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Returns to scale, technical and efficiency changes in the Spanish hotel industry using technological heterogeneity models

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ABSTRACT

This paper analyses returns to scale, productivity growth and its decomposition in the Spanish hotel industry (period 1997–2019). To do so, we consider that hotels can have technological heterogeneity and, therefore, parameters in their production function can differ between them. Also, we use a multiple input and output production function based on an output distance stochastic frontier approach with random parameters in a Bayesian framework. Results indicate that the percentage of hotels working under increasing returns to scale decreased during the period considered. Furthermore, productivity growth was low, indicating signs of stagnation. Efficiency change appears to be the main driving force behind productivity growth, although technical change had a positive effect on productivity after the start of the global financial crisis. Several practical implications are proposed based on these results.

1. Introduction

There are some interesting aspects that have been given little consideration in the estimation of hotel efficiency using parametric approaches. For example, the analysis of returns to scale (RTS) and productivity growth using a parametric framework has scarcely been addressed in accommodation market studies (e.g., hotels, apartments or peer-to-peer markets such as, for example, Airbnb), with the exception of Assaf and Tsionas (2018) for hotels. In fact, most studies have used non-parametric and non-robust approaches to evaluate RTS and productivity (e.g. Barros et al., 2011; Cordero and Tzeremes, 2017). Despite their important merits, such approaches usually ignore measurement errors when estimating efficiency and are especially sensitive to the presence of outliers.

Another barely considered question is the existence of technological heterogeneity (with some exceptions such as Assaf and Tsionas, 2018; Arbelo-Pérez et al., 2020; or Arbelo et al., 2021), in other words that hotels cannot share the same technology (e.g., Tsionas, 2002; Arbelo-Pérez et al., 2020 or Arbelo et al., 2021; among others). There are two aspects which deserve attention in this regard. First, in economic and managerial terms, this assumption is motivated by theories such as the resource-based view (RBV) of the firm (Wernerfelt, 1984; Barney, 1991),[1] the knowledge-based view of the firm (King and Zeithaml, 2003; Martin and Salomon, 2003) or the diffusion of innovations theory (Rogers, 1962). For example, the knowledge-based view of the firm explains the presence of heterogeneous long-run competitive advantages as being due to the existence of distinct knowledge-based resources (e.g., routines, different managerial structures or collaboration with external firms such as travel agencies or tour operators, among many others; see Nieves et al., 2014) which cannot easily be imitated by the competition (Nieves et al., 2014) and which can be considered entry barriers in accordance with the industrial organization theory (Sinclair and Stabler, 1997, pp. 103). For its part, the diffusion of innovations theory allows distinction between innovator and laggard hotels when adopting up-to date resources/techniques in the sector. In this sense, we could assume that hotels possess different technologies (i.e., they are heterogeneous) and, therefore, different patterns of technological adoption exist (e.g., Siguaw et al., 2000; Hua et al., 2015; among others). Second, it should also be noted that, econometrically, the existence of technological heterogeneity leads to biased and inconsistent results if it is not accounted for in the panel data estimation of a stochastic frontier model (Greene, 2005), as heterogeneity can be wrongly measured as

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[1] See Nieves and Quintana (2018), page 73), Arbelo-Pérez et al. (2020), pp. 171–172) and Arbelo et al. (2021), pp. 70–72) for in-depth explanations of the RBV of the firm theory and its applicability to the hotel sector.

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inefficiency (Tsionas, 2002).

Methodologically, the literature has used two approaches to treat technological heterogeneity. First, the metafrontier approach in the non-parametric context allows the analysis of group heterogeneity (e.g., Assaf et al., 2010; Yu and Chen, 2016; Pérez-Rodríguez and Acosta-González, 2023a; among others). Second, the empirical literature has considered that production, cost or profit functions are not equal for hotels using the random parameters model (RPM) in the panel data stochastic frontier framework through Bayesian estimation.[2] However, it should be noted that, despite the important advantages shown by Bayesian approaches in the estimation of the stochastic frontier (see Assaf et al., 2017; for a review of the subject), frequentist methodologies have also been widely applied in the analysis of hotel efficiency (Assaf and Josiassen, 2016). Recently, Arbelo et al. (2021) used random coefficient Bayesian methods following Tsionas (2002) to estimate efficiency, but not productivity or RTS. Other authors such as Assaf and Tsionas (2018) have proposed a new methodological framework to account for productivity, efficiency and RTS in a random parameters context based on an artificial neural network with G nodes and a vector auto-regressive model which relates productivity and efficiency. Their study investigated technological heterogeneity to estimate hotel efficiency using random parameter models in a stochastic frontier framework considering time-varying technical efficiencies and productivities, allowing not only the evolution of transient efficiency over time to be obtained, but also RTS and productivity growth. In fact, estimation of RTS enabled them to distinguish between hotels working at increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS), expressing the correlation, or lack thereof, between variations in output after altering all inputs in equal measure. However, they did not decompose the productivity growth into technical (i.e., frontier shifts) and efficiency (i.e., catching-up factor) changes (TC and EC, respectively), despite the importance of such decomposition for hoteliers and policymakers. Thus, it is not only important to know whether productivity increases or decreases, but also to distinguish between the forces driving this measure. In fact, such desegregation allows the design of policies oriented towards obtaining a sustainable advantage in the medium and long run, which is of especial relevance in the current context of increasing competition in the international lodging industry (Arbelo et al., 2021).

In this sense, our main contribution to the empirical literature on hotel efficiency is based not only on the assessment of hotel productivity growth, decomposing it into its TC and EC over time, but also on the measurement of hotel-specific RTS, accounting for technological heterogeneity using the random coefficients model in a parametric stochastic frontier analysis.

To do so, our hotels' random parameters model is formulated in a Bayesian context following Tsionas (2002) and Feng and Zhang (2014), instead of the general and flexible Bayesian framework proposed by Assaf and Tsionas (2018).[3] For example, unlike Assaf and Tsionas (2018), we decompose productivity growth following Feng and Zhang (2014) expressions performed within a continuous Divisia index framework, because, as Assaf and Tsionas (2018), page 80), they do not distinguish between TC and EC when obtaining productivity in their dynamic formulation. More particularly, we specify an output distance stochastic frontier translog model to account for multiple outputs and inputs. However, we allow for time-varying efficiencies by including a set of determinant variables which can explain the conditional mean hotel inefficiency over time based on distributional assumptions regarding the inefficiency term, instead of, for example, a vector autoregressive (VAR) model for efficiency and productivity such as in Assaf and Tsionas (2018).

Our empirical analysis is based on the Spanish hotel industry, which is characterized by its relevance from economic and labor perspectives. For example, on average 14,897 hotels were open each month in Spain in 2019, offering an average of 1,517,583 beds per month (56.355 % of the total number of beds offered by the Spanish lodging industry, including hotels, campsites, tourist apartments and rural tourism accommodation) according to the Hotel Occupancy Survey conducted by the Spanish Statistical Institute (INE by its initials in Spanish). Spanish hotels welcomed 55,981,859 international travelers in 2019 (83.108 % of all international travelers hosted by the Spanish lodging industry) who made 223,386,354 overnight stays (74.927 % of the total nights spent by international tourists in the Spanish lodging industry). It is noteworthy that Spain was ranked second in 2019 in terms of international tourist arrivals and international tourism returns (UNWTO, 2020), showing the importance of the Spanish hotel industry. From a labor perspective, hotels had a monthly average of 219,475 employees in 2019, which corresponded to 78.183 % of the total labor force employed by the Spanish lodging sector. Therefore, an analysis of hotel efficiency, productivity and RTS is of extreme importance for policy and managerial purposes, especially in the current situation of international competition among hotels in the Mediterranean area.

We use a balanced data set which covers the period 1997–2019 for 73 hotels belonging to independent hotels and different hotel chains (international, national or local) located in several Spanish destinations which specialize in different tourism markets and show differences in several aspects, including efficiency (Devesa and Peñalver, 2013; Lado-Sestayo and Fernández-Castro, 2019; among others), productivity (Cordero and Tzeremes, 2017; Tzeremes, 2020; among others) and seasonality (Duro, 2016). For example, while the capital city of Madrid focuses on business and cultural tourism, the Balearic and Canary Islands offer services aimed at sun and sand tourists.

The rest of the paper is structured as follows. In section 2, a revision of the literature is made. Section 3 contains the methodology, and sections 4 and 5 show, respectively, the data and empirical results. Finally, section 6 summarizes the main conclusions of the paper and introduces some methodological and practical implications.

2. Literature review on RTS and productivity in hotel efficiency

Efficiency, productivity and RTS in the hotel sector have been analysed following non-parametric and parametric frontier methodologies, in both frequentist and Bayesian approaches, although they have been studied in greater depth in the former case (see Assaf and Josiassen, 2016; or Pérez-Rodríguez and Acosta-González, 2023a; for recent reviews).

Among non-parametric methods, data envelopment analysis (DEA) is the most applied technique (e.g., Barros and Dieke, 2008; Barros et al., 2011; among many others). This method does not require assumptions regarding the functional form (i.e., only the traditional axioms of the production theory hold). Nevertheless, DEA approaches assume that all deviations from the benchmark frontier are caused by inefficiency (Assaf and Tsionas, 2019; Assaf et al., 2021), which could generate misleading outcomes (Bifulco and Bretschneider, 2001; Chatzimichael and Liasidou, 2019), as measurement errors and unpredictability often appear in empirical data (Assaf and Cvelbar, 2011). Additionally, DEA results are affected by the presence of outliers (Arbelo et al., 2021).

[2] Note also that when studying panel data, stochastic frontier methods are preferable to non-parametric DEA approaches, as the latter do not obviously take into account the panel features existing along the dataset (Assaf et al., 2021).

[3] Recent advances have been made in the measurement of efficiency, RTS, productivity growth, TC, and EC from both frequentist (Tsionas, 2023b,2024) and Bayesian (Tsionas, 2023a) approaches, generally using fixed-coefficients and panel data models. For instance, Tsionas (2023a) analysed the efficiency, RTS, TC, and EC of a sample of relatively homogeneous large American banks using a Bayesian stochastic frontier framework, with a minimax regret empirical prior used to model inefficiencies and other parameters of the frontier. It was shown that the use of minimax regret priors allowed the author to successfully combine the advantages of DEA and SFA when estimating efficiency, RTS, TC, and EC.

For its part, the parametric stochastic frontier approach (SFA; Aigner et al., 1977; and Meeusen and van Den Broeck, 1977) incorporates a composite error term formed by random disturbances and inefficiency. This is an important advantage when assessing hotel productivity, as the lodging sector suffers from important oscillations in demand and measurement errors appear to be significant, affecting estimations when they are not correctly taken into account (Chatzimichael and Liasidou, 2019).

Parameters associated with the SFA have been traditionally estimated using sampling theory frequentist approaches such as maximum likelihood (ML; e.g. Pérez-Rodríguez and Acosta-González, 2007; Kim, 2011) or maximum simulated likelihood estimators (Pérez-Rodríguez and Acosta-González, 2023b). However, these frequentist and semi-frequentist approaches are outperformed by Bayesian methodologies for several reasons that will not be explained in this paper (see Chen et al., 2015,2016; or Assaf et al., 2017, for further information).

This section describes studies for RTS and productivity growth in the empirical literature on hotels distinguishing between papers using frequentist and Bayesian approaches.

2.1. Frequentist approaches to estimate efficiency, RTS and productivity

The empirical literature analyzing productivity and RTS in a frequentist context can be categorized into parametric or non-parametric approaches.

Several papers have addressed productivity and RTS using non-parametric frequentist approaches.

Concerning RTS, for example Yang and Wen-Min (2006) studied the efficiency and RTS of 56 Taiwanese hotels in 2002 applying the input-oriented DEA approach and the slack-based method proposed by Cooper et al. (2001), with the latter measuring input congestion. Results showed that almost 61 % of hotels were operating at DRS and showed diseconomies of scale, while only 9 % were performing under IRS. Barros et al. (2011) analysed the efficiency and RTS of French tourism regions from a macro-economic perspective using a DEA two-stage approach. A high degree of inefficiency was found, with the majority of locations showing DRS. Recently, Lee et al. (2019) studied the efficiency of a sample of Taiwanese hotels for the period 2005–2007 using a directional distance function considering a meta-frontier approach. They distinguished between variable and quasi-fixed inputs, with the latter being fixed in the short run. The long-run analysis indicated that about 70 % of hotels were operating at IRS.

Regarding productivity, for example Cordero and Tzeremes (2017) analysed the productivity growth of a sample of hotels located in the Balearic and Canary Islands for the period 2004–2013 using the Malmquist Productivity Index (MPI) based on DEA results. Tzeremes (2019) analysed the productivity of 176 Canary hotels for the period 2004–2013 applying the Luenberger Productivity Indicator (LPI) calculated by order-*m* estimators. Results indicated that the Canary hotel industry was resistant to economic crises.

Other papers have investigated efficiency, RTS and productivity using a parametric frequentist perspective. For example, Chen (2007) studied the cost efficiency of 55 Taiwanese international hotels for the year 2002 using ML methods. In overall terms, hotels were working at 80.3 % of efficiency, showing a generally moderate situation of IRS. Pérez-Rodríguez and Acosta-González (2007) analysed the cost efficiency and economies of scale of 44 lodging firms located in Gran Canaria (Spain) applying a stochastic translog frontier approach for the period 1991–2002. They found that the majority of firms showed DRS, requiring a reorganization to adapt to changes in demand. Kim (2011) studied the efficiency and productivity of 157 Malaysian hotels for the period 2002–2004 using an SFA. Average efficiency was equal to 41 % and total factor productivity (TFP) increased annually by 7 %. Chatzimichael and Liasidou (2019) analysed the TFP of the hotel sector of 25 European countries for the period 2008–2015 applying a translog SFA. In overall terms, productivity increased during the period. Scandinavian countries obtained the highest productivity measures, followed by Mediterranean countries. Similarly, Liu and Tsai (2021) analysed the TFP change and convergence of the star-rated hotel sector of 31 Chinese provinces for the period 2001–2015 applying a translog SFA estimated using ML techniques. In overall terms, productivity increased at an average rate of 3.52 %.

2.2. Hotel efficiency, RTS and productivity using Bayesian methods

Although some advances have been made recently concerning Bayesian non-parametric methods (e.g., Zervopoulos et al., 2023), these have not yet been applied in the hotel sector, so we will not expand on this.

In the parametric field, the application of Bayesian approaches to estimate the SFA parameters is characterized by its scarcity, despite Bayesian methods enabling the management of more complex stochastic frontier approaches Assaf and Tsionas, (2018) and outperforming frequentist methods in several aspects (see Arbelo et al., 2018; for a recent review of the subject).

The literature focusing on the application of Bayesian methods to measure hotel efficiency can be differentiated based on whether it takes into account or not the heterogeneity existing between hotels. Thus, authors such as Assaf and Cvelbar (2011), Assaf and Magnini (2012), Assaf and Barros (2013) or Arbelo et al. (2018) analysed hotel efficiency considering that hotels share a common technology, differing uniquely in their degree of inefficiency. For example, Assaf and Cvelbar (2011) analysed the cost efficiency of a sample of 23 Slovenian hotels for the period 2004–2008 considering a Bayesian approach. Assaf and Magnini (2012) studied the efficiency of a sample of US hotel chains for the period 1999–2009 applying a Bayesian distance stochastic frontier approach which allowed them to consider several outputs (customer satisfaction, total revenue and occupancy rate). Results showed that misleading outcomes were obtained when customer satisfaction was not taken into account. Assaf and Barros (2013) analysed the efficiency of a sample of 519 hotels located in 37 countries for the period 2006–2008 considering a Bayesian distance stochastic frontier method. They considered that the inefficiency term distribution followed a non-parametric Dirichlet process. Among other interesting results, hotels managed by international chains achieved higher efficiency outcomes than hotels belonging to national chains, while independent hotels obtained lower efficiency scores than chain-affiliated hotels. Arbelo et al. (2018) analysed the profit efficiency and its determinants for a sample of 312 Spanish hotels (period 2010–2014). They applied a Bayesian stochastic frontier approach and found that mean profit efficiency was 51.48 %, although it increased during the period. Several determinant variables (e.g. size or customer satisfaction) had an effect on the inefficiency obtained by hotels.

On the other hand, authors such as Assaf and Agbola (2014), Assaf and Tsionas (2018), Arbelo-Pérez et al. (2020) or Arbelo et al. (2021) did consider the heterogeneity existing in the hotel sector in their estimation of efficiency. For example, Assaf and Agbola (2014) analysed the efficiency of the Australian hotel, guest house-motel and apartment sectors for the period 1998–2009 considering a macro perspective. They applied a Bayesian translog output distance approach, taking multiple outputs and random effects into account. The hotel sector achieved the highest efficiency outcomes, followed by the guest-house motel sector. Regional efficiency was positively influenced by international attractiveness, the size of the accommodation firms, and the existence of a positive economic environment. Assaf and Tsionas (2018) proposed a Bayesian stochastic frontier approach based on a G-nodes artificial neural network that takes heterogeneity into account and allowed them to obtain efficiency, productivity and RTS in parallel. Their approach also considered the endogeneity problem of inputs and the existence of unobserved prices. They applied their model to a sample of 613 hotels (period 2012–2016) located in an important number of regions (e.g., USA or Europe). Among several results, low productivity growth was found. Arbelo-Pérez et al. (2020) analysed the cost and profit efficiency of 101 Spanish hotels for the period 2010–2014 considering the presence of heterogeneity through the stochastic frontier model with random coefficients introduced by Tsionas (2002). Results showed that an overestimation of inefficiency was obtained when heterogeneity was not taken into account. The latter approach was also applied by Arbelo et al. (2021), who analysed profit efficiency and its determinants for a sample of 461 Spanish hotels (period 2012–2017). An average profit efficiency of 61.17 % that showed an upward trend during the period was found. The analysis of determinant factors (e.g., age and number of competitors) reinforced the idea of the presence of an important heterogeneity among hotels.

The review of the literature shows that there is a lack of research focusing on estimating efficiency, productivity and RTS considering the heterogeneity existent in the hotel sector. Thus, this paper aims to analyse the Spanish hotel industry, obtaining several measures which are important for managerial and policy purposes (e.g., efficiency, productivity and RTS) and taking the heterogeneity existent among hotels into account.

3. Methodology

3.1. The output distance function stochastic frontier model

The output distance function stochastic frontier model enables us to gauge efficiency and productivity through an examination of the interplay between several inputs and outputs (Assaf and Magnini, 2012).

In this paper, we consider a general production technology function based on the translog output distance production function where parameters are random. Technological heterogeneity can be introduced in this model assuming that parameters can vary for each hotel and time. However, the technological heterogeneity we consider in this paper is related only to the hotels because we assume that hotels can have different technologies but that this technology is constant over time.

In our model, hotel technology uses K inputs, $x = (x_1, x_2, \ldots, x_K)$ to produce M outputs, $y = (y_1, y_2, \ldots, y_M)$. Also, our model includes the linear and squared trends to represent technological progress to capture any non-linear relationship between time and efficiency or productivity over time. It also allows us to account for the possibility of DRS or IRS.

Following O'Donnell and Coelli (2005), who exploited the linear homogeneity property of distance function normalized by output M, we can define the following general form corresponding to our random parameters model for each hotel (i.e., parameters are written including the sub-index i to represent this issue). This model is expressed as an estimable output distance stochastic frontier function such that:

$$
\begin{aligned}
-\log y_{M,it} = {} & \alpha_i + \sum_{m=1}^{M-1} \gamma_{m,i} \log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \frac{1}{2}\sum_{j=1}^{M-1}\sum_{m=1}^{M-1} \gamma_{jm,i} \log\left(\frac{y_{j,it}}{y_{M,it}}\right) \log\left(\frac{y_{m,it}}{y_{M,it}}\right) \\
& + \sum_{k=1}^{K} \alpha_{k,i} \log x_{k,it} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj,i} \log x_{k,it} \log x_{j,it} \\
& + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \beta_{km,i} \log x_{k,it} \log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \kappa_{1,i} t + \frac{1}{2}\kappa_{2,i} t^2 \\
& + \sum_{m=1}^{M-1} \nu_{m,i}\, t \log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \sum_{k=1}^{K} \theta_{k,i}\, t \log x_{k,it} + (v_{it} + u_{it}),
\end{aligned} \tag{1}
$$

where log is the natural logarithm; n is the number of hotels with $i = 1, \ldots, n$; and T is the number of periods with $t = 1, \ldots, T$. The idiosyncratic error defined by $v_{it} \sim N(0, 1/\sigma_v^2)$, and the inefficiency term is defined by $u_{it} \sim \text{Exp}\ (\lambda_{it})$, which is supposed to follow an exponential distribution as in Koop et al. (1997) and Feng and Zhang (2014), among others. In general, the model supposes that the compound error $\epsilon_{it} = v_{it} + u_{it}$ is asymmetric.

It should also be noted that we include other explanatory variables which may influence mean inefficiency. This allows us to introduce time-varying inefficiencies. We consider that the mean of the exponential distribution, λ_{it}^{-1}, depends on environmental variables, z_{it}. In particular, we consider the exponential link, $\lambda_{it}^{-1} = \text{Exp}(\delta' z_{it})$, with δ' representing a row vector of unknown parameters which represent the effects of covariates on the mean inefficiency.

3.2. Bayesian estimation

In this section, we briefly outline the Bayesian procedure for estimating the models. In order to facilitate comparisons, we consider the same priors for the coefficients that are common for all models.

We suppose the coefficients follow uninformative normal priors (i.e., a zero mean and a variance sufficiently large to express this misinformation), except for the coefficients of the inputs, α_k, and outputs, γ_m, that are supposed to follow a flat Gamma distribution to specify priors that meet the monotonicity conditions. These conditions are analyzed in O'Donnell and Coelli (2005) and Feng and Zhang (2014), among others. So:

$$\beta \sim N(0, 1/\sigma), \tag{2}$$

where β refers to the vector of the coefficients of the translog function which appear on the right hand side of Eq. (1), including the intercept; and $1/\sigma = 10^6$ to convey disinformation. Regarding the coefficients α_k and γ_m:

$$
\begin{aligned}
\gamma_m &\sim G(a_m, b_m), \text{ and} \\
-\alpha_k &\sim G(a_k, b_k),
\end{aligned} \tag{3}
$$

where $a_m = a_k = 1$ and $b_m = b_k = 10^{-3}$, as in Kerman (2011). Eq. (3) satisfied monotonicity conditions and differs from Feng and Zhang (2014) where normal distributions were assumed.

Regarding the compound error, $v_{it} \sim N(0, 1/\sigma_v^2)$, where $1/\sigma_v^2$ follows an uninformative Gamma distribution, $G(0.01,\ 0.01)$, and the inefficiency term is assumed to follow an exponential distribution, as in Koop et al. (1997) and Feng and Zhang (2014), with mean $\lambda_{it}^{-1} = \text{Exp}(\delta' z_{it})$, as mentioned above. This distribution is defined to capture time-varying inefficiencies by incorporating time-covariates into the vector z'_{it}. In this study, the vector δ follows an exponential distribution with a location parameter of $-\log r^*$, indicating that the prior mean efficiency is equal to r^*. Consequently, the efficiency of the i-hotel is expressed as $r_i = \text{Exp}(-u_i)$.

Random coefficient models include hotel-specific parameters, α_i and $\alpha_{k,i}$, for the constant and the inputs, respectively. Both parameters are decomposed into a mean vector, $\overline{\alpha}$ and $\overline{\alpha}_k$, and a random vector, ε_i^{α} and $\varepsilon_i^{\alpha_k}$. Following the previous assumptions, we suppose uninformative priors for these parameters in this way:

$$
\begin{aligned}
\overline{\alpha},\ \overline{\alpha}_k, &\sim N(0, 1/\sigma_\alpha), \text{ and} \\
\varepsilon_i^{\alpha},\ \varepsilon_i^{\alpha_k} &\sim N(0, 1/\sigma_\varepsilon),
\end{aligned} \tag{4}
$$

where $1/\sigma = 10^6$ and σ_ε follows an uninformative Gamma distribution, $G(0.01,\ 0.01)$.

This allows us to denote the stochastic frontier model presented in Eq. (1) as:

$$y_{it} = f(x_{it}, \beta) + v_{it} + u_{it}, \tag{5}$$

where y_{it} is the log of the output variable for the hotel i in period t, and x_{it} contains all the explanatory variables.

The joint distribution of y_{it} and u_{it} conditional on x_{it} and the coefficients is:

$$p(y_{it}, u_{it} | x_{it}, \beta, \sigma^2, \lambda_{it}) = f_N(y_{it} | f(x_{it}, \beta) + u_{it}, \sigma^2) f_G(u_{it} | \lambda_{it}^{-1}), \tag{6}$$

where σ^2 is the variance and covariance matrix of the compound error

ϵ_{it}. The conditional density for u_{it} is expressed as:

$$p(u_{it}|y_{it},x_{it},\beta,\sigma^2,\lambda_{it}) = \Phi^{-1}\left(\frac{y_{it}-f(x_{it},\beta)-\sigma^2/\lambda_{it}}{\sigma}\right) \times f_N(u_{it}|y_{it}-f(x_{it},\beta)-\sigma^2/\lambda_{it},\sigma^2)\times I(u_{it}\geq 0). \quad (7)$$

Thus, the sampling density of y_{it} is:

$$p(y_{it}|x_{it},\beta,\sigma^2,\lambda_{it}) = \frac{\lambda_{it}-1}{\Gamma(1)}\exp\left(-\frac{y_{it}-f(x_{it},\beta)-\sigma^2/\lambda_{it}}{\lambda_{it}}-\frac{\sigma^2}{2\lambda_{it}^2}\right) \times \Phi\left(\frac{y_{it}-f(x_{it},\beta)-\sigma^2/\lambda_{it}}{\sigma}\right). \quad (8)$$

The likelihood function can be expressed as:

$$L(\beta,\sigma^2,\lambda|y,x) = \prod_{i=1}^{N}\prod_{t=1}^{T}p(y_{it}|x_{it},\beta,\sigma^2,\lambda_{it}). \quad (9)$$

Given this likelihood function and the prior densities expressed above, integrals involved using Bayes theorem cannot be computed analytically. Therefore, Gibbs sampling algorithm is used to draw estimations from conditional posteriors.

4. Data

The data used in this paper was extracted from the Iberian Balance Sheets Analysis System (SABI by its initials in Spanish) database, maintained by Bureau van Dijk (BvD). A balanced panel comprising 73 hotels for the period 1997–2019 was considered. The spatial distribution of these hotels is shown in Figure 1.

Next, we describe the inputs, outputs and determinant variables used in this study.

4.1. Inputs and outputs

The inputs and outputs used in this paper were chosen based on the literature and data availability.

We assume that hotels produce outputs utilizing labor, capital, material and other operating costs. Labor costs are introduced as the total costs of workers (Barros and Alves, 2004; Deng et al., 2019; among others). Capital costs are incorporated as annual amortization, which includes depreciation (Lado-Sestayo and Fernández-Castro, 2019; Pérez-Rodríguez and Acosta-González, 2023a; among others). Material costs consider expenses in materials that are used to produce outputs (Assaf and Cvelbar, 2010; Pérez-Rodríguez and Acosta-González, 2023a; among others). This includes, for instance, expenses on food and beverage which are served in buffets. Finally, other operating costs (Assaf, 2012; Assaf and Magnini, 2012; among others) allow the inclusion of other expenditures which are not incorporated in the previous accounts but which are relevant for explaining the production process of hotels (e.g. expenses in energy supplies or repairs).

Outputs were measured as operating revenue (Assaf and Magnini, 2012; Assaf and Barros, 2013; among others) and EBITDA (Earnings before Interest, Taxes, Depreciation, and Amortization; Neves and Lourenço, 2009).

Economic variables were adjusted based on the World Bank CPI (base 2010) and are incorporated in thousand of euros. Table 1 provides

Fig. 1. Spatial distribution of the hotels considered in the sample.

Table 1
Main characteristics of the quantitative and categorical variables.

Variables	Mean	Median	St. Dev.	Kurtosis	Skew	Min.	Max.
Inputs							
Labor costs	7,307.643	3,226.435	16,645.262	50.828	6.789	44.373	156,668.219
Capital costs	1,951.661	813.392	3,432.069	23.076	4.313	15.216	31,545.260
Material costs	3,783.991	1,620.040	7,994.359	48.192	6.363	0.491	80,235.123
Other operating costs	5,567.161	2,224.131	14,406.379	54.901	7.001	176.957	150,919.751
Outputs							
EBITDA	5,656.210	2,179.856	12,507.532	63.586	6.942	17.674	167,639.563
Operating revenue	22,213.047	9,348.039	49,782.906	47.994	6.557	786.845	477,192.014
Determinant variables							
Age (In years)	29.834	27.693	16.392	4.652	1.691	0.715	109.729
Type of company (Corporation)	0.658					0	1
Type of company (Limited liability)	0.342					0	1
Chain type (Int. Foreign chain)	0.041					0	1
Chain type (Int. Spanish chain)	0.342					0	1
Chain type (National chain)	0.151					0	1
Chain type (Local chain)	0.274					0	1
Chain type (Independent hotel)	0.192					0	1
Location (Andalusia)	0.123					0	1
Location (Balearic Islands)	0.315					0	1
Location (Canary Islands)	0.151					0	1
Location (Catalonia)	0.137					0	1
Location (Madrid)	0.068					0	1
Location (Valencian Community)	0.151					0	1
Location (Other Spanish regions)	0.055					0	1

Notes. St. Dev. = standard deviation; Min. = minimum value; Max.= maximum value; EBITDA = Earnings before Interest, Taxes, Depreciation, and Amortization; Int. = International. All monetary values are expressed in thousands of euros, adjusted according to the World Bank CPI (base 2010). Statistics were obtained for the pooled sample.

descriptive information for the inputs, outputs and determinant variables. The average hotel annual operating revenue was 22, 213.047 thousands of euros. Labor and other operating costs were the most important expenditures for hotels.

4.2. Determinant variables

Following Arbelo et al. (2017) and Sellers-Rubio and Casado-Díaz (2018), we distinguish between internal (i.e., hotel specific factors) and external (i.e., factors which are not under managerial control) determinant variables when analysing the inefficiency obtained by hotels.

Three internal factors are considered. First, the age variable is introduced as the number of years that the hotel has been operating. In the hotel industry, there are no clear conclusions concerning the effect of this variable on hotel performance. For instance, authors such as Arbelo et al. (2017) or Arbelo et al. (2021) associate age (i.e., years in business) with accumulated knowledge in accordance with the concept of "learning by doing", while authors such as Hurley and Hult (1998) or Fraj et al. (2015) point out that although experienced hotels have superior market intelligence than new entry firms the former are more rigid and less innovative than the latter.

The second internal factor refers to the type of company, distinguishing between corporation and limited liability. There are certain differences between the two types. For instance, corporations generally refer to large companies with an important number of stakeholders, while limited liability refers principally to small and medium firms with a relatively low number of investors. Authors such as Parte-Esteban and Alberca-Oliver (2015) or Hernández-Guedes et al. (2024) considered these variables when analysing determinants of efficiency.

The third internal factor distinguishes between independent hotels and different types of chain-affiliated hotels (international foreign, international Spanish, national and local). The incorporation of this variable is justified, for example, by the agency and adverse selection theories. The former states that differences in objectives existent between hotel managers and hotel stakeholders could generate specific costs (Carlbäck, 2012). Thus, this kind of cost is likely to appear in certain chain-affiliated hotels. On the other hand, according to adverse selection theory, independent hotels managed by their own owners could experience specific adverse selection costs, such as issues in the hiring and management of workers or obstacles when accessing vital information (Schulze et al., 2001; Carlbäck, 2012). In our sample, 19.2 % of hotels are managed independently, while 4.1 % of hotels are affiliated to international foreign hotel chains, such as *Robinson Club GmbH* or *InterContinental*. 34.2 % of hotels are managed by international Spanish hotel chains, including for instance, *RIU Hotels & Resorts* or *Meliá Hotels International*, among others.

As external factor, a location variable which allows us to distinguish between different Spanish destinations is introduced. Several papers have pointed out the relationship that exists between hotels and their location (e.g., Sellers-Rubio and Casado-Díaz, 2018; Assaf and Tsionas, 2018). Furthermore, competitiveness is significantly affected by location according to the destination competitiveness model introduced by Crouch and Ritchie (1999). In our paper, the most important Spanish regions in terms of tourism are introduced individually (these accounted for 90.3 % of tourist arrivals to Spain in 2019 according to the Tourist Movement on Borders released by the Spanish Statistical Institute, INE), while the category named "Other Spanish regions" considers hotels located in Aragon, Murcia and Navarre. For instance, 13.7 % of hotels included in the sample where located in Catalonia, the most important Spanish region in terms of tourist arrivals. Furthermore, according to the INE, Catalonia ranked second in terms of average daily expenditure of international tourists (€198) after Madrid (€272).

5. Empirical results

Table 2 shows the Bayesian results for the distance stochastic translog production frontier defined by Eq. (1) considering four scenarios: first, the fixed parameters model where technological heterogeneity is not supposed (Model 1). Second, a model that considers the constant, α, varying across the hotels, $\alpha_i = \overline{\alpha} + \varepsilon_i^{\alpha}$, where $\overline{\alpha}$ is the mean

Table 2
Bayesian panel data estimates.

Variables	Model 1: Fixed coefficients		Model 2: RPM with only random constant term		Model 3: RPM with random input coefficients		Model 4: RPM with random constant and input coefficients	
	Coefficient	St. Dev	Coefficient	St. Dev	Coefficient	St. Dev	Coefficient	St. Dev
Panel A. Translog stochastic frontier								
log (y_1/y_2)	1.849***	0.017	1.816***	0.023	1.473***	0.099	1.684***	0.018
$(\log (y_1/y_2))^2$	− 0.284***	0.007	− 0.252***	0.008	− 0.098**	0.055	− 0.200***	0.006
log x_1	− 0.441***	0.009	− 0.362***	0.01	− 1.041***	0.032	− 0.905***	0.014
log x_2	− 0.139**	0.023	− 0.038**	0.019	− 0.400***	0.025	− 0.423***	0.016
log x_3	− 0.231***	0.009	− 0.374***	0.019	− 0.500***	0.03	− 0.473***	0.012
log x_4	− 0.165**	0.027	− 0.138***	0.015	− 0.613***	0.028	− 0.537***	0.008
$(\log x_1)^2$	− 0.146***	0.004	− 0.105***	0.005	0.036***	0.007	0.042***	0.002
$(\log x_2)^2$	− 0.146***	0.009	− 0.125***	0.004	− 0.069***	0.009	− 0.015**	0.005
$(\log x_3)^2$	− 0.151***	0.006	− 0.075***	0.012	− 0.025***	0.003	0.006	0.003
$(\log x_4)^2$	− 0.044***	0.003	− 0.015***	0.003	0.017***	0.008	0.011***	0.001
log x_1 × log x_2	0.049***	0.005	0.012***	0.004	0.006***	0.001	0.005***	0.001
log x_1 × log x_3	0.095***	0.003	0.087***	0.001	0.041***	0.005	0.018***	0.002
log x_1 × log x_4	0.022***	0.006	0.016***	0.001	− 0.018***	0.003	0.0003	0.0008
log x_2 × log x_3	0.042***	0.003	0.028***	0.003	0.013***	0.002	− 0.002	0.002
log x_2 × log x_4	0.034***	0.003	0.052***	0.001	0.049***	0.006	0.007***	0.001
log x_3 × log x_4	0.0009	0.002	− 0.039***	0.002	− 0.031***	0.004	− 0.003***	0.0009
log (y_1/y_2) × log x_1	− 0.023***	0.003	− 0.034***	0.004	− 0.011	0.017	0.008**	0.003
log (y_1/y_2) × log x_2	0.011***	0.005	0.021***	0.004	0.016**	0.007	− 0.002	0.007
log (y_1/y_2) × log x_3	0.0001	0.004	− 0.007	0.005	− 0.071**	0.013	− 0.031***	0.002
log (y_1/y_2) × log x_4	0.004	0.003	0.011**	0.002	0.069**	0.028	0.016***	0.007
time	0.012**	0.001	0.009***	0.001	0.023***	0.003	0.010***	0.001
time^2	− 0.0002***	0.000	− 0.0002***	0.000	− 0.0005*	0.0001	− 0.0004***	0.000
time × log (y_1/y_2)	− 0.003***	0.0003	− 0.002***	0.0003	− 0.003**	0.001	− 0.001***	0.0003
time × log x_1	− 0.002***	0.0004	− 0.002***	0.0004	− 0.003***	0.0008	− 0.002***	0.0003
time × log x_2	0.001***	0.0003	0.002***	0.0003	0.0002	0.0006	0.0025***	0.0003
time × log x_3	0.0002	0.0002	− 0.0006**	0.0003	0.001***	0.0006	0.0006**	0.0002
time × log x_4	− 0.0003	0.0003	0.0003	0.0003	0.0001	0.0008	− 0.0009***	0.0002
Constant	− 2.481**	0.046	—	—	− 0.103	0.081	—	—
Panel B. Mean inefficiency								
Age	0.114**	0.055	0.128**	0.064	0.11	0.189	0.131**	0.065
Type of company (Limited liability)								
Type of company (Corporation)	− 0.226***	0.069	0.097	0.095	2.642**	1.768	0.343***	0.083
Chain type (International foreign chain)								
Chain type (International Spanish chain)	0.208	0.177	0.014	0.008	− 1.874	1.255	− 0.187	0.239
Chain type (National Spanish chain)	− 0.202	0.183	− 0.398*	0.24	− 1.406**	0.615	− 0.683**	0.255
Chain type (Local chain)	− 0.057	0.18	− 0.265	0.238	− 0.889	2.091	− 0.494**	0.245
Chain type (Independent hotel)	0.174	0.187	0.044	0.236	2.436**	1.121	0.181	0.247
Location (Catalonia)								
Location (Andalusia)	− 0.272*	0.144	− 0.156	0.207	1.868	1.718	− 0.708***	0.183
Location (Balearic Islands)	− 0.791**	0.121	− 0.744***	0.005	0.922	1.48	− 0.913***	0.165
Location (Canary Islands)	− 0.345**	0.149	− 0.305	0.219	2.565	1.434	− 0.968***	0.172
Location (Madrid)	− 0.771***	0.176	− 1.024***	0.005	− 1.246	0.763	− 1.332***	0.193
Location (Valencian Community)	− 0.568**	0.134	− 0.467***	0.006	1.861	1.881	− 0.660***	0.187
Location (Other Spanish regions)	− 0.351**	0.172	− 0.750***	0.005	− 0.848	1.887	− 0.917***	0.212
Constant	3.575***	0.258	3.548***	0.296	3.754***	0.703	3.924***	0.305
DIC	− 6,701		− 6,871		− 5,922		− 8,057	
Panel C. Descriptive statistics for efficiency								
Mean	0.968		0.969		0.964		0.969	
St. Dev.	0.053		0.05		0.059		0.047	
Median	0.977		0.979		0.979		0.982	
Minimum	0.083		0.092		0.145		0.151	
Maximum	0.998		0.998		0.997		0.997	
Number of hotels	73		73		73		73	
Total observations	1,679		1,679		1,679		1,679	

Notes. St. Dev. = Standard Deviation; DIC = Deviance Information Criterion.

vector and ε_i^{α} is a random vector for each hotel. This model is called the random parameters model (RPM) considering technological heterogeneity only for the constant term (Model 2). Third, a model that supposes heterogeneity across the K inputs by adding to Eq. (1) the following expression: $\sum_{k=1}^{K}\sum_{i=1}^{n}\alpha_{k,i}\log x_{k,it}$. Now, $\alpha_{k,i} = \overline{\alpha}_k + \varepsilon_i^{\alpha_k}$, where $\overline{\alpha}_k$ is the mean vector and $\varepsilon_i^{\alpha_k}$ is the random vector that holds differences among hotels. This model is called the RPM for the inputs coefficients (Model 3, $K = 4$ inputs). Finally, we have the RPM for the constant and inputs coefficients (Model 4). Model 4 combines both assumptions made in Models 2 and 3. As we can observe, the RPMs 2, 3 and 4 capture hotel-specific persistent unobserved heterogeneity in various ways.

In these models, we also consider the inclusion of several covariates (defined in Section 4.2) in the mean inefficiency model using an exponential distribution. Note that input and output parameter estimates were restricted in order to maintain monotonicity conditions valid for our distance production function, namely positive values for output coefficients and negative values for input coefficients (see Feng and Zhang, 2014; and references therein).

Bayesian estimation results were obtained using the OpenBUGS program. The Markov chain Monte Carlo (MCMC) algorithm encompassed 200,000 iterations, with the initial 100,000 iterations discarded during the "burn-in" phase. A sensitivity analysis was conducted on alterations to the initial values of prior parameters, demonstrating that the posterior inference exhibited relative insensitivity to minor adjustments in these parameters. Visual representations were realized using Python libraries *scikit learn* (version 1.2.0; Pedregosa et al., 2011), *matplotlib* (version 3.7.1; Hunter, 2007), *pandas* (version 1.4.2; McKinney, 2010), and *seaborn* (version 0.12.1; Waskom, 2021).

Several parameter coefficients are statistically significant considering the MCMC error for the distance stochastic translog production function in all models. Comparing all models, the deviance information criterion (DIC; Spiegelhalter et al., 2002) statistic shows that a random parameters model for constant and inputs coefficients (Model 4) is preferred to the rest of the models, indicating the pertinence of the unobserved technological heterogeneity assumption for hotels.

5.1. Time-varying hotel efficiencies

Figure 2 shows the efficiency distribution and the year-by-year evolution of efficiency considering results obtained by the RPM with random constant and input coefficients (graphical efficiency outcomes for the rest of the models are shown in Figures A.1 and A.2 in Appendix A). Figure 2a represents the kernel density estimates for the overall efficiencies. Note that efficiencies are skewed to the left (similar results were also obtained by the rest of the models). Figure 2b shows the year-by-year evolution in boxplot form. As can be seen, efficiency is stable from 1997 to 2019 (the median of efficiency is around 0.98). These high efficiency scores can be attributed to the maturity of the Spanish hotel sector in accordance with the classification proposed by Knowles and Curtis (1999). Therefore, under the market circumstances, hotels need to perform efficiently in order to survive in the medium/long run.

Interesting results were observed in relation to covariates explaining time-varying hotel efficiencies (results of covariates introduced in Table 2 refer to mean inefficiency, so a positive effect on inefficiency is equivalent to a negative effect on efficiency). Firstly, age has a negative and significant effect on efficiency. This could be explained by the lower rigidities faced by young hotels when compared with older hotels in terms of, for example, the adoption of innovations or the implementation of modern routines (Nieves et al., 2014; Fraj et al., 2015). However, these results are not in line with that of Arbelo et al. (2021), who found a general positive effect of age on the profit efficiency obtained by Spanish hotels. Nevertheless, we estimate here a production frontier, so comparisons should be carefully addressed.

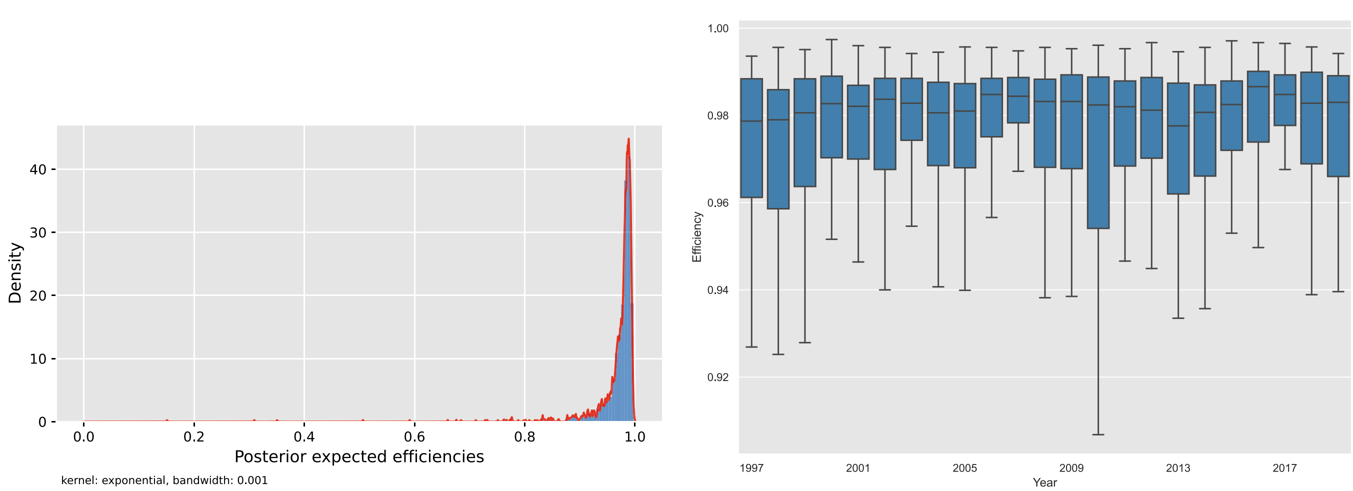
Secondly, corporations are outperformed by limited liability companies in terms of efficiency, which could be explained by the superior size of the former. For instance, while mean fixed assets of limited liabilities amounted to €43,800.00 thousands, corporations had average fixed assets of €53,944.01 thousands. Authors such as Dhawan (2001) pointed out that large firms have a lack of control over costs. In the Spanish hotel sector, authors such as De Jorge and Suarez (2014) or Lado-Sestayo and Fernández-Castro (2019) found that size had a negative effect on efficiency.

Thirdly, there are no significant efficiency differences between hotels affiliated to Spanish international chains and independent hotels when compared with hotels run by international foreign chains. However, hotels managed by national and local Spanish chains outperform hotels affiliated to foreign chains. Although Yu and Lee (2009) found that Taiwanese hotels managed by international chains outperformed hotels affiliated to local chains, Sinclair and Stabler (1997) stated that local chains focusing on a unique market can attain better results than hotels affiliated to chains which provide standardized services. In our sample. for instance, the local hotel chain *Set Hotels* operates 9 lodging firms in Menorca (Balearic Islands) which offer a high quality product focused on sustainability (e.g., consumption of local products or restrictions on single-use plastic products). Similarly, in Majorca (Balearic Islands), the local hotel chain *Eix Hotels* manages three 4-star hotels which focus on sun and sand tourism in the well-known *Bahía de Alcudia*, whereas *Insotel Hotel Group* runs several hotels solely in the Balearic Archipelago. It is important to note that such specialization in a single market could be seen as a source of efficiency. However, a further analysis should be made to corroborate these results.

Fourthly, despite being located in the most important Spanish region in terms of tourist arrivals, Catalan hotels achieved the lowest efficiency scores. The highest efficiency scores were obtained by hotels located in Madrid. De Jorge and Suarez (2014) also found that hotels in Madrid achieved the highest efficiency scores when studying the efficiency and productivity of 303 Spanish hotels during the period 1999–2007 using a non-parametric DEA approach.

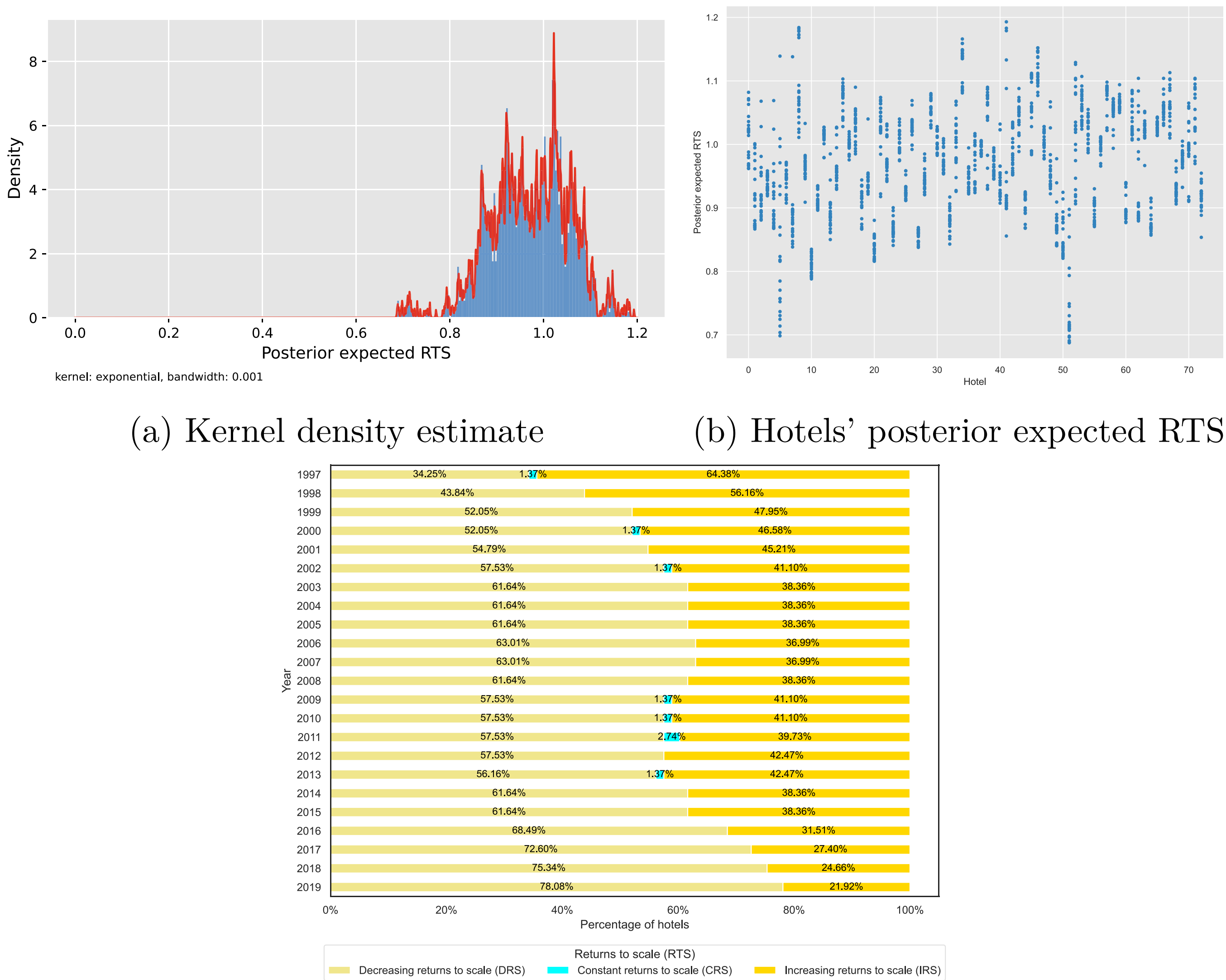
5.2. RTS of hotels

The RTS measure is calculated through the expression for the output distance function in Feng and Zhang (2014) using model estimates in Table 2. Figure 3 shows the RTS obtained through estimation of the RPM with random constant and input coefficients (graphical results for the rest of the models are shown in Figures A.3, A.4, and A.5 in Appendix A). More specifically, Figure 3a introduces the kernel density estimates, Figure 3b shows the RTS by hotel, and Figure 3c shows the evolution of the different types of RTS along the period distinguishing between DRS, CRS and IRS (that is, RTS < 1, RTS $= 1$ and RTS > 1, respectively). Note



(a) Kernel density estimate (b) Boxplot for efficiencies per year

Fig. 2. Efficiency statistics for the RPM with random constant and input coefficients.



(a) Kernel density estimate

(b) Hotels' posterior expected RTS

(c) Returns to scale evolution

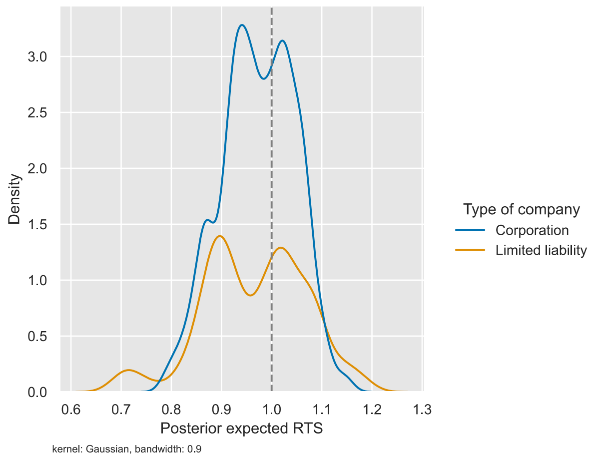
Fig. 3. RTS statistics for the RPM with random constant and input coefficients.

that Table C.1 in Appendix C shows the numerical results of different RTS by year, distinguishing between models.

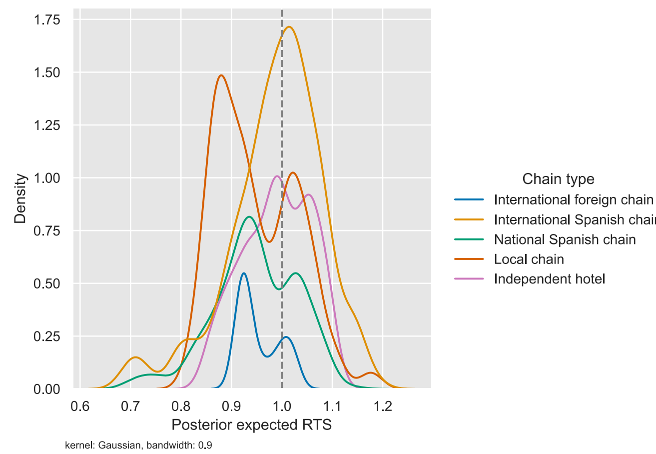
Importantly, there are significant differences in calculated RTS measures between the fixed coefficients model and the RPM with random constant and input coefficients. Thus, considering technological homogeneity would lead to a misleading ranking of hotels concerning RTS. In average terms, for the RPM with random constant and input coefficients, 59.62 % of hotels suffered from DRS, while 39.90 % of hotels had IRS. Only 0.48 % operated under CRS, which would indicate that the Spanish hotel industry is far from working in a situation of perfect competition. This is in agreement with other papers (e.g., Bull, 1995; Davies, 1999) which have pointed out that the hospitality sector does not show perfect competition.

Figure 3c shows different patterns that need to be clarified. For instance, it appears that the last years of the twentieth century displayed a general situation of IRS in the Spanish hotel industry. However, the years prior to the global financial crisis were characterized by a rise in the percentage of hotels working at DRS, which could be explained by the situation of oversupply existing in the sector during these years. During the global financial and sovereign debt crises, the percentage of hotels working at IRS increased slightly, indicating that the sector responded resiliently to both crises. However, the proportion of hotels operating at DRS has increased constantly since 2013, which could be partially explained by the recovery of competitor countries after the Arab Spring (see Afonso-Rodríguez and Santana-Gallego, 2018).

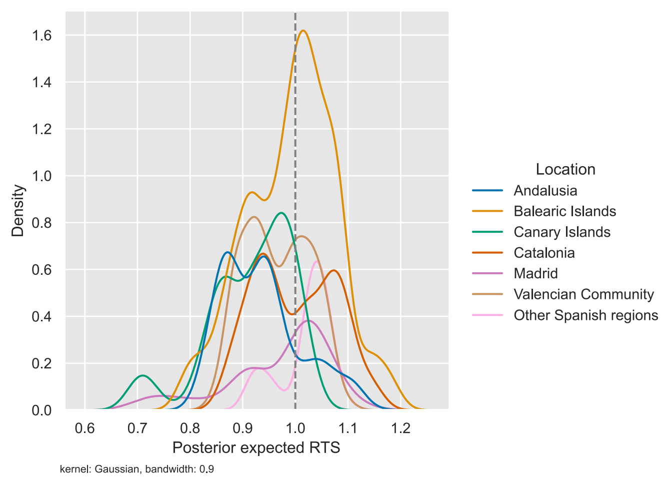
Figure 4 shows the RTS by determinant variables introduced in Section 4.2. Several conclusions can be drawn based on these results. Firstly, distribution of RTS by type of company is bimodal. In fact, it appears that there is room for improvement for the two types considered, as a significant number of hotels show IRS. Concerning chain type,



(a) Type of company



(b) Chain type



(c) Location

Fig. 4. Returns to scale by determinant variables.

the distribution of RTS associated to international foreign, national and local chains shows a certain bimodality. In fact, although the majority of hotels managed by these chains perform under DRS, some hotels show IRS. Note too that, although hotels managed by local and national chains outperformed hotels belonging to international foreign chains in efficiency terms, a high percentage of them are working under DRS. On the other hand, a unimodal distribution of RTS is shown by hotels managed by international Spanish chains, indicating that a significant number of them perform at IRS. Similarly, a high percentage of independent hotels work at IRS. This could indicate that these establishments are performing below their maximum potential levels, as they might have chosen to guarantee their survival offering easily controllable services instead of growing and losing some control over costs. Concerning the location variable, some interesting results were found. For instance, when comparing the Balearic and Canary Islands (the most important Spanish destinations in terms of sun and sand tourism), while an important percentage of hotels located in the Balearic Islands are working at IRS, the majority of hotels located in the Canary Islands perform at DRS, despite the seasonality that characterizes the former destination. As stated by Giannoni et al. (2020), some policies have recently been applied in the Balearic Islands focusing on attracting tourists with high purchasing power, while the Canary Islands continue to attract mainly traditional sun and sand tourists. Furthermore, although both locations have enacted tourism laws to control the growth of tourism, Balearic institutions have deployed more flexible policies than their Canary counterparts to deal with this issue (see Hernández-Guedes et al., 2024; for further details). For their part, the majority of hotels located in Andalusia and the Valencian Community are performing at DRS. Interestingly, the distribution of RTS shown by Catalan hotels is bimodal, with a large number of them working at IRS. Therefore, although Catalan hotels were outperformed by hotels located in the rest of the Spanish regions in terms of efficiency, there is room for improvement in this destination. A high number of hotels located in Madrid and the other Spanish regions also show IRS.

Finally, we analyse whether there is a relationship between hotel size, represented by the value of their fixed assets, and estimated RTS, in a similar fashion to Feng and Zhang (2014). This is an important issue when analysing hotel industry performance, as it allows us to check for

Fig. 5. Estimated RTS and fixed assets.

the presence of rigidities among larger hotels which could affect their economic viability. Firstly, Figure 5 shows the relationship existent between posterior expected RTS estimated through the RPM with random constant and input coefficients and the value of fixed assets per hotel (Figure A.6 in Appendix A shows the results for the rest of the models). Although there appears to be a negative visual association between estimated RTS and hotel size, any conclusions are not clear. Thus, in order to attain robust conclusions, we estimated the following equation considering a fixed-effects model under panel data[4] for the results obtained applying the RPM with random constant and input coefficients[5]:

$$\text{RTS}_{it} = \beta_0 + \beta_1 \times \text{Asset}_{it} + \gamma_i + \varepsilon_{it} \tag{10}$$

where RTS_{it} and Asset_{it} represent, respectively, the RTS and fixed assets (in thousands of euros) for hotel i in year t. β_0 refers to the constant and β_1 is the coefficient for the Asset variable. Finally, γ_i is the firm specific error term and ε_{it} represents the error term for hotel i at year t. The results are shown in Table D.1 in Appendix D and show that $\widehat{\beta}_1$ is negative and significant at 10 % significance level. Therefore, a negative relationship between size and RTS is found. This could be explained by the high rigidities faced by large hotels. For example, Dhawan (2001) explained that large firms have a lack of control over costs.

5.3. Productivity growth and its decomposition for hotels

Finally, we estimate productivity and we disentangle it into TC and EC, in line with the explanation introduced by Feng and Zhang (2014) who followed the decomposition of the output-distance-function-based Divisia productivity index by Diewert and Fox (2010) into two components: TC and EC. In this sense:

$$\frac{d \log \text{TFP}}{dt} = \text{TC} + \text{EC} = -\left(\frac{\partial \log y_M}{\partial t}\right) - \left(\frac{\partial \log \phi(t)}{\partial t}\right) \tag{11}$$

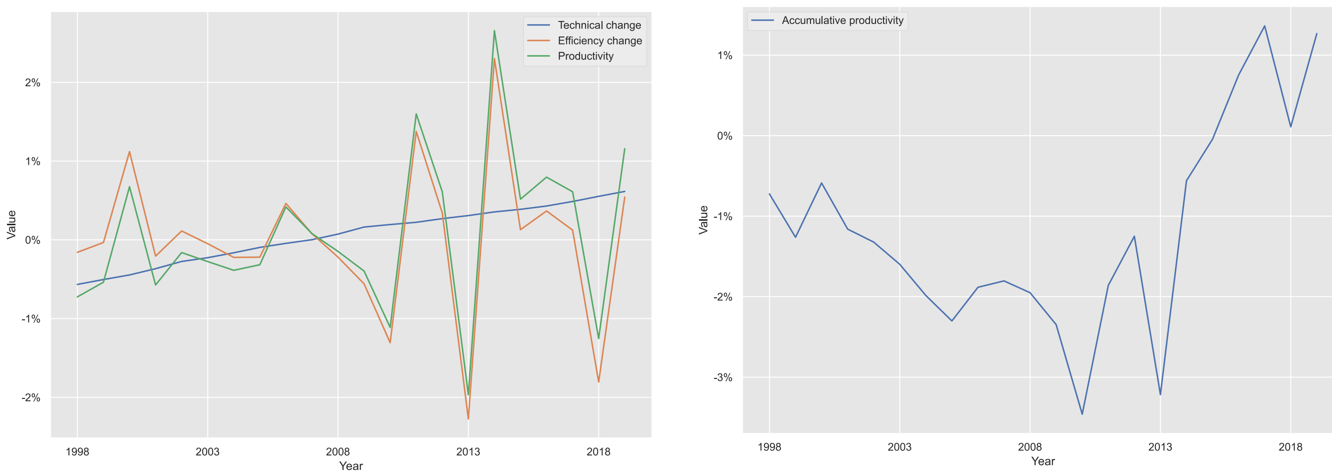
where $\phi(t)$ reflects the deviation of the output distance function compared to one due to technical inefficiency, $y_M \times \phi(t) = 1$.[6]

A graphical representation of average productivity and its decomposition into TC and EC is shown in Figure 6a for the results obtained through the RPM with random constant and input coefficients (Table B.1 in Appendix B shows the results for all the models in average terms). Note that productivity change is mainly driven by efficiency change (70.39 %), although the technical change effect (29.61 %) is also relevant. In fact, although the technical change effect was negative until the beginning of the global financial crisis, it showed a positive trend throughout the period. That is, technical change had a positive effect on productivity after the start of the global financial crisis. The evolution of efficiency change was negative between 2000 and 2005, which could be attributable to the following reasons: (1) Excess of supply in the Spanish hotel industry, explained by the entrance of a large number of Spanish real estate companies in the lodging industry due to the low costs of credits and the high margins that existed (Vila et al., 2012; Alberca and Parte, 2013); (2) Increase of international competition, mainly from North African Mediterranean countries; (3) Rise in several costs for

[4] Note that a random-effects model was also estimated. However, Hausman (1978) specification test rejects the null hypothesis which establishes that the individual-level effects are satisfactorily framed considering a random-effects approach.

[5] Results for the rest of the models are available if requested from the authors.

[6] It should be noted that other methods have been applied in the American banking sector to calculate measures such as TC, EC and productivity growth in a stochastic frontier framework using both frequentist (see Tsionas, 2023b, 2024; for further information) and Bayesian (e.g. Tsionas, 2023a) approaches. Concerning the former methods, for example Tsionas (2023b) calculated TC and EC in an input distance function with a methodology based on the fast Fourier transform. Furthermore, Tsionas (2024) proposed a model estimated by maximum simulated likelihood in which technical inefficiency was defined as a function of inputs, outputs and determinant variables. He obtained several performance measures, including TC, EC and productivity growth.



(a) Productivity, technical change and efficiency change evolution

(b) Cumulative productivity evolution

Fig. 6. Productivity decomposition for the RPM with random constant and input coefficients.

hotels (mainly material and labor; Oliver et al., 2011); and (4) Availability of new marketing channels due to new advances on the Internet, which considerably increased national competition. Efficiency change was not negatively affected by the global financial and sovereign debt crises, but by recent events such as the recovery of North African Mediterranean competitors after the Arab Spring.

Figure 6b introduces the evolution of cumulative productivity. Considering mean (median) results, productivity grew in cumulative terms by 1.27% (2%) during the period. More specifically, cumulative productivity increased notably after the end of the sovereign debt crisis. Results obtained here considering the RPM with random constant and input coefficients are in line with that of Assaf and Tsionas (2018), who pointed out that productivity growth was not a vigorous factor for the US hotel industry due to the lack of innovations adopted by hotels (see Bilgihan and Nejad, 2015; for a detailed list of the reasons that explain the low adoption of technology in the hotel sector). Furthermore, the poor productivity growth found in this paper can be explained by the maturity of the Spanish hotel sector, which might have reached a stagnation stage according to the tourism area life cycle model introduced by Butler (1980). It is important to note that, if heterogeneity is not taken into account, a decrease of productivity during the period would be found. Thus, accounting for heterogeneity is justified again.

In order to check the robustness of results found here, we applied a non-parametric input-oriented Malmquist VRS DEA method to measure productivity. Results show that mean (median) cumulative productivity was equal to 22.19% (3.34%).[7] Although outcomes do not differ importantly considering median results, mean outcomes show notable differences. The non-parametric DEA approach does not take technological heterogeneity into account when measuring efficiency. Furthermore, this method is highly sensitive to the presence of outliers. Both problems are successfully addressed by the Bayesian RPM introduced by Tsionas (2002), therefore justifying the parametric method executed in this paper.

Finally, Figure 7 shows the graphical relationship between the determinant variables, introduced in section 4.2, and TFP change, TC and EC obtained through the RPM with random constant and input coefficients. Firstly, although the distribution of TFP change and EC is similar for corporations and limited liabilities in terms of dispersion, it appears that the former show a slightly greater degree of TC when compared with the latter. Corporations have a bigger size than limited liabilities, which could explain these results as the former could be submitted to lower capital restrictions when adopting modern technological advances. Regarding chain type factor, the distribution of TFP change and EC is similar when comparing different kinds of hotel, showing discrete outcomes concentrated around zero. The distribution of TC shows that a large number of hotels obtained a positive, although reduced, TC independently of their type, although hotels managed by international Spanish chains appear to obtain the highest TC scores. Finally, concerning the location variable, Catalan hotels obtained the least dispersed TFP change results, indicating a low variation during the period. The distribution of productivity for other Spanish regions shows a higher dispersion in comparison with Catalan hotels, especially in the Balearic Islands. On the other hand, an important amount of hotels shows a positive TC independently of the region under consideration, although hotels located in the Balearic Islands appear to obtain the highest TC scores.

6. Conclusions

This paper analyzed RTS, productivity and its decomposition for a sample of Spanish hotels (period 1997–2019) using an output distance stochastic frontier model with random coefficients in a Bayesian framework (Tsionas, 2002) and in a similar fashion to Feng and Zhang (2014).

6.1. Methodological implications

Results show that the Spanish hotel sector is characterized by having technological heterogeneity, which is in agreement with strategic management theories (e.g., RBV of the firm theory) and recent studies which have analysed the Spanish and American hotel industries (Assaf and Tsionas, 2018; Arbelo-Pérez et al., 2020; Arbelo et al., 2021). Thus, it is important to note that, if such heterogeneity is not taken into account, misleading implications would have been obtained.

In addition, we differentiated between technical and efficiency

[7] Results are similar when applying an output orientation or a CRS approach. Though these results are not reproduced here, they are available if requested from the authors.

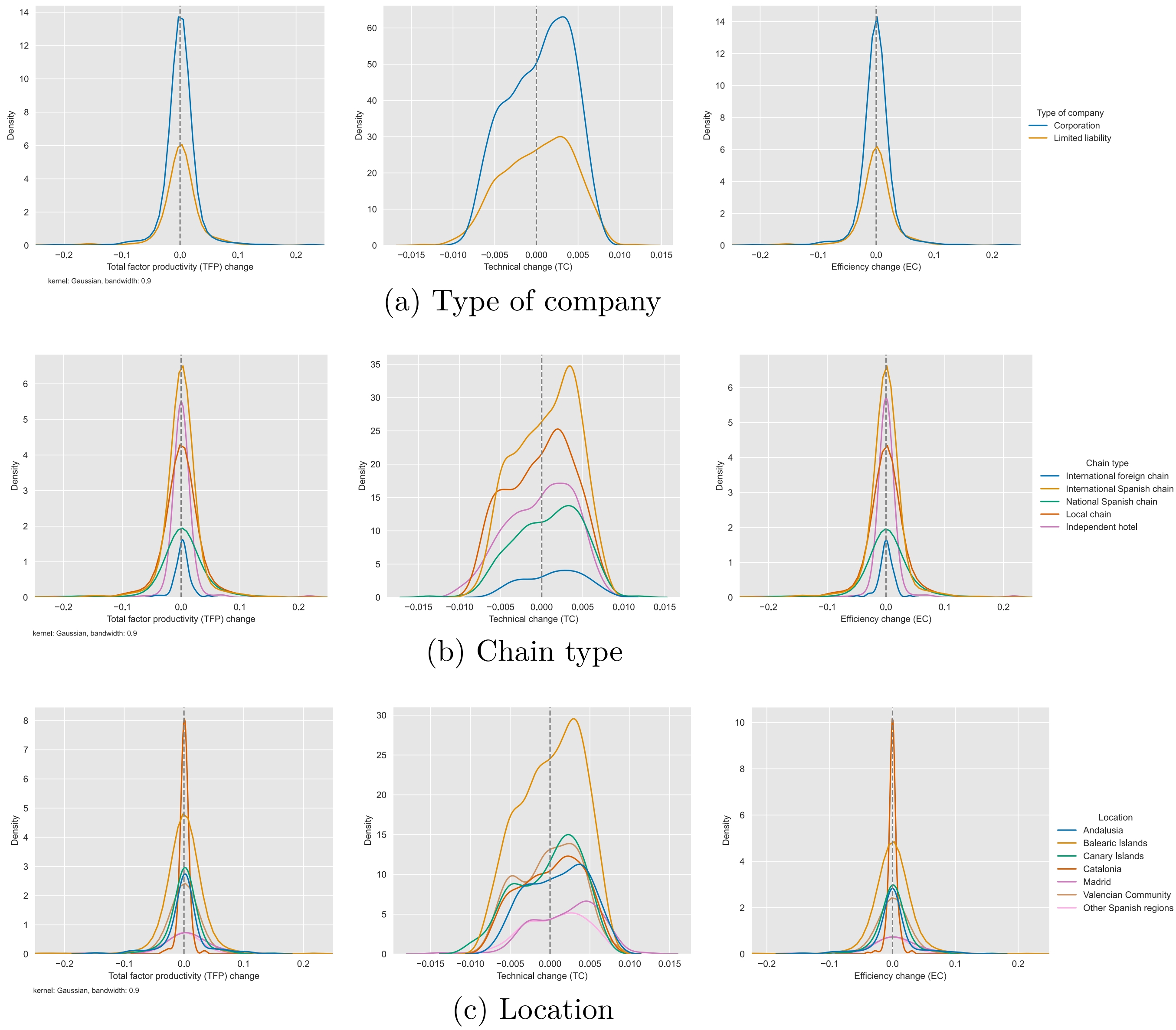


Fig. 7. Productivity and its determinants by factor variables.

changes when analysing productivity as in Feng and Zhang (2014). As far as we are aware, this is the first time that this differentiation has been performed considering an RPM for hotels, although it has been taken into account in the banking sector through novel frequentist (Tsionas, 2023b,2024) and Bayesian (Tsionas, 2023a) stochastic frontier procedures.

6.2. Management implications

Based on the effect of determinant variables on efficiency, several managerial implications can be drawn. Firstly, the age factor shows a negative effect on the efficiency obtained by hotels. Results found here justify the adoption of innovations and updated managerial procedures by experienced Spanish hotels. Furthermore, policies related to the modernization of their infrastructure should be carefully studied by experienced hotels in order to satisfy the growing requirements of tourists. For example, in the Canary Islands, the modernization of hotel infrastructure could be at least partially funded through tax reductions for undistributed profits of hotels framed in the Canary Islands Investment Reserve law (RIC by its initials in Spanish).

It appears that national and local Spanish chains outperform independent hotels and hotels managed by international chains in efficiency terms. Independent hotels could offer, for example, loyalty cards in collaboration with other independent hotels (e.g., *The Leading Hotels of the World*) to reduce their differences with chain-affiliated hotels and continue maintaining their flexibility. On the other hand, although hotels affiliated to international chains have advantages in terms of, for instance, the adoption of technology or better agreements with tour operators and travel agencies (see Almeida et al., 2020; for a further discussion on this issue), they should develop specific products for tourists visiting a particular region instead of offering a single product throughout the brand. For example, it is clear that tourists visiting the Spanish capital city of Madrid have different preferences to tourists lodging in the island of Majorca. To promote a more interesting product for such different territories, international chains should study policies applied by national and local chains in the region of interest.

Hotels located in Catalonia were outperformed in efficiency terms by hotels in the rest of the Spanish regions, especially Madrid. Madrid has notably increased its importance as a tourist region in recent years due to several factors, including: (1) Increased air connectivity; (2) Improved private investments in the tourism sector; (3) Increased number of facilities oriented towards business tourism; and (4) Celebration of international events such as the UN Climate Action Summit in December 2019, among many others. Catalan hotels and tourist institutions might follow policies applied in Madrid and take advantage of the important flows of tourism visiting Catalonia, especially proceeding from France. The promotion of international events is also of particular interest for the region, which accounts for an important supply of urban hotels focusing on business tourism in cities such as Barcelona, Tarragona or Girona. For instance, episodes such as the transfer of the Barcelona Beach Festival to Galicia (Spain) in 2024 or of the Spanish Grand Prix, which has traditionally been celebrated in Catalonia (*Circuit de Barcelona-Catalunya*), to Madrid in 2026 should be avoided by Catalan institutions if they want to enhance the hotel efficiency of the region.

The analysis of RTS during the last years of the sample shows that Spanish hotels should better manage their resources, as a general and growing situation of decreasing RTS is observed. Thus, investments in more efficient technologies to manage the input side of their production process (e.g., measures seeking to increase labor productivity or the adoption of green technologies to reduce energy cost) are of vital importance for Spanish hotels. For example, the *Hotel Palm Beach*, located in the island of Gran Canaria (Canary Islands, Spain) and managed by the international hotel chain *Seaside Hotels*, reformed in 2018 its heating/cooling installations to reduce its energy consumption partly using capital from the European Regional Development Fund (ERDF). Such kinds of policy can be of special interest for Spanish hotels as a way to reduce their operating costs (e.g., energy supplies) and satisfy the growing demands of European tourists concerning sustainability.

It appears that productivity growth was low during the period, which could indicate that the Spanish hotel industry is under a situation of stagnation. Although technical change showed a positive effect on productivity after the global financial crisis, productivity is mainly driven by efficiency change, which showed an important variability during the period. Thus, Spanish hoteliers should focus on increasing productivity levels of hotels through the adoption of innovations which allow them to increase their competitive advantages, especially when compared with competitors located along the African Mediterranean coast. As lodging firms tend to apply innovations due to the lack of legal protection existing in the sector concerning the adoption of third ideas (González and León, 2001; Vila et al., 2012), hoteliers should focus on designing singular policies which are difficult to copy. For example, as highlighted by Vila et al. (2012), the Spanish international hotel chain *NH Hotel Group* has developed a computer system which has enabled it to design successful marketing operations that show superior responses when compared with its competitors. Furthermore, this hotel chain has developed, in alliance with *Siemens*, a key card designed to reduce energy consumption while also offering personalized services for tourists Carrillo-Hermosilla et al., (2010). Other Spanish lodging chains, including *Hesperia Hotels* or *Meliá Hotels International*, cooperate with distinguished Spanish chefs to enhance their F&B departments, generating notable economic outcomes. Thus, new technological advances in the *Industry 4.0* framework constitute an interesting opportunity for Spanish hotels and should be carefully considered by hoteliers as effective ways to enhance their productivity.

The separation of productivity into technical and efficiency changes also provides important conclusions for policymakers, including the need to focus on supporting efficiency change as a way to enhance overall productivity, as it appears to be the driving force behind productivity growth. To do so, they should promote technological adoptions made by hotels (e.g., mobile check-in, smart key system or the adoption of modern payment methods such as PayPal or Apple Pay), allowing them to catch up with the best performing hotels.

6.3. Limitations and future research

Some limitations of the present study should be recognized. Firstly, hotel financial information is utilized rather than physical data due to data availability. However, we consider that the conclusions obtained here are not affected by this limitation. Secondly, other outputs that were not considered in the present analysis could be introduced in future research. This includes, for instance, customer satisfaction (Assaf and Magnini, 2012) or other revenues obtained by hotels (e.g., laundry or gambling, see Arbelo et al., 2021). Thirdly, adding other external factors when studying inefficiency (e.g., hotel category, seasonality or number of competitors) would have been interesting, although this could not be performed due to data limitations. Fourthly, analysing determinants affecting productivity would be of special relevance for managers and policymakers. Fifthly, the application of novel stochastic frontier analysis methods which allow the calculation of efficiency and other performance measures (e.g. productivity growth and RTS) while overcoming critical aspects traditionally neglected in frontier performance estimation methods would be of special interest to shed light on the evolution of the hotel sector. For instance, considering an unknown distribution for the one-sided error component associated to inefficiency (Tsionas, 2023b) could be of special interest when calculating efficiency and other performance measures. Furthermore, applying a minimax regret empirical prior in a Bayesian context for modeling inefficiency and other elements of the parametric frontier (Tsionas, 2023a) could be seen as a suitable way to combine the advantages of DEA and SFA approaches. Finally, assuming the rationality of inefficiency due to the existence of certain costs associated to movements in the input-output space while addressing endogeneity problems arising from such a consideration (Tsionas, 2024) would be especially relevant from an economic perspective.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

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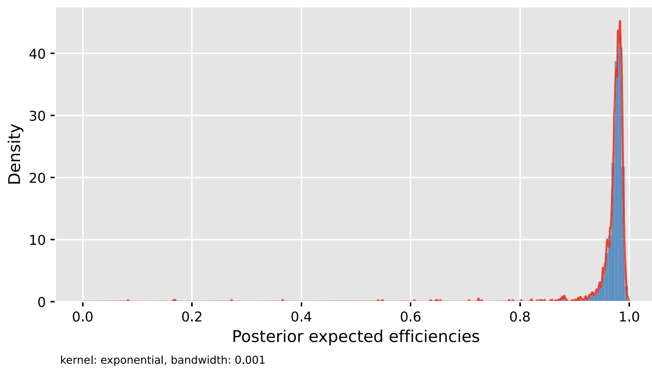
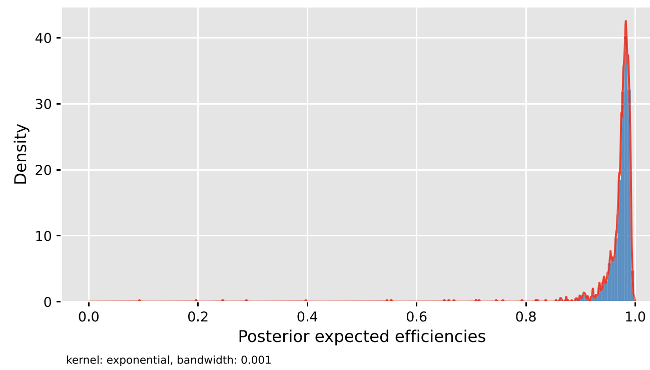
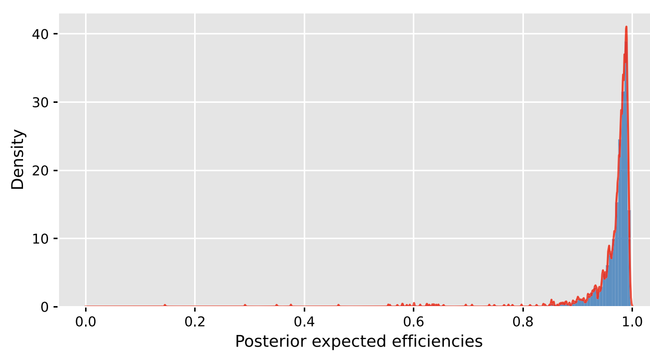
Appendix A. Graphical comparison of models



(a) Fixed coefficients model

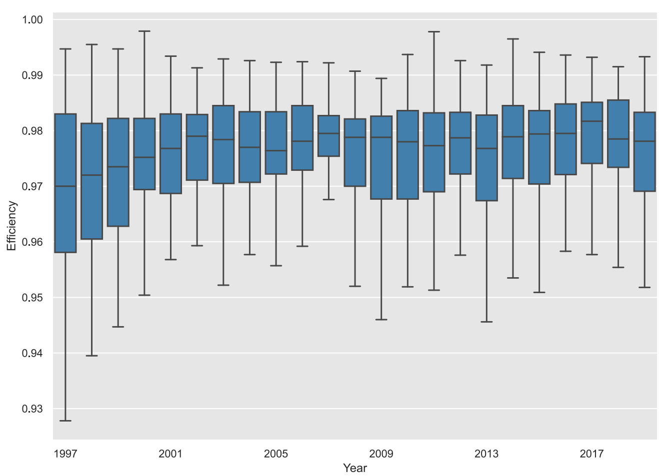


(b) RPM with only random constant term

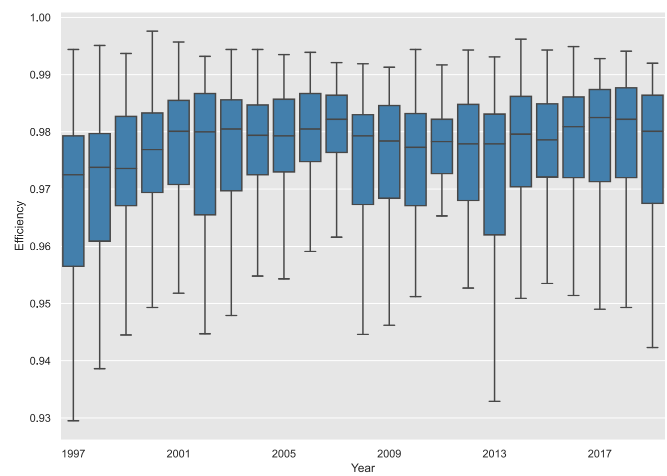


(c) RPM with random input coefficients

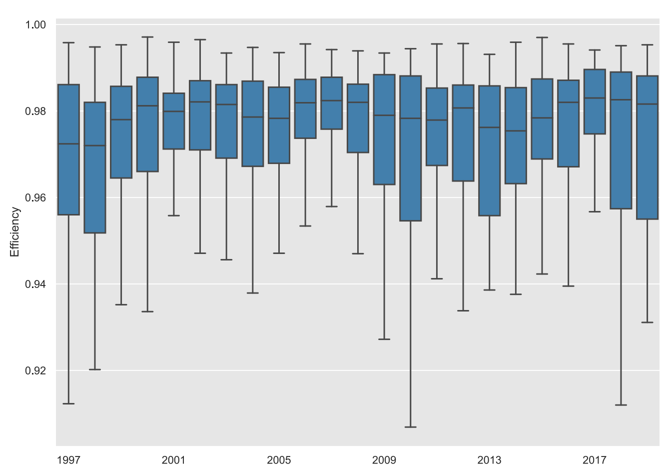
Fig. A.1. Kernel density estimate for models.



(a) Fixed coefficients model

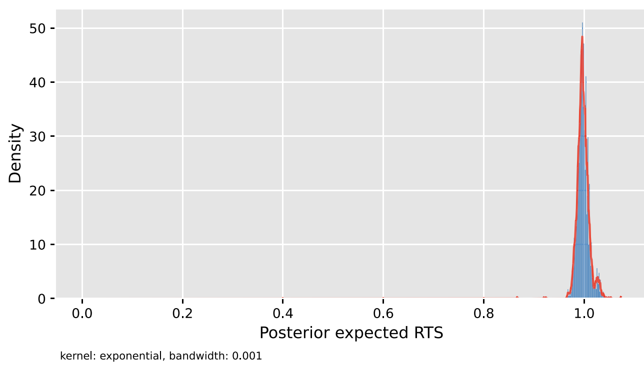


(b) RPM with only random constant term

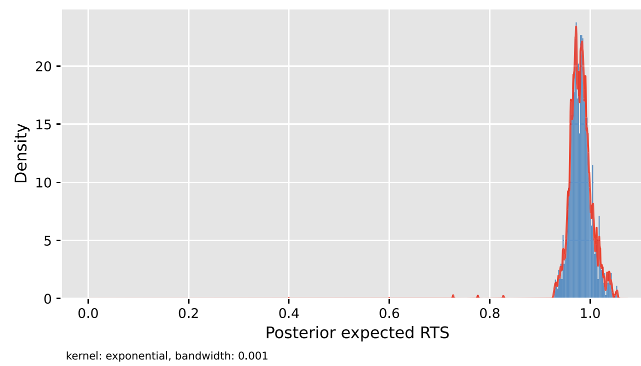


(c) RPM with random input coefficients

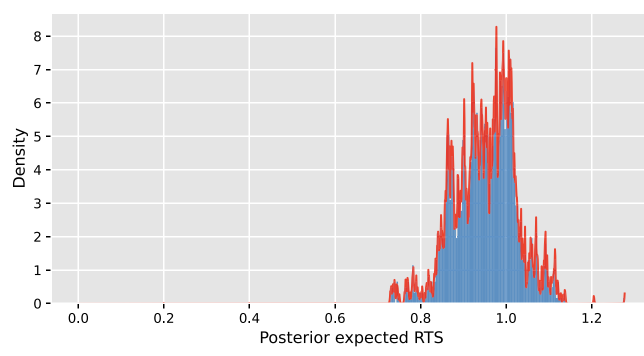
Fig. A.2. Boxplot for efficiencies per year (removing outliers for graphical purposes).



(a) Fixed coefficients model

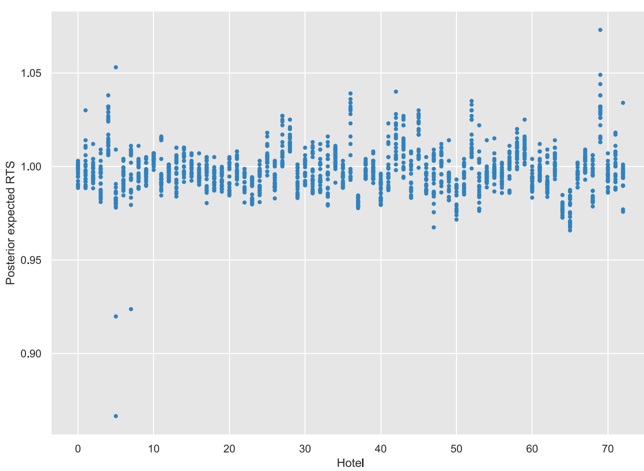


(b) RPM with only random constant

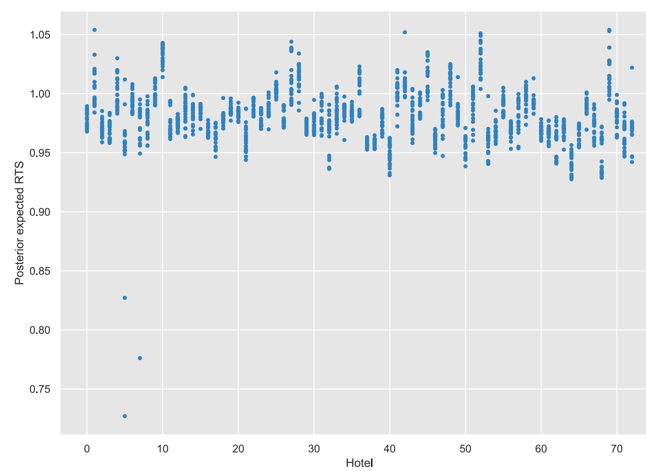


(c) RPM with input random coefficients

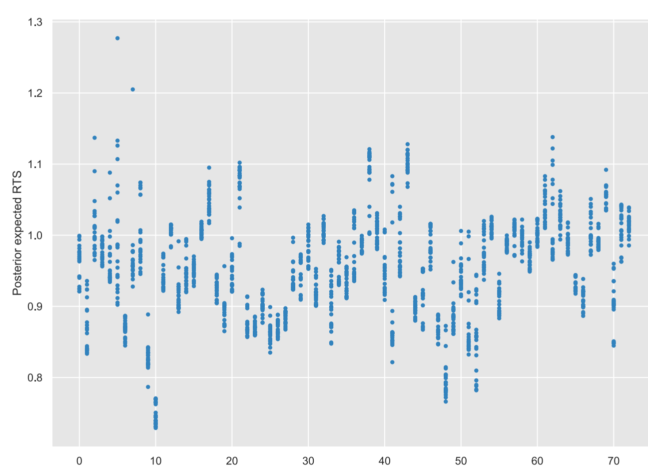
Fig. A.3. Kernel density estimate for models.



(a) Fixed coefficients model

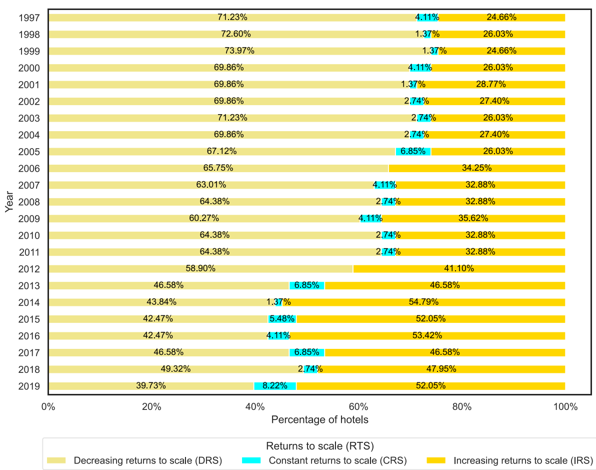


(b) RPM with only random constant term

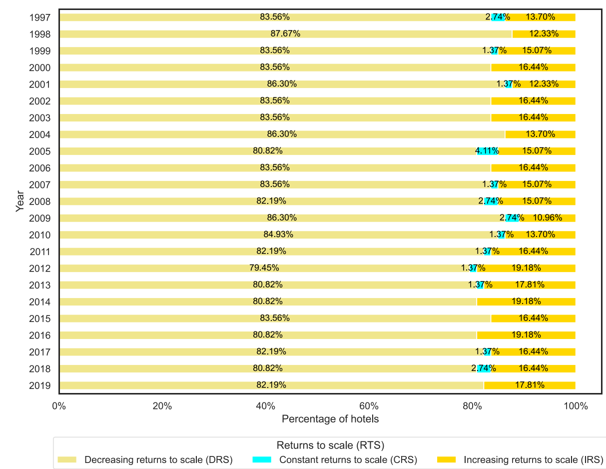


(c) RPM with random input coefficients

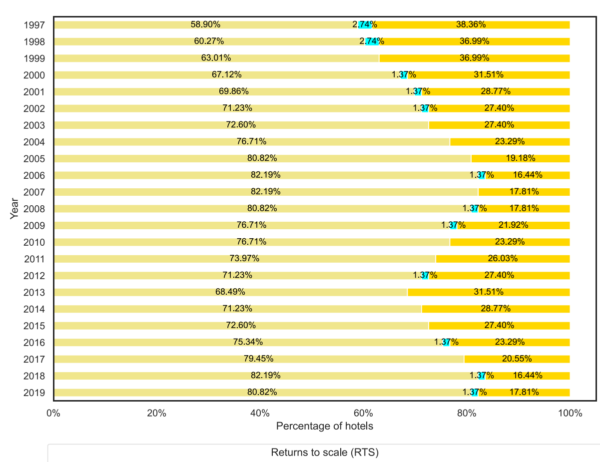
Fig. A.4. Posterior expected RTS for each hotel.



(a) Fixed coefficients model

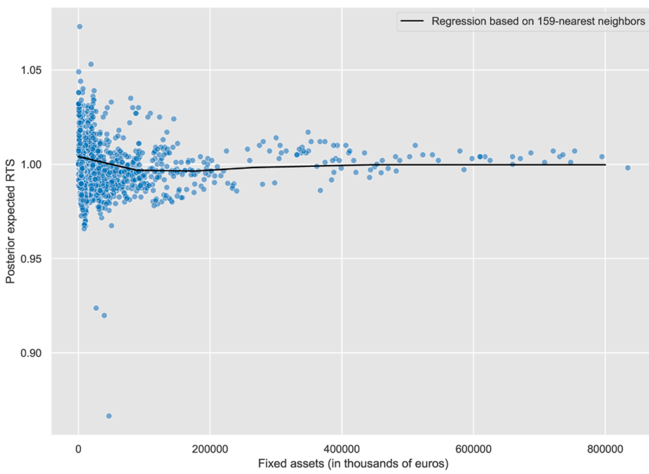


(b) RPM with only random constant term

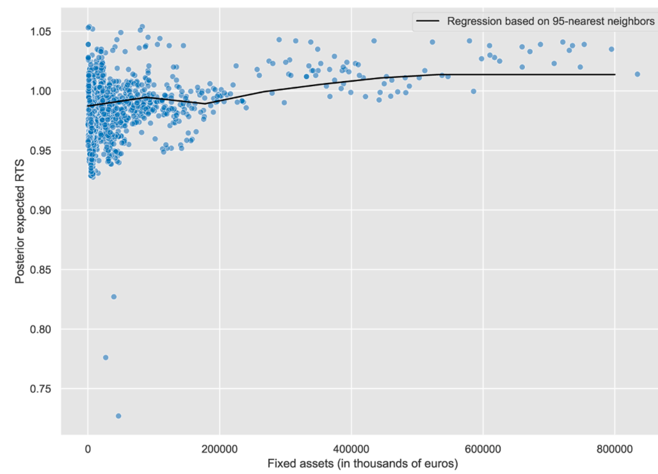


(c) RPM with random input coefficients

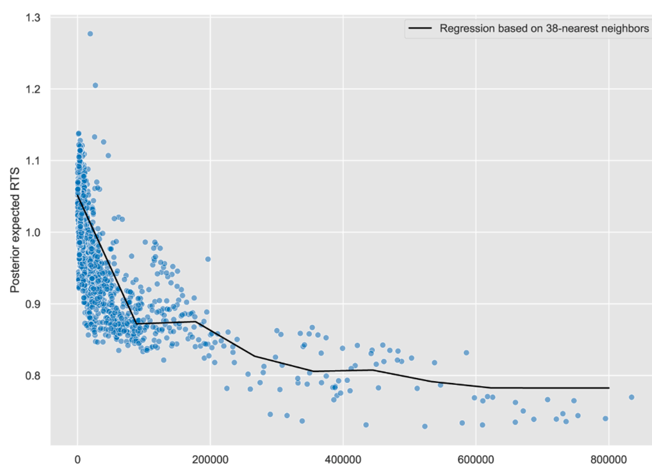
Fig. A.5. Returns to scale evolution.



(a) Fixed coefficients model



(b) RPM with only random constant term



(c) RPM with random input coefficients

Fig. A.6. Estimated RTS and fixed assets per hotel.

B. Productivity and its decomposition

Table B.1
Productivity and its decomposition per estimated model.

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Fixed coefficients model																							
Technical change	−0.0031	−0.0029	−0.0028	−0.0023	−0.0016	−0.0013	−0.0010	−0.0006	−0.0003	−0.0001	0.0002	0.0011	0.0010	0.0007	0.0009	0.0009	0.0010	0.0008	0.0007	0.0008	0.0011	0.0016	−0.0002
Technical change contribution to productivity (%)	61.93	57.89	−54.65	439.91	12.36	−12.36	52.98	−68.65	39.24	24.16	−5.36	−39.00	−10.59	6.05	10.29	−3.71	3.52	−19.18	56.09	−175.04	−8.49	16.16	17.43
Efficiency change	−0.002	−0.002	0.008	0.002	−0.011	0.012	−0.001	0.001	−0.001	0.000	−0.004	−0.004	−0.010	0.010	0.008	−0.026	0.026	−0.005	0.001	−0.001	−0.015	0.008	0.000
Efficiency change contribution to productivity (%)	38.07	42.11	154.65	−339.91	87.64	112.36	47.02	168.65	60.76	75.84	105.36	139.00	110.59	93.95	89.71	103.71	96.48	119.18	43.91	275.04	108.49	83.84	82.57
Productivity	−0.005	−0.005	0.005	−0.001	−0.013	0.010	−0.002	0.001	−0.001	0.000	−0.004	−0.003	−0.009	0.011	0.009	−0.025	0.027	−0.004	0.001	0.000	−0.013	0.010	−0.001
Cumulative Productivity (%)	−0.50	−1.01	−0.49	−0.55	−1.81	−0.77	−0.96	−0.88	−0.96	−1.00	−1.38	−1.67	−2.61	−1.50	−0.65	−3.15	−0.43	−0.84	−0.72	−0.76	−2.11	−1.13	
RPM with only random constant term																							
Technical change	−0.0031	−0.0029	−0.0027	−0.0023	−0.0016	−0.0014	−0.0011	−0.0007	−0.0005	−0.0002	0.0002	0.0010	0.0009	0.0009	0.0011	0.0013	0.0015	0.0015	0.0016	0.0018	0.0021	0.0025	0.0000
Technical change contribution to productivity (%)	121.67	71.11	−47.74	153.06	13.67	−15.51	70.22	483.16	68.85	41.21	−5.41	−48.66	−8.98	7.56	17.79	−5.58	5.44	1472.27	72.36	50.94	−13.76	28.54	115.10
Efficiency change	0.0006	−0.0012	0.0084	0.0008	−0.0099	0.0106	−0.0005	0.0006	−0.0002	−0.0003	−0.0038	−0.0030	−0.0114	0.0106	0.0053	−0.0238	0.0252	−0.0014	0.0006	0.0018	−0.0176	0.0064	−0.0001
Efficiency change contribution to productivity (%)	−21.67	28.89	147.74	−53.06	86.33	115.51	29.78	−383.16	31.15	58.79	105.41	148.66	108.98	92.44	82.21	105.58	94.56	−1372.27	27.64	49.06	113.76	71.46	−15.10
Productivity	−0.0026	−0.0041	0.0057	−0.0015	−0.0114	0.0092	−0.0016	−0.0001	−0.0007	−0.0005	−0.0036	−0.0020	−0.0104	0.0115	0.0064	−0.0225	0.0267	0.0001	0.0021	0.0036	−0.0154	0.0089	−0.0001
Cumulative Productivity (%)	−0.26	−0.67	−0.10	−0.25	−1.39	−0.47	−0.63	−0.64	−0.71	−0.76	−1.13	−1.32	−2.37	−1.22	−0.58	−2.83	−0.17	−0.16	0.06	0.42	−1.13	−0.24	
RPM with random input coefficients																							
Technical change	−0.0057	−0.0050	−0.0045	−0.0037	−0.0027	−0.0023	−0.0016	−0.0010	−0.0004	0.0000	0.0007	0.0016	0.0019	0.0022	0.0027	0.0031	0.0035	0.0039	0.0043	0.0049	0.0055	0.0061	0.0006
Technical change contribution to productivity (%)	78.14	93.70	−66.08	63.89	169.85	82.11	42.45	30.42	−10.69	2.17	−49.65	−40.97	−17.46	13.94	44.13	−15.67	13.35	75.06	53.94	79.77	−44.08	53.14	29.61
Efficiency change	−0.0016	−0.0003	0.0112	−0.0021	0.0011	−0.0005	−0.0022	−0.0022	0.0046	0.0008	−0.0022	−0.0056	−0.0131	0.0138	0.0034	−0.0227	0.0230	0.0013	0.0037	0.0012	−0.0181	0.0054	0.0000
Efficiency change contribution to productivity (%)	21.86	6.30	166.08	36.11	−69.85	17.89	57.55	69.58	110.69	97.83	149.65	140.97	117.46	86.06	55.87	115.67	86.65	24.94	46.06	20.23	144.08	46.86	70.39
Productivity	−0.0072	−0.0054	0.0067	−0.0057	−0.0016	−0.0028	−0.0039	−0.0032	0.0042	0.0008	−0.0015	−0.0040	−0.0111	0.0160	0.0061	−0.0197	0.0266	0.0052	0.0080	0.0061	−0.0125	0.0116	0.0006
Cumulative Productivity (%)	−0.72	−1.26	−0.59	−1.16	−1.32	−1.60	−1.99	−2.30	−1.88	−1.80	−1.95	−2.35	−3.46	−1.86	−1.25	−3.22	−0.56	−0.04	0.75	1.36	0.11	1.27	
RPM with random constant and input coefficients																							
Technical change	−0.0057	−0.0050	−0.0045	−0.0037	−0.0027	−0.0023	−0.0016	−0.0010	−0.0004	0.0000	0.0007	0.0016	0.0019	0.0022	0.0027	0.0031	0.0035	0.0039	0.0043	0.0049	0.0055	0.0061	0.0006
Technical change contribution to productivity (%)	78.14	93.70	−66.08	63.89	169.85	82.11	42.45	30.42	−10.69	2.17	−49.65	−40.97	−17.46	13.94	44.13	−15.67	13.35	75.06	53.94	79.77	−44.08	53.14	29.61
Efficiency change	−0.0016	−0.0003	0.0112	−0.0021	0.0011	−0.0005	−0.0022	−0.0022	0.0046	0.0008	−0.0022	−0.0056	−0.0131	0.0138	0.0034	−0.0227	0.0230	0.0013	0.0037	0.0012	−0.0181	0.0054	0.0000
Efficiency change contribution to productivity (%)	21.86	6.30	166.08	36.11	−69.85	17.89	57.55	69.58	110.69	97.83	149.65	140.97	117.46	86.06	55.87	115.67	86.65	24.94	46.06	20.23	144.08	46.86	70.39
Productivity	−0.0072	−0.0054	0.0067	−0.0057	−0.0016	−0.0028	−0.0039	−0.0032	0.0042	0.0008	−0.0015	−0.0040	−0.0111	0.0160	0.0061	−0.0197	0.0266	0.0052	0.0080	0.0061	−0.0125	0.0116	0.0006
Cumulative Productivity (%)	−0.72	−1.26	−0.59	−1.16	−1.32	−1.60	−1.99	−2.30	−1.88	−1.80	−1.95	−2.35	−3.46	−1.86	−1.25	−3.22	−0.56	−0.04	0.75	1.36	0.11	1.27	

C. Returns to scale

Table C.1
Evolution of returns to scale differentiating between DRS, CRS and IRS.

Model	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Fixed coefficients model																								
Decreasing returns to scale (DRS)	71.23%	72.60%	73.97%	69.86%	69.86%	69.86%	71.23%	69.86%	67.12%	65.75%	63.01%	64.38%	60.27%	64.38%	64.38%	58.90%	46.58%	43.84%	42.47%	42.47%	46.58%	49.32%	39.73%	60.33%
Constant returns to scale (CRS)	4.11%	1.37%	1.37%	4.11%	1.37%	2.74%	2.74%	2.74%	6.85%	0%	4.11%	2.74%	4.11%	2.74%	2.74%	0%	6.85%	1.37%	5.48%	4.11%	6.85%	2.74%	8.22%	3.45%
Increasing returns to scale (IRS)	24.66%	26.03%	24.66%	26.03%	28.77%	27.40%	26.03%	27.40%	26.03%	34.25%	32.88%	32.88%	35.62%	32.88%	32.88%	41.10%	46.58%	54.79%	52.05%	53.42%	46.58%	47.95%	52.05%	36.21%
RPM with only random constant term																								
Decreasing returns to scale (DRS)	83.56%	87.67%	83.56%	83.56%	86.30%	83.56%	83.56%	86.30%	80.82%	83.56%	83.56%	82.19%	86.30%	84.93%	82.19%	79.45%	80.82%	80.82%	83.56%	80.82%	82.19%	80.82%	82.19%	83.14%
Constant returns to scale (CRS)	2.74%	0%	1.37%	0%	1.37%	0%	0%	0%	4.11%	0%	1.37%	2.74%	2.74%	1.37%	1.37%	1.37%	1.37%	0%	0%	0%	1.37%	2.74%	0%	1.13%
Increasing returns to scale (IRS)	13.70%	12.33%	15.07%	16.44%	12.33%	16.44%	16.44%	13.70%	15.07%	16.44%	15.07%	15.07%	10.96%	13.70%	16.44%	19.18%	17.81%	19.18%	16.44%	19.18%	16.44%	16.44%	17.81%	15.72%
RPM with random input coefficients																								
Decreasing returns to scale (DRS)	58.90%	60.27%	63.01%	67.12%	69.86%	71.23%	72.60%	76.71%	80.82%	82.19%	82.19%	80.82%	76.71%	76.71%	73.97%	71.23%	68.49%	71.23%	72.60%	75.34%	79.45%	82.19%	80.82%	73.67%
Constant returns to scale (CRS)	2.74%	2.74%	0%	1.37%	1.37%	1.37%	0%	0%	0%	1.37%	0%	1.37%	1.37%	0%	0%	1.37%	0%	0%	0%	1.37%	0%	1.37%	1.37%	0.83%
Increasing returns to scale (IRS)	38.36%	36.99%	36.99%	31.51%	28.77%	27.40%	27.40%	23.29%	19.18%	16.44%	17.81%	17.81%	21.92%	23.29%	26.03%	27.40%	31.51%	28.77%	27.40%	23.29%	20.55%	16.44%	17.81%	25.49%
RPM with random constant and input coefficients																								
Decreasing returns to scale (DRS)	34.25%	43.84%	52.05%	52.05%	54.79%	57.53%	61.64%	61.64%	61.64%	63.01%	63.01%	61.64%	57.53%	57.53%	57.53%	57.53%	56.16%	61.64%	61.64%	68.49%	72.60%	75.34%	78.08%	59.62%
Constant returns to scale (CRS)	1.37%	0%	0%	1.37%	0%	1.37%	0%	0%	0%	0%	0%	0%	1.37%	1.37%	2.74%	0%	1.37%	0%	0%	0%	0%	0%	0%	0.48%
Increasing returns to scale (IRS)	64.38%	56.16%	47.95%	46.58%	45.21%	41.10%	38.36%	38.36%	38.36%	36.99%	36.99%	38.36%	41.10%	41.10%	39.73%	42.47%	42.47%	38.36%	38.36%	31.51%	27.40%	24.66%	21.92%	39.90%

D. Regression results for size and RTS

Table D.1
Results for the regression models considering outcomes obtained through the RPM with random constant and input coefficients.

	Linear fixed effects	Linear random effects
$\widehat{\beta}_0$	0.984***	0.985***
	(0.00212)	(0.00214)
$\widehat{\beta}_1$	− 2.77e−07***	− 2.93e−07***
	(1.87e−08)	(1.87e−08)
Observations	1,679	1,679
R^2	0.117	
Number of years	23	23

Notes. Standard errors in parentheses. ***$p < 0.01$. Results for (Hausman, 1978) test: Prob $> chi^2 = 0.0000$.

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