Fernández and Becerra (2015)	Spain	166 hotels	DEA	Binomial logistic regression	Physical capital, employment.	Sales
Parte-Esteban and Alberca-Oliver (2015)	Spain	1385 hotels	DEA	Tobit regression	Full-time employees, book value of the property, operational costs	Sales
Cordero and Tzeremes (2017)	Spanish islands	758 hotels	Malmquist DEA	--	Number of employees and total fixed assets	Total sales
Cruz (2017)	Philippines	10 deluxe hotels	SBM and Malmquist	--	Operating expenses, capital, number of employees, number of rooms	Total revenue
Cordero and Tzeremes (2018)	Spanish islands	820 hotels	DEA	--	Number of employees and total fixed assets	Total sales
Tzeremes (2019)	Canary Islands (Spain)	176 hotels	Luenberger productivity indicator Order-m	--	Number of employees and total fixed assets	Total revenues
Tzeremes (2020)	Spanish islands	820 hotels	Malmquist Order-m	--	Number of employees and total fixed assets	Total revenues
Deng et al. (2020)	Mainland China	Hotels in 31 provinces and 4 regions	SBM	--	Number of hotels and guest rooms, amount of fixed capital stock, and number of employees	Occupancy rates and operating revenues
Tzeremes and Tzeremes (2021)	Balearic Islands	270 hotels	Malmquist Order-α	--	Total employees,and total fixed assets	Total sales

Table A1.2. Parametric and semiparametric studies on hotel efficiency based on non-metafrontier approach.

Authors	Territory	Data	Method	Efficiency model	Exogenous variables	Dependent variables
Barros (2004)	Portugal	42 hotels	SF	--	Input prices (prices of labour, capital and food) and two outputs (sales and night occupied)	Operational costs
Barros (2006)	Portugal	15 hotels	SF	--	Input prices (prices of labour and capital) and two outputs (sales and market share)	Operational costs
Pérez-Rodríguez and Acosta-González (2007)	Spain	44 hotels	SF	Battesse and Coelli (1992, 1995) models	Input prices (prices of labour and capital) and one output (sales)	Operational costs
Chen (2007)	Taiwan	55 international tourist hotels	SF	--	Price of labour, price of food and beverage, and price of materials	Total revenue
Barros and Matias (2007)	Portugal	42 hotels	SF	Technical Efficient Effects model by Coelli et al. (1998)	Labour and capital	Sales
Barros et al. (2010)	Luanda	12 hotels	SF	Greene (2005) random parameter model	Input prices (labour and capital prices), outputs (gross operational profit and RevPar), and market share.	Costs
Kim (2011)	Malaysia	157 hotels	SF	Battese and Coelli (1992) model	Labour, capital, value added	Production
Assaf (2012)	Asia- Pacific	192 hotels	SF	--	Number of rooms (proxy for fixed capital), number of full time equivalent (FTE) employees and other operational costs (administrative costs, costs of utilities and rent)	Total revenue
Assaf and Barros (2013)	World	519 hotels in 37 countries	Semi-parametric SF	--	Number of outlets (proxy for fixed capital); number of FTE employees; other operational costs	Operational revenue; annual occupancy rate; and market share
Arbelo et al. (2017a)	Spain	231	SF	Battesse and Coelli (1995) model	Input prices (labour, capital, food and beverages and other operating costs), outputs (operating revenues (rooms, food and beverages) and other operating revenue)	Operational costs
Arbelo et al. (2017b)	Spain	345	SF	Battesse and Coelli (1995) model	Input prices (labour, capital and material prices), outputs (operating revenues (rooms, food and beverages) and other operating revenue)	Operational costs and profit
Assaf and Tsionas (2018)	USA, Europe, Middle East and Asia-Pacific	613 hotels	SF	Bayesian inference	Total room expenses, total other expenses (food and beverage expenses, other department expenses, and administrative and general expenses) total utility and communication expenses, total marketing expenses, total property and maintenance expenses, and number of rooms available	Total room revenue, total other revenue, and occupancy rate
Deng et al. (2019)	Spain	44 hotel chains	SF	Bayesian stochastic frontier model	Average room price, average food price, total number of rooms, total assets, material expenses, employee expenses, number of employees, financial expenses, funds, cash flow, operating expenditure and number of establishments	Total operating revenue
Arbelo et al. (2020a)	Spain	101 hotels	SF	Bayesian stochastic frontier model with random coefficients (Tsionas, 2002)	Input prices (labour, capital, material and other operations), outputs (operating revenues and other revenues)	Total operating costs and earnings before interest and taxes
Arbelo et al. (2020b)	Spain	461 hotels	SF	Bayesian stochastic frontier model with random coefficients (Tsionas, 2002)	Input prices (labour, capital, material and other operating costs prices), outputs (net sales and other revenues)	Earnings before interest and taxes
Pérez-Rodríguez and Acosta-González (2020)	Canary Islands (Spain)	127	SF	Filippini and Greene (2016)	Input prices (labour, capital, material and other operating costs), output (total revenues)	Operational costs

Table 1.3. Parametric and non-parametric studies of hotel efficiency based on the metafrontier approach.

Authors	**Territory**	**Data**	**Method**	**Efficiency model**	**Exogenous variables**	**Dependent variables**
Panel A: Non-parametric models						
Assaf et al. (2010)	Taiwan	78 hotels	Metafrontier DEA	--	Number of rooms (proxy of capital cost), number of full-time equivalent employees in the room division, number of full-time equivalent employees in the food and beverage division, and number of full-time equivalent employees in other departments	Total room revenues, total food and beverage revenues, total other revenues, market share for each hotel and employee performance
Huang et al. (2013)	Taiwan	58 hotels	Metafrontier FDH	--	Number of employees, number of rooms, area of catering space, operating expenses	Total revenues, occupancy rate
Yu and Chen (2016)	Taiwan	54 international tourist hotels	Metafrontier Malmquist DEA	--	Number of guest rooms, number of employees, total floor area of the food and beverage department, and other expenses	Room revenues, food and beverage revenues, and other revenues
Cho and Wang (2018)	Taiwan	44 international tourist hotels	Cost metafrontier Malmquist FDH	Simar & Wilson method	Number of guest rooms, restaurant floor area, employees, room price, salary costs, food and beverage price	Room income, food and beverage income, other income
Panel B: Parametric models						
Huang et al. (2014)	Taiwan	58 hotels	Two-step SF-metafrontier	--	Total full-time employees, total guest rooms, total floor area of the catering division, and other operating expenses	Overall operational revenue
Bernini and Guizzardi (2015)	Italy	2705 hotels	SF metafrontier	Battese and Coelli (1995)	Employment, number of beds, total floor area of reception services, bar and restaurants and other services	Sales minus outside purchases (of material and services)

Appendix 2. Heterogeneity results for sub-periods.

Table A2.1. Metafrontier, group and technological gap ratio (TGR) mean estimates for each efficiency estimator. Pre-crisis period: 2002-2007.

Heterogeneity	DEA			FDH	Order-α
	CRS	**VRS**	**Scale**		**Automatic selection for each year**
I. Metafrontier (same technology)					
A. ***Ownership***					
Independently-operated (n_1=65)	0.7318	0.7885	0.9194	0.9716	0.9979
Chain-operated (n_2=341)	0.7738	0.864	0.8948	0.9852	0.9966
Mean difference test	-1.943 [0.05]	-3.989 [0.00]	1.713 [0.00]	-1.520 [0.13]	0.2309 [0.82]
B. ***Size***					
Small and medium-sized hotels (n_1=392)	0.7705	0.8392	0.9151	0.9812	0.9725
Large hotels (n_2=98)	0.7970	0.9404	0.8437	0.9989	0.9998
Mean difference test	-1.444 [0.15]	-6.613 [0.00]	6.070 [0.00]	-2.584 [0.00]	-8.041 [0.00]
II. Groups (different technologies)					
A. ***Ownership***					
Independently-operated (n_1=65)	0.9330	0.9798	0.9519	0.9956	1.0000
Chain-operated (n_2=341)	0.7789	0.8840	0.8819	0.9853	0.9975
Mean difference test	7.441 [0.00]	5.696 [0.00]	4.542 [0.00]	1.323 [0.00]	0.808 [0.42]
B. ***Size***					
Small and medium-sized hotels (n_1=392)	0.7774	0.8720	0.8916	0.9812	0.9939
Large hotels (n_2=98)	0.8632	0.9292	0.9289	0.9989	1.0000
Mean difference test	-4.748 [0.00]	-3.783 [0.00]	-2.821 [0.00]	-2.584 [0.00]	-1.633 [0.11]
III. TGR					
A. ***Ownership***					
Independently-operated (n_1=65)	0.3383	0.8030	0.9320	0.9757	0.6405
Chain-operated (n_2=341)	0.2826	0.9776	0.9944	0.9998	0.9465
Mean difference test	2.551 [0.01]	-16.99 [0.00]	-9.428 [0.00]	-5.537 [0.00]	-15.29 [0.00]
B. ***Size***					
Small and medium-sized hotels (n_1=392)	0.3944	0.9540	0.9879	1.0000	0.9551
Large hotels (n_2=98)	0.2820	0.9745	0.8887	1.0000	0.7673
Mean difference test	4.935 [0.00]	-1.963 [0.05]	11.88 [0.00]	. [.]	8.389 [0.00]

Notes: The programs were run year by year and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different for each year. The mean difference test is the two-sample t-test (two-way) with equal variances for the mean differences between the first and second groups. The p-value is shown in parentheses.

Table A2.2. Metafrontier, group and technological gap ratio (TGR) mean estimates for each efficiency estimator. Crisis period: 2008-2009.

Heterogeneity	**DEA**			**FDH**	**Order-α**
	CRS	**VRS**	**Scale**		**Automatic selection for each year**
I. Metafrontier (same technology)					
A. ***Ownership***					
Independently-operated (n_1=23)	0.7993	0.8166	0.9717	0.9676	0.9712
Chain-operated (n_2=137)	0.7962	0.8587	0.9258	0.9831	0.9923
Mean difference test	0.090 [0.93]	1.288 [0.20]	2.429 [0.02]	-1.259 [0.21]	-1.481 [0.15]
B. ***Size***					
Small and medium-sized hotels (n_1=161)	0.7974	0.8437	0.9234	0.9806	0.9793
Large hotels (n_2=32)	0.8386	0.9456	0.8857	0.9993	0.9993
Mean difference test	-1.364 [0.17]	-3.792 [0.00]	3.454 [0.00]	-1.928 [0.05]	-2.858 [0.01]
II. Groups (different technologies)					
A. ***Ownership***					
Independently-operated (n_1=23)	0.9045	0.9769	0.9248	0.9937	1.0000
Chain-operated (n_2=137)	0.8441	0.8951	0.9419	0.9856	0.9929
Mean difference test	1.845 [0.00]	2.916 [0.00]	-0.841 [0.40]	0.790 [0.43]	0.769 [0.45]
B. ***Size***					
Small and medium-sized hotels (n_1=161)	0.7989	0.8593	0.9283	0.9806	0.9765
Large hotels (n_2=32)	0.9193	0.9549	0.9266	0.9993	1.0000
Mean difference test	-4.074 [0.00]	-3.598 [0.00]	-1.991 [0.05]	-1.928 [0.06]	-1.088 [0.28]
III. TGR					
A. ***Ownership***					
Independently-operated (n_1=23)	0.8797	0.8353	0.9829	0.9738	0.7395
Chain-operated (n_2=137)	0.9417	0.9586	0.9527	0.9973	0.8499
Mean difference test	-4.361 [0.00]	-6.797 [0.00]	1.945 [0.05]	-3.390 [0.00]	-2.2574 [0.02]
B. ***Size***					
Small and medium-sized hotels (n_1=161)	0.9965	0.9819	0.9984	1.0000	1.0000
Large hotels (n_2=32)	0.8857	0.9734	0.8981	1.0000	0.6721
Mean difference test	16.56 [0.00]	0.971 [0.33]	13.75 [0.00]	. [.]	15.22 [0.00]

Notes: The programs were run year by year and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different for each year. The mean difference test is the two-sample t-test (two-way) with equal variances for the mean differences between the first and second groups. The p-value is shown in parentheses.

Table A2.3. Metafrontier, group and technological gap ratio (TGR) mean estimates for each efficiency estimator. Crisis period: 2010-2013.

Heterogeneity	**DEA**			**FDH**	**Order-α**
	CRS	**VRS**	**Scale**		**Automatic selection for each year**
I. Metafrontier (same technology)					
A. ***Ownership***					
Independently-operated (n_1=48)	0.8351	0.8538	0.9778	0.9945	0.9975
Chain-operated (n_2=290)	0.837	0.8704	0.9554	0.9942	0.9982
Mean difference test	0.227 [0.82]	-0.865 [0.39]	2.415 [0.02]	0.016 [0.99]	-0.151 [0.88]
B. ***Size***					
Small and medium-sized hotels (n_1=322)	0.8255	0.8620	0.9581	0.9922	0.9971
Large hotels (n_2=84)	0.8625	0.9210	0.9373	0.9988	0.9986
Mean difference test	-2.345 [0.02]	-3.947 [0.00]	2.507 [0.01]	-1.727 [0.08]	-0.576 [0.57]
II. Groups (different technologies)					
A. ***Ownership***					
Independently-operated (n_1=48)	0.9107	0.9613	0.9474	0.9995	1.0000
Chain-operated (n_2=290)	0.8608	0.8957	0.9612	0.9964	0.9997
Mean difference test	2.659 [0.01]	3.770 [0.00]	-1.420 [0.16]	0.920 [0.36]	0.544 [0.59]
B. ***Size***					
Small and medium-sized hotels (n_1=322)	0.8288	0.9613	0.9499	0.9923	0.9927
Large hotels (n_2=84)	0.9045	0.8957	0.9739	0.9988	1.0000
Mean difference test	-4.619 [0.00]	3.770 [0.00]	-2.502 [0.01]	-1.521 [0.13]	-1.282 [0.20]
III. TGR					
A. ***Ownership***					
Independently-operated (n_1=48)	0.9164	0.8883	0.9840	0.9947	0.7634
Chain-operated (n_2=290)	0.9653	0.9703	0.9702	0.9937	0.9173
Mean difference test	-5.666 [0.00]	-9.266 [0.00]	1.231 [0.22]	-1.263 [0.21]	-5.010 [0.00]
B. ***Size***					
Small and medium-sized hotels (n_1=322)	0.9925	0.9865	0.9937	0.9989	0.979
Large hotels (n_2=84)	0.9219	0.9637	0.9403	1.0000	0.8032
Mean difference test	15.85 [0.00]	4.209 [0.00]	11.78 [0.00]	-0.861 [0.39]	9.367 [0.00]

Notes: The programs were run year by year and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different for each year. The mean difference test is the two-sample t-test (two-way) with equal variances for the mean differences between the first and second groups. The p-value is shown in parentheses.

Table A2.4. Metafrontier, group and technological gap ratio (TGR) mean estimates for each efficiency estimator. Post-crisis period: 2014-2015.

Heterogeneity	**DEA**			**FDH**	**Order-α**
	CRS	**VRS**	**Scale**		**Automatic selection for each year**
I. Metafrontier (same technology)					
A. ***Ownership***					
Independently-operated (n_1=22)	0.8192	0.8312	0.9824	0.9794	0.9843
Chain-operated (n_2=151)	0.8398	0.8674	0.9684	0.9856	0.9837
Mean difference test	-0.671 [0.50]	-1.213 [0.23]	1.294 [0.20]	-0.545 [0.59]	0.022 [0.98]
B. ***Size***					
Small and medium-sized hotels (n_1=141)	0.8261	0.8616	0.9595	0.9862	0.9713
Large hotels (n_2=57)	0.8730	0.8988	0.9720	0.9853	0.9863
Mean difference test	-2.213 [0.03]	-1.807 [0.07]	-1.437 [0.15]	0.125 [0.90]	-0.879 [0.38]
II. Groups (different technologies)					
A. ***Ownership***					
Independently-operated (n_1=22)	0.9361	0.9787	0.9557	1.0000	1.0000
Chain-operated (n_2=151)	0.8415	0.8789	0.9584	0.9885	0.9916
Mean difference test	3.158 [0.00]	3.508 [0.00]	-0.179 [0.86]	1.232 [0.22]	0.785 [0.44]
B. ***Size***					
Small and medium-sized hotels (n_1=141)	0.8511	0.8933	0.9508	0.9869	0.9745
Large hotels (n_2=57)	0.8520	0.8846	0.9611	0.9853	0.9955
Mean difference test	-0.045 [0.96]	0.440 [0.66]	-1.088 [0.28]	0.217 [0.83]	-1.361 [0.18]
III. TGR					
A. ***Ownership***					
Independently-operated (n_1=22)	0.8739	0.8486	0.9877	0.9794	0.8275
Chain-operated (n_2=151)	0.9980	0.9867	0.9974	0.9970	0.8773
Mean difference test	18.68 [0.00]	-13.09 [0.00]	-2.741 [0.00]	-2.778 [0.01]	-1.040 [0.30]
B. ***Size***					
Small and medium-sized hotels (n_1=141)	0.9693	0.9636	0.9847	0.9993	0.9719
Large hotels (n_2=57)	0.9806	0.9876	0.9772	1.0000	0.7822
Mean difference test	-1.432 [0.15]	-2.075 [0.04]	1.186 [0.24]	-0.635 [0.53]	8.116 [0.00]

Notes: The programs were run year by year and then pooled data were used for the period 2002-2015. Automatic selection in the order-α refers to the value of α which is the suggested point of discontinuity obtained by using order-α based outlier detection and is related to prime suggestion by criterion smoothing at α based on Daraio and Simar's (2007) procedure (see Tauchmann, 2012). It is noteworthy that α is different for each year. The mean difference test is the two-sample t-test (two-way) with equal variances for the mean differences between the first and second groups. The p-value is shown in parentheses.