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Technological heterogeneity and time-varying efficiency of sharing accommodation: Evidence from the Canary Islands

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A B S T R A C T

The production of services in the accommodation sharing industry is heterogeneous in the sense that listings with different strategic management could adopt distinct technologies. This paper analyses the time-varying efficiency of the peer-to-peer accommodation sector using the input distance stochastic frontier model with random coefficients to accommodate both multi-input and multi-output technology and the technological heterogeneity among listings. An empirical analysis is conducted based on data from Airbnb and HomeAway listings in the Canary Islands (Spain), before, during and after the COVID-19 lockdown (source: AirDNA), in the period January 2019-September 2020 (monthly data). The results show technological heterogeneity between listings and time-varying inefficiency which negatively depends on productivity. Moreover, multi-unit hosts are clearly more efficient than single-unit hosts. A mean efficiency of around 78% during the study period was estimated.

1. Introduction

Peer-to-peer (P2P) accommodation (e.g., Airbnb or HomeAway/Vrbo) has gained in popularity in the last decade and its success in the tourism accommodation market is undeniable. For example, Airbnb (the largest vacation rental online platform) reported an increase in its global market share in April 2021, with more than 5.6 million properties for rent in 100,000 cities from more than 220 countries (Airbnb, 2021). The P2P accommodation platforms can compete with hotels by expanding the number of available rooms, especially in periods of high seasonal demand and in cities with restrictions on increasing the hotel supply (Farronato and Fradkin, 2018). The flexible scaling of supply is one of the characteristics that make P2P accommodation networks viable alternatives to the traditional accommodation services (Zervas et al., 2017). Other characteristics that contribute to explaining the success of these platforms include their offer of a non-standardised, variated product (Dolničar, 2018), more social connections and lower costs than hotels (Tussyadiah, 2015).

Although it is a recent phenomenon, many empirical studies on P2P accommodation industry have been conducted, mostly in the last five years. From the supply side, most studies have focused on describing its characteristics, such as the price determinants of the lodgings (e.g. Wang and Nicolau, 2017; Gibbs et al., 2018), location (Jang et al., 2021; Yang and Mao, 2020) and the level of professionalism of hosts (Dogru et al., 2021; Xie et al., 2021).

In this regard, an increasing process of host professionalisation has been observed in the last few years in P2P accommodation (Dogru et al., 2020). This process has been promoted by the service providers. In fact, Airbnb has quietly changed the rules of its own game and has incentivized large investors to purchase numerous homes, even entire buildings. Today, according to data provided to Business Insider by the watchdog organisation Inside Airbnb, about a quarter of hosts on the platform manage roughly two thirds of listings (Korducki, 2022). The scientific literature distinguishes between two types of manager: non-professionals or microentrepreneurs (single-unit hosts), and professional managers (multi-unit hosts). The latter are seen as more experienced and profit-oriented than the former (Giannoni et al., 2021; Reinhold and Dolnicar, 2021).

Listings managed by multi-unit hosts and those managed by single-unit hosts have different performances (Xie et al., 2021; Xie and Mao,

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2017). In this sense, an efficiency analysis can be justified. Basically, there are two motives to do this. First, managers (single and multi-unit hosts) need to allocate different inputs (e.g., resources such as rooms, guest capacity and labour such as cleaning services, among others) efficiently to maximise outputs (e.g., occupancy rates, revenue, reservations and average daily rates (ADR), among others). In this context, microentrepreneurs have more limited resources than professionals who manage more properties. Additionally, it is expected that professionals have more management experience than single-unit hosts, allowing them to earn extra income from renting their space without the time commitment. Second, an analysis of efficiency by managers can detect management problems and allow the assessment of the correct use of resources to provide services, increasing competitiveness and helping the construction of a marketing strategy (Barros, 2005; Hwang and Chang, 2003). These aspects reinforce listing operations and improve the quality of service not only in terms of profitability, but also with respect to the survival of listings.

The production of services in the accommodation sharing industry is heterogeneous in the sense that hosts (single- and multi-unit) managing differently their resources could adopt distinct technologies. However, the P2P efficiency analyses conducted to date (Pérez-Rodríguez and Hernández, 2022; Zekan and Gunter, 2022; Zekan et al., 2019) do not account for the technological differences between listings, which could be important because not all listings in the P2P accommodation industry share the same possibility frontier, as strategic management theories of firm have pointed out (e.g., environmental model theories (Porter, 1980) or the resource-based view (RBV) theory (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984); see (Arbelo et al., 2021) for an excellent overview). For example, following the RBV theory, firms are heterogeneous in terms of resources and capabilities employed in managerial practices. In the context of hotel efficiency, Assaf, Barros, and Josiassen (Assaf et al., 2010) have pointed out that the production technology can differ in terms of environmental characteristics such as size, location, type of ownership (e.g., chain and independent hotels) and quality classifications. In this regard, the existence of different managerial practices in the P2P listings due to the presence of different levels of professionalism could also motivate the use of different production technologies.

In this paper, we contribute to the empirical literature on vacation rental online efficiency proposing a model which accounts for technological heterogeneity and time-varying efficiencies in the production of services in the P2P accommodation market. To do this, we consider several methodological aspects.

First, we take into account that the accommodation industry is a multi-input and multi-output business. Therefore, we model the multi-input and multi-output technology of P2P listings using the distance function in an estimable regression equation as a standard stochastic frontier model (Coelli et al., 2005). The general specification for stochastic distance function is based on the translog stochastic production frontier model. It is a more general and flexible form for the technology (with inputs and outputs interactions). This approach has been used, for example, by Assaf and Magnini (2012) and Assaf and Barros (2013) for the hotel industry, Eling and Luhnen (2010) in the insurance industry, and also Feng and Zhang (2014) for the bank industry, among others.

Second, we use a stochastic frontier approach based on a random parameter panel data framework which allows the joint modelling and estimation of time-varying inefficiencies and technological heterogeneity of listings. The time-varying efficiencies are relevant because we can detect management problems over time (see e.g., Pérez-Rodríguez and Hernández, 2022, in the P2P accommodation sector), while technological heterogeneity is important because this is a key point when efficiency depends on different production technologies. Therefore, traditional stochastic frontier methods with fixed coefficients are not suitable for estimating efficiency because they can lead to incorrect efficiency estimates when there exists heterogeneity in the production technology (Assaf, 2009; Tsionas, 2002). Moreover, disregarding heterogeneity can strongly bias efficiency results (Assaf and Tsionas, 2019). Thus, we deal with technological heterogeneity across listings using a random parameter model because it would be incorrect to assume that listings operate under the same frontier, since that assumption does not allow the distinction between the specific inefficiency of a property from the effects of technological heterogeneity. In this sense, heterogeneity in the production technology of services can make it difficult to adequately assess listing efficiency, as is the case in hotels (Arbelo-Pérez et al., 2020; Arbelo et al., 2021).

For the empirical analysis, we conduct an efficiency analysis of the P2P accommodation sector in a traditional tourism destination. We use data obtained from the accommodation sharing industry in the Canary Islands (Spain). We selected this destination for three major reasons. First, it is an attractive destination for European citizens that, unlike all other 'sun and beach' tourist destinations in Spain, does not present strong seasonal variation in the flow of tourist arrivals (FRONTUR, 2021b). Second, the tourism sector is the most important source of income for the Canary Islands region, accounting for 35% of its GDP in 2018 (IMPACTUR, 2018). And third, it is the third most important Spanish region in terms of tourism arrivals, which are mainly composed of visitors from Germany, the UK and mainland Spain (FRONTUR, 2021a).

We use a monthly panel data for a sample of different types of accommodation, from January 2019 to September 2020, a period that includes the COVID-19 pandemic crisis that started in March of 2020. The pandemic devastated the tourism industry, which experienced a 74% decrease in tourist arrivals in 2020, with a global economic loss of around 1.3 trillion dollars in export revenues (UNWTO, 2021). Some authors hypothesised several transformations of the P2P accommodation market after the irruption of COVID-19, such as the decline of commercial hosts in favour of those more interested in social aspects and the principle of sharing (Dolnicar and Zare, 2020). This is partially confirmed by some empirical research, which found an intention on the part of some hosts to move to long-term renting (Farmaki et al., 2020) or to abandon the activity (Zhang et al., 2021). Other studies found a significant increase in the geographical dispersion of listings (Adamiak, 2021) and that entire homes are preferred in the post COVID-19 era (Bresciani et al., 2021). In this context, this paper contributes to the research on the effect of the crisis on the P2P accommodation sector by analysing its impact on the efficiency of listings. A negative effect in the first months after the pandemic outbreak is to be expected given the imposition of a strict lockdown and limitation on movements. As a result, outputs such as occupation rate were seriously affected, although accommodation inputs, such as number of guest rooms, cannot be easily modified when such a sudden exogeneous shock takes place. However, the situation after the lockdown is uncertain, given the changes produced in the market. We will analyse the time path of the efficiency of listings, covering also the first months of the recovery period.

The rest of this paper is structured as follows. The following section reviews the literature on efficiency and heterogeneity in tourist accommodation, mainly focused on the hotel sector. Section 3 then describes the stochastic frontier random parameter model by Greene (Greene, 2005). Section 4 presents the case study and the results derived from the empirical analysis. Section 5 compares our results with previous findings and highlights the theoretical and managerial contributions. Finally, the main conclusions are summarised in Section 6.

2. Literature review

2.1. Efficiency of P2P listings

Very few analyses of the efficiency of the P2P accommodation sector have been performed and it has been much less studied than the hotel accommodation sector. The few studies that have been published have used several types of efficiency approaches. For example, the production frontier has been analysed using non-parametric methods (e.g., Zekan et al., 2019; Zekan and Gunter, 2022). Production technology has also been analysed using the stochastic frontier analysis (SFA) approach, disentangling unobserved heterogeneity and time-varying efficiency in a panel data framework (e.g., Pérez-Rodríguez and Hernández, 2022).

Zekan et al. (2019) examined the efficiency of listings of European cities using a non-parametric data envelopment analysis (DEA) in a comprehensive benchmark study in the domain of the sharing economy. Later, Zekan and Gunter (2022) included hotel-related data in an efficiency analysis of 28 European cities. They analysed efficiency for single- and multi-unit hosts (which they called private and commercial listings) and found that, generally, private listings are less efficient than commercial ones.

Pérez-Rodríguez and Hernández (2022) used a panel data stochastic frontier model to analyse the time-varying technical efficiency of P2P listings in the Canary Islands. Their analysis focuses on the effect professionalism and accommodation type on the technical efficiency. In contrast to previous findings, their study concluded that listings managed by multi-unit hosts are less efficient than those managed by single-unit hosts.

The study conducted in this paper estimates efficiency taking into account technological heterogeneity in the industry, which has been disregarded in previous studies.

2.2. Technological heterogeneity and efficiency in the tourist accommodation industry

Efficiency analyses in the tourist accommodation industry have mostly been conducted on hotels. Several approaches have been used, mainly non-parametric such as DEA, but also parametric ones such as the stochastic frontier technique (e.g., see Pérez-Rodríguez and Acosta-González, 2021, for a general overview). However, few efficiency studies have considered that accommodation units are heterogeneous and cannot operate under the same possibility frontier (Arbelo-Pérez et al., 2020; Tsionas, 2002; among others). Nevertheless, the units maximise their performance by choosing strategies that exploit their heterogeneous resources and their individual conditions in managerial practices (Arbelo-Pérez et al., 2020; Mackey et al., 2017).

In this regard, technological heterogeneity in hotels has been investigated using either the metafrontier approach or adopting a random parameter framework.

Regarding the metafrontier approach, several papers have analysed the differences in technology by grouping hotels according to, for example, size, ownership and classification (Assaf et al., 2010), domestic, franchise and membership chain technologies (Huang et al., 2013) and international chain versus independent hotels (Cho and Wang, 2018). Other authors have reported that the use of different technologies affects changes in hotel productivity (Yu and Chen, 2016). Recently, Pérez-Rodríguez and Acosta-González (2021) studied the influence of technological differences on hotel efficiency in the Canary Islands (Spain), specifically analysing the heterogeneity observed in hotel ownership and size. The aforementioned papers investigated the technological differences using the non-parametric approach. However, other authors have used stochastic frontier modelling to analyse the different technologies between hotels (Bernini and Guizzardi, 2015; Huang et al., 2014).

Several papers have studied technological differences using SFA with random parameters, in other words, considering that parameters can be random due to technological differences among hotels. In this regard, we highlight two methodological approaches: the random parameter model of Greene (2005) and a Bayesian approach to account for heterogeneity in a flexible manner, as proposed recently by Assaf and Tsionas (2018). Also noteworthy in this respect are the recent contributions of Deng et al. (2019), Arbelo-Pérez et al. (2020) and Arbelo et al. (2021). Deng et al. (2019) analysed the efficiency of hotel chains in Spain using a stochastic frontier mode, taking several inputs such as total staff or number of rooms in a Bayesian stochastic frontier framework and accounting for heterogeneity in hotel chains by means of variables such as the proportion of three or fewer star hotels in the chain. Finally, Arbelo-Pérez et al. (2020) and Arbelo et al. (2021) made use the Bayesian stochastic frontier model with random coefficients (Tsionas, 2002).[2]

However, to our knowledge, no studies have been published in the relevant academic literature that consider technological heterogeneity and efficiency for P2P accommodation in a stochastic frontier approach across listings. This paper fills this gap by considering the multi-input and -output nature of the P2P business and using the translog input distance frontier with random parameters in a panel data framework. The random parameter model we use is the model proposed by Greene (2005), in which it is assumed that listings do not operate under a common frontier in a similar way to Barros et al. (2010) for hotels. Greene's random parameter model includes a simulation-based random parameters estimator which is a more general and flexible specification than the simple random effects model.

3. The random coefficient stochastic input distance frontier model

To estimate the efficiency frontier of the listings, we consider a multi-input and multi-output technology. The literature shows that distance functions allow this task by specifying either an input or an output orientation approach. Although these functions can be used in a non-parametric context (e.g., DEA, among others), there are parametric frontier methods which have also attempted to solve both multiple input and output problem. However, in this paper, we use the parametric stochastic frontier framework because it is more developed than nonparametric DEA in the case of panel data, and accounts for statistical error in the data (Assaf and Barros, 2013).

In this parametric context, we specify the production process considering several issues. First, we use the transcendental logarithmic (translog) distance function. The translog specification allows to add the effects of interactions between inputs and outputs and is more flexible than the traditional Cobb-Douglas specification. Second, the distance function we have chosen is input-oriented as opposed to output-oriented because we assume that managers can control some inputs. That is, we assume that the amount of business available to a listing depends largely on customer demand for the property's services and is beyond the listing manager's control. However, it is worth noting that we have not addressed the issue of whether the inputs and outputs are endogenous, which is our major limitation. To address the endogeneity of inputs we would need to develop a system approach, for example in a cost minimisation setup (Kumbhakar and Wang, 2006), and use data prices. However, this cannot be applied because data prices are unavailable in our case.

The general specification for the proposed translog input distance stochastic frontier model, with a random parameter panel data model, can be written as the following technical efficiency SFA model:

[2] The random coefficient model of Greene (2005) resembles the random parameters model proposed by several authors using a Bayesian estimator, such as Tsionas (2002) among others (see Greene, 2005; p.297).

$$-\log x_{K,it} = \alpha_{0i} + \sum_{m=1}^{M} \alpha_{m,i} \log y_{m,it} + \frac{1}{2} \sum_{m=1}^{M} \sum_{s=1}^{S} \alpha_{ms,i} \log y_{m,it} \log y_{s,it}$$
$$+ \sum_{k=1}^{K-1} \alpha_{k,i} \log x^{*}_{k,it} + \frac{1}{2} \sum_{k=1}^{K-1} \sum_{j=1}^{J-1} \alpha_{kj,i} \log x^{*}_{k,it} \log x^{*}_{j,it}$$
$$+ \sum_{k=1}^{K-1} \sum_{m=1}^{M} \gamma_{km,i} \log x^{*}_{k,it} \log y_{m,it} \tag{1}$$
$$+\kappa_{1i} t + \kappa_{2i} t^2 + \sum_{m=1}^{M} \delta_{1m,i} t \log y_{m,it} + \sum_{k=1}^{K-1} \delta_{2k,i} t \log x^{*}_{k,it} + (v_{it} - u_{it})$$
$$v_{it} \sim N\left(0, \sigma_v^2\right)$$
$$u_{it} \sim N^{+}\left(\mu_{it}, \sigma^2_{u,it}\right), \quad where: \ \ \mu_{it} = \phi_i' z_{it}, \ \ \sigma_{u,it} = \sigma_u \exp(\theta_i' d_{it})$$

where log is the natural logarithm $i = 1, 2, ., n$ is the number of listings, $t = 1, 2, ., T_i$ is the number of time periods, which may vary for each listing if the panel is unbalanced, and $y_{m,it}$is the m-th output variable of listing i in period t. To ensure linear homogeneity of degree 1 in inputs, we choose (randomly) one input as numeraire ($x_{K,it}$in our case). Thus, $x^{*}_{k,it} = x_{k,it}/x_{K,it}$, where $x_{k,it}$is the k-th input of listing i in period t (level, squares and cross products). Technological change is accounted for by including the time trend as a regressor in the model. $v_{it} \sim N(0, \sigma_v^2)$ is the idiosyncratic term (symmetric) and $u_{it} \sim N^{+}(\mu_{it}, \sigma^2_{u,it})$ is the inefficiency term (asymmetric) distributed as truncated normal with mean and variance non-constant over time and listings. In particular, $\mu_{it} = \phi_i' z_{it}$, where z_{it} is a vector of s_1 explanatory variables for the mean, and $\sigma_{u,it} = \sigma_u \exp(\theta_i' d_{it})$, with d_{it} a vector of s_2 explanatory variables for the variance of inefficiency. For greater flexibility of the model, all parameters can be random, including those for the mean and variance of the inefficiency term.

Following Greene (2005), the parameter heterogeneity for the stochastic frontier defined by [1] can be written as:

$$\beta_i = \overline{\beta} + \Delta_\beta q_i + \Gamma_\beta w_{\beta i} \tag{2}$$

where $\beta = (\alpha', \gamma', \kappa_1, \kappa_2, \delta')'$, $\overline{\beta}$ is a vector of fixed constant terms in the means of the distributions for the random parameters; q_i is a set of time invariant related variables which enters the distribution of the random parameters, indicating interaction terms with the inputs (omitting these variables, the scenario considers no interaction terms), and the heterogeneity parameter for the mean and variance parameters of the inefficiency term can be expressed by:

$$\lambda_i = \overline{\lambda} + \Delta_\lambda q_i + \Gamma_\lambda w_{\lambda i}$$
$$\theta_i = \overline{\theta} + \Delta_\theta q_i + \Gamma_\theta w_{\theta i}$$

where Δ_j, with $j = \beta, \lambda, \theta$, is a conformable matrix of parameters to be estimated. The random vector w_j induces the random variation in the reduced form parameters of the model, and is assumed to have mean vector zero and known diagonal covariance matrix Σ_j (for example, the identity when considering that the error term is distributed as N(0,1)). The term Γ_j is a free and lower triangular unrestricted covariance matrix.

The estimation of model [1] is done using the simulated maximum likelihood method. The simulated log likelihood is expressed by:

$$\log L_S = \sum_{i=1}^{n} \frac{1}{R} \sum_{r=1}^{R} \left[\sum_{t=1}^{T} \log f\left(\Theta_i / y_{it}, x^{*}_{it}, z_{it}, d_{it}, q_i, w_{ir}\right) \right]$$

where R is the number of simulated draws of w_{ir} from the standard normal population, for example using Halton or generalised Halton sequences; $f(\Theta_i / y_{it}, x^{*}_{it}, z_{it}, d_{it}, q_i, w_{ir})$ is the conditional density of parameters to the observed and unobserved variables, where Θ_i is a vector which contains all parameters of the model [1], including those for Δ_j and Γ_j, respectively. See Greene (2005) for more details.

4. Empirical analysis

4.1. The accommodation sharing industry in the Canary Islands

The Spanish region of the Canary Islands (Spain) is a major national and international tourist destination thanks to its many excellent beaches, attractive landscape, climate, sports facilities and other cultural and tourist attractions. More than 15 million tourists were hosted in the Canary Islands in the year 2019, representing an increment of around 44.9% over the period 2010–2019 (ISTAC, 2021). In this context, the importance of P2P lodgings in the accommodation market of the islands has also increased over the years. To illustrate this, Fig. 1 presents the percentage of tourist arrivals hosted in traditional (hotel and apartments) accommodation (blue dashed line) and in P2P accommodation (solid black line). As can be observed, the market share of traditional accommodation shows a declining tendency, which intensified considerably after the lockdown period. By contrast, the P2P accommodation industry has maintained and even gained market share after the lockdown period, reaching a maximum of 0.14.

The P2P accommodation units in the islands are mainly supplied by two platforms, Airbnb and HomeAway. Table 1 shows various indicators of the characteristics and performance of these units. The first block of Table 1 (All Properties) shows a steep increase in the number of listings and lodging capacity up to 2019, followed by a fall in 2020 due primarily to the pandemic outbreak. Other performance indicators, such as the minimum days of stay, have continuously decreased over the last four years, very likely due to the competition effect of an increasing supply. The occupancy rate and the average reservation days show a slight decreasing trend up to 2020 when a severe decline took place, again due to the effect of the pandemic. However, the average daily rate (ADR) has been stable over the years and slightly increased in 2020.

The second and third blocks show the same indicators for properties offered by Airbnb and HomeAway, respectively. As can be observed, in each year the former presents more favourable occupancy rate and average reservation per month indicators. However, the ADR is higher for properties exclusively hosted in HomeAway which, on average, offers accommodation units of a larger size (number of guest rooms). An approximately constant 39% of hosts in Airbnb manage few properties (three or less), whereas this percentage increases to 80% in the case of HomeAway managers.

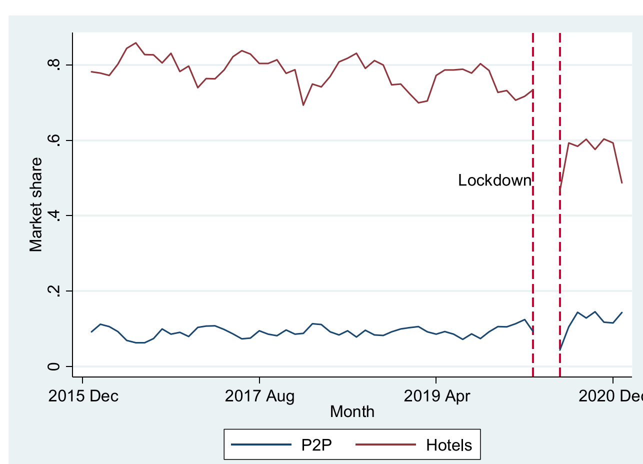

Fig. 1. Market share (percentage of total tourist arrivals) of Hotel & Apartments and P2P accommodation industry in the Canary Islands (January 2016 – January 2021). *Note*: The lockdown period is situated between the red-dashed lines when no tourist arrivals were registered.
Source: ISTAC (2021).

Table 1
Airbnb and HomeAway accommodation market in the Canary Islands (2016–2020) (Source: AirDNA).

	2017	2018	2019	2020
All Properties				
Number of listings	59,694	81,069	93,286	85,095
Number of guest rooms	1.78	1.76	1.77	1.79
Guest capacity	4.18	4.17	4.19	4.24
Minimum stay	4.85	4.63	4.41	4.35
Average reservation (m)	7.91	7.00	6.55	4.57
Occupancy rate	0.30	0.27	0.26	0.19
ADR	105.32	111.40	108.83	112.15
Airbnb[a] Properties				
Number of listings	41,978	56,220	62,590	52,958
Small host rate	0.39	0.38	0.38	0.39
Number of guest rooms	1.64	1.64	1.66	1.68
Guest capacity	3.93	3.95	3.99	4.03
Minimum stay	5.01	4.76	4.56	4.58
Average reservation (m)	7.96	7.27	7.22	5.23
Occupancy rate	0.31	0.28	0.29	0.21
ADR	93.57	97.52	96.55	99.03
HomeAway Properties				
Number of listings	17,716	24,849	30,696	32,137
Small host rate	0.82	0.79	0.80	0.85
Number of guest rooms	2.11	2.03	2.00	1.97
Guest capacity	4.77	4.67	4.61	4.60
Minimum stay	4.46	4.29	4.03	3.87
Average reservation (m)	7.80	6.40	5.19	3.48
Occupancy rate	0.28	0.24	0.20	0.14
ADR	136.84	145.71	141.22	147.06
Hotels & Apartments				
Number of rooms/app.	170,056	169,805	170,609	82,917
Occupancy rate	0.82	0.79	0.76	0.49
ADR	80.98	82.49	84.35	86.63

Notes: Number of rooms/app. = number of rooms in hotels + number of apartments; Small host rate = number of hosts managing three properties at most / number of hosts (Airbnb), not integrated property manager (HomeAway); Guest capacity = maximum number of guests; Min. stay = minimum night stay; Average reservation (m) = average number of reservation days per month; Occupancy rate = total booked days / (total booked days + total available days); ADR = average daily rate (USD), total revenue / booked nights.
[a] Properties hosted in both platforms are assigned to Airbnb.

The last block shows some of the same performance indicators for traditional accommodation. It can be seen that the occupation rate in this sector was around three times as high as that of the P2P accommodation industry in all years, but the ADR was approximately 20% lower, showing the higher competitiveness of the Hotels & Apartments industry in the islands.

4.2. Data

The data analysed were obtained from the AirDNA daily reports from January 2019 to September 2020, containing information on inputs and outputs, and environmental variables. From this database, we initially selected 130 decision making units (DMUs) which are active listings (i.e., those that had a non-zero number of bookings) operating in the Canary Islands through Airbnb (105 listings) and HomeAway (25 listings, approximately 19% of the sample). These include townhouses, cottages, bungalows, condominiums, villas, houses, and apartments, which represent most types of accommodation in the Canary Islands. We aggregated the data on a monthly basis to analyse the time varying efficiencies with a monthly frequency. In total, we consider 21 months as time periods. Finally, an unbalanced panel dataset formed by 130 listings and 21 months was used with 2183 total observations.

4.2.1. Inputs and outputs

Inputs and outputs were selected according to sample data availability (source AirDNA) and in accordance with Zekan et al. (2019) and Zekan and Gunter (2022). The following inputs were collected for each listing: (1) number of guest rooms, (2) maximum number of guests the vacation rental property can accommodate, (3) minimum number of nights (the default minimum night stay required by the host), and (4) number of photos in a vacation rental listing. Specifically, the maximum number of guests is used to represent the size of Airbnb listings; the minimum number of nights is used to measure the minimum length of stay, while the number of photos is used as a measure of the informational content of Airbnb ads. Also, we have added the guest rooms.

The outputs are as follows: (1) average daily rate (ADR) of booked nights (ADR = Total Revenue / Booked Nights), where the revenue is in USD (total revenue earned during the reporting period) and includes the advertised price from the time of booking and cleaning fees; (2) occupancy rate (=Total Booked Days / (Total Booked Days + Total Available Days)), the calculation of which only includes vacation rentals with at least one booked night; (3) number of bookings (number of unique reservations in the reporting period); and (4) overall rating (average guest rating of the property, from 1 to 5). With respect to these four output variables, total revenue is used as a measure of monetary success, while occupancy rate, the number of reservations and the overall rating are used as measures of success in real terms, where both occupancy rate and number of bookings can be interpreted as different measures for Airbnb demand (Gunter and Önder, 2018).

4.2.2. Environmental factors

Efficiency drivers were evaluated using relevant environmental factors to explain mean efficiency. These determinants may be external (e.g., the degree of competitiveness in its market, or the influence of the pandemic crisis) or characteristic to the listing (e.g., type of accommodation, location, etc.). We used the productivity of guest rooms with respect to total revenue: total revenue over the number of guest rooms. In addition, we included the linear time effect and the market share of the property, calculated as the total income of the listing i over the total income generated by all listings in the sample. Finally, we included three dummy variables: the variable called HomeAway which takes value 1 if the property is offered in the HomeAway online platform and 0 if offered by Airbnb; the variable multi-unit host which takes value 1 if the property is managed by a multi-unit host and 0 if managed by a single-unit host; a dummy variable which took a value of 1 during the Spanish lockdown (March-June 2020) and 0 otherwise. Although there were zero tourist arrivals during part of the lockdown, the P2P accommodation sector in the islands was active, hosting mostly Spanish customers.

Table 2 shows the descriptive characteristics of the inputs, outputs and environmental variables for the whole sample and considering Airbnb and HomeAway listings separately. As can be observed, the average listing has 2 guest rooms, a maximum capacity of 5 guests and the occupancy rate is 43%. The mean ADR is $117.71, including cleaning fees. The lockdown corresponds to 19% of the active listings in the sample. Similar results are found for Airbnb and HomeAway listings.

4.3. Estimation results for random parameter model

The model presented in Section 3 assumes that each listing has its own optimal possibilities frontier. Instead of estimating models separately for each online platform, we estimate Eq. (1) including all listings for Airbnb and HomeAway properties.

It should be noted that several models were estimated including covariates to explain inefficiency, but the majority did not reach satisfactory simulated log likelihood results. In this sense, Table 3 shows the results with the best model selected from several approaches. In particular, this model considers randomness for only some input parameters and that inefficiency can be explained by two explanatory factors: productivity of the number of rooms and the COVID-19 period.

Table 3 shows the results for the standard panel data translog stochastic input distance frontier (based on the truncated normal distribution) and the previously mentioned random parameter model with covariates for comparative purposes. Also, we have included the logarithm of the maximum likelihood (Log L), the standard deviation of the

Table 2
Descriptive statistics of inputs, outputs and environmental factors.

	All listings		Airbnb		HomeAway	
Variables	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Panel A. Inputs						
Number of guest rooms (GR)	2.01	1.21	1.98	1.23	2.15	1.10
Guest capacity (GC)	4.80	2.23	4.80	2.25	4.80	2.16
Number of photos (Ph)	30.01	18.51	31.04	19.34	24.38	11.65
Minimum stay (MS)	4.04	2.06	3.73	1.94	5.72	1.88
Panel B. Outputs						
ADR ($)	117.71	95.76	118.37	101.01	113.47	50.01
Occupancy rate (OR) (×100)	42.82	34.22	43.77	34.12	37.69	34.32
Number of bookings (NB)	3.23	2.21	3.37	2.27	2.36	1.56
Overall rating (OvR)	4.71	0.39	4.71	0.35	4.69	0.58
Panel C. Environmental factors						
Guest room productivity	746.50	610.73	741.48	617.43	776.71	568.33
Market share (×100)	0.026	0.027	0.026	0.028	0.027	0.019
Multi-unit hosts	0.649	–	0.757	–	0	–
Lockdown (=1, 0 otherwise)	0.19	–	0.19	–	0.19	–

Notes: Descriptive statistics are reported for the pooled sample. ADR is the average daily rate of the listing (including cleaning fees). There are not multi-unit hosts in HomeAway in our sample.

idiosyncratic term, σ_v, the standard deviation of inefficiency, σ_u, the number of total listings, and the Akaike information criteria (AIC) divided by the number of total observations in the panel (N). All estimates were obtained using LIMDEP v.11 econometric software. The simulation process to estimate the random parameter model was based on 1000 Halton draws, which can be roughly equivalent to random simulations of several hundred draws (Greene, 2005).

Based on the results for the random parameter model, which is clearly preferred in terms of the AIC criteria, the estimated model presents interesting results with regards parameter estimates.

Firstly, the non-random parameters related time effects (Panel A), which are related to the technological change, are both statistically significant at the 1% level, indicating their relevance to explaining the occupancy rate. Moreover, the coefficient for the time effect is positive, although the positive effect in the quadratic term indicates that the technological change increases more than proportionally over time. This result could indicate that listings are driven by technology improvements, but rather by managerial procedures.

Secondly, the coefficients of the mean of the underlying truncated normal distribution (Panel B) are all statistically significant at the 1% level. Also, the productivity variable (in logs) has a positive impact on inefficiency, indicating that an increment in productivity increases inefficiency in our case. The coefficient for the market share is negative indicating that an increase in the market quota decreases inefficiency. HomeAway and Spanish lockdown period coefficients are positive indicating that inefficiency of HomeAway is greater than Airbnb, and the crisis period increased the inefficiency. Finally, the coefficient for the linear time trend is positive showing an increase of inefficiency during the period.

Thirdly, the standard deviations for the inefficiency and idiosyncratic terms are statistically significant (Panels C and G, respectively), indicating that the random parameter model is adequate. It is worth noting that the quotient between the two standard deviations, $\lambda = \sigma_u/\sigma_v$, is equal to 0.19, which indicates that σ_v is greater than σ_u, or in other words that the inefficiency term is less relevant than the noise term. In addition, $\sigma_u^2/(\sigma_u^2 + \sigma_v^2) = 0.34$.

Fourthly, Panels D and E show estimates for the random parameters without including heterogeneity effects (q_i). The random parameters were assumed to follow a standard normal random variable, and the final estimated coefficients were for the constant term and some relative inputs (mainly guest rooms, number of photos and minimum stay against guest capacity). Regarding the results, some comments can be made. On the one hand, we can distinguish the fixed constant terms in the means of the distribution for the random parameters for inputs (Panel D) and the scale parameters in the Eq. (2) (Panel F). As can be seen, there are statistically significant fixed constant terms ($\overline{\beta}$) for the means of random parameters, which is to say they cannot be considered equal to zero.

Table 4 shows the main descriptive statistics for the efficiency scores (mean, standard deviation, maximum and minimum, and several percentiles including the median) for all listings and restricted to Airbnb and HomeAway listings, respectively. These scores were computed following the approach suggested by Jondrow et al. (1982) (see Eq. (6) in Greene, 2005). In the table, we can observe 87% median efficiency scores for all listings and 78% mean efficiency, indicating a skewed-to-the-left distribution. In median terms, the efficiency scores indicates that these listings tend to be relatively well-managed enterprises in terms of their resources. Finally, we can say that efficiencies scores are high in the pre-COVID period (78% on average) and also in the intra-COVID period (77% on average).

Fig. 2 analyse the patterns of the distribution of efficiencies for the listings in both the Airbnb and HomeAway platforms. Fig. 2 shows the year-by-year boxplot, summarising the distribution of the efficiency estimates for both the Airbnb and HomeAway listings. The figure offers a picture of the evolution of the empirical distribution of efficiencies over time. To interpret it accordingly, it should be borne in mind that the box portion represents the first and third quartiles (middle 50% of the cost efficiency data), the median is depicted by a line through the centre of the box and the data points outside the inner fence are outliers. The time-varying efficiencies estimated by the random parameter model show that these efficiencies are skewed to the left. Importantly, part of the period analysed in the present study corresponds to the Spanish lockdown due to the COVID-19 pandemic (months 3–6 in year 2020) when median efficiency was lower than the rest of the period for HomeAway, but remained almost unchanged for Airbnb. As can be seen, the interquartile rank increased in April 2020 in the HomeAway listings. In general, the results show that the lockdown more negatively impacted listing efficiency for HomeAway than for Airbnb. The result for HomeAway could be explained by an extremely sub-optimal use of their resources during this period, mainly due to the decrease in the occupancy rate as a consequence of the restriction to peoples' movement. However, Airbnb was not so affected by the lockdown possible due to its higher performance values in the pre-pandemic period.

Fig. 3 plots the median efficiency trends over the study period for listings managed by single- and multi-unit hosts. As can be observed, there are relevant differences in the efficiency of listings managed by one and another type of host. For example, the median efficiency for multi-unit hosts (88%) is clearly above the median efficiency for single-unit hosts (74%), clearly indicating that properties are better managed by professionals than by microentrepreneurs.

Table 3
Panel data estimates for the translog stochastic input distance frontier model.

	Standard model (fixed parameters)		Random parameter model	
Variables	Coefficient	p-value	Coefficient	p-value
Panel A: Non-random parameters				
Constant	3.99846***	0.00	–	–
log ADR	-0.2557**	0.02	-0.2423***	0.00
log OR	-0.015	0.67	0.0651***	0.00
log NB	-0.012	0.59	0.0322***	0.00
log OvR	-6.6770***	0.00	-1.4826***	0.00
log GR*	0.2761	0.11	–	–
log Ph*	1.0244***	0.00	–	–
log MS*	0.0872***	0.00	–	–
log ADR^2	-0.0044	0.86	0.0232***	0.00
log OR^2	-0.0059	0.61	-0.0219***	0.00
log NB^2	0.0367*	0.09	-0.0385***	0.00
log OvR^2	4.7129***	0.00	1.1750***	0.00
log GR2*	-0.2782	0.11	-0.2873***	0.00
log Ph2*	-0.4094***	0.00	0.2322***	0.00
log MS^2*	-0.0871***	0.00	0.8406***	0.00
Time	-0.0026	0.41	0.0032***	0.00
$Time^2$	0.0003	0.27	0.0003***	0.00
Panel B: Mean of the underlying truncated normal distribution				
Constant	-1.3481	0.88	-0.1452***	0.00
Time	0.0002	0.97	0.0551***	0.00
log of Guest rooms productivity	-0.0039	0.99	0.0045***	0.00
Market share	-6.5019	0.80	-1.2757***	0.00
HomeAway	0.0750	0.89	0.4455***	0.00
Spanish lockdown	-0.0643	0.35	0.1827***	0.00
Panel C: Standard deviation of the half-normal distribution (u_{it})				
log of the standard deviation	–	–	-1.6646***	0.00
Panel D: Means for random parameters				
Constant	–	–	0.7113***	0.00
log GR*	–	–	0.4229***	0.00
log Ph*	–	–	-0.0507***	0.00
log MS*	–	–	1.2117***	0.00
Panel E: Scale parameters for distributions of random parameters				
Constant	–	–	0.3694***	0.00
log GR*	–	–	0.3688***	0.00
log Ph*	–	–	0.0058***	0.00
log MS*	–	–	0.4422***	0.00
Panel F: Standard deviation from symmetric disturbance v_{it}				
σ_v	–	–	0.0472***	0.00
Panel G: Standard deviation from inefficiency and λ				
σ_u	0.2643***	0.00	0.0081	–
λ	0.7057***	0.00	0.4283	–
Number of listings	130		130	
Number of total observations (N)	2183		2183	
Log L	204.56		6689.61	
AIC/N	-0.165		-6.102	

Notes: log is the natural logarithm. $\lambda = \sigma u/\sigma v$. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively. The total number of parameters estimated is 22 for standard stochastic translog and 26 for random parameter model. Log L is the simulated maximum likelihood value. AIC is the Akaike information criteria. N is the number of total observations. Between brackets appears p-value. It is interesting to note that fixed model and random parameter models do not improve the logarithm function at iterations 201 and 21, respectively, and the derivatives were quite small at this point. It is mainly due that the log likelihood is relatively flat near the maximum. This suggest that the optimisation has not failed. Hence, we have taken the estimates as given (see, for example, LIMDEP v.11 Reference Guide, pages R-633 and R-700, respectively).

Table 4
Efficiency scores for the whole sample and for the two online platforms.

	All listings	Airbnb	HomeAway
Mean	0.78	0.81	0.61
Std. Dev.	0.18	0.17	0.18
Minimum	0.15	0.15	0.09
25th	0.64	0.70	0.49
Median	0.87	0.88	0.60
75th	0.93	0.94	0.66
Maximum	0.98	0.98	0.98

5. Discussion

Efficiency is one of the most important factors of management control and is essential to optimise performance. Listing managers are fundamental for efficient operations and need a range of skills (e.g., guest experience and customer relations, revenue and budget management, familiarity with the latest accommodation technologies, among others). In short, listing managers must strategize long-term solutions to make their business viable. Therefore, sources of inefficiency must be identified so that listing managers can address deficiencies and thereby enhance performance.

One way to detect such problems is to apply production or cost efficiency methods to estimate efficiency scores for the business in question. The few contributions analysing the P2P accommodation efficiency in the scientific literature have adopted the production approach (Zekan et al., 2019; Zekan and Gunter, 2022; Pérez-Rodríguez and Hernández, 2022). This paper also adopts a production approach because of data availability limitations. Nevertheless, we disentangle efficiency from technological heterogeneity.

The method and results presented in this paper have certain interesting theoretical and practical implications for the study of technical efficiency in the P2P lodging sector.

5.1. Theoretical implications

This paper is the first to conduct an analysis considering the assumption that not all listings operate under the same production possibilities frontier and the same technology. Based on strategic management theories (Arbelo-Pérez et al., 2020; Arbelo et al., 2021), we assume that different technologies coexist simultaneously in firms of the same industry due to the presence of accommodations managed by different types of manager (i.e., single-unit hosts or microentrepreneurs, and multi-unit hosts or professionals). Then, it is expected that units with different types of managers will have different production and cost technologies and therefore different performances.

Our study describes listing efficiency adequately and proves the suitability of the random parameter stochastic frontier model as a tool to analyse the technological heterogeneity of P2P accommodation efficiency, as other papers have also previously shown for the hotel industry (e.g., using the random parameter model of Greene (2005), see (Barros et al., 2010); or (Arbelo-Pérez et al., 2020) and (Arbelo et al., 2021) using a Bayesian approach; among others). Therefore, our model identifies heterogeneous variables (e.g., the constant term and relative inputs such as guest rooms, number of photos and minimum stay against guest capacity) and separates technological heterogeneity and time-varying efficiency, but also obtains evidence from some environmental factors explaining inefficiency such as time effect, productivity, market share, the specific online platform, and lockdown due to the COVID-19 pandemic. Another noteworthy point is that we consider a multi-input and multi-output technology using an input distance stochastic frontier model in a flexible translog panel data model.

The estimates show that multi-unit hosts are more efficient than single-unit host. This result agrees with previous empirical efficiency analysis for different European cities (Zekan and Gunter, 2022). However, other previous efficiency estimates for the P2P accommodation

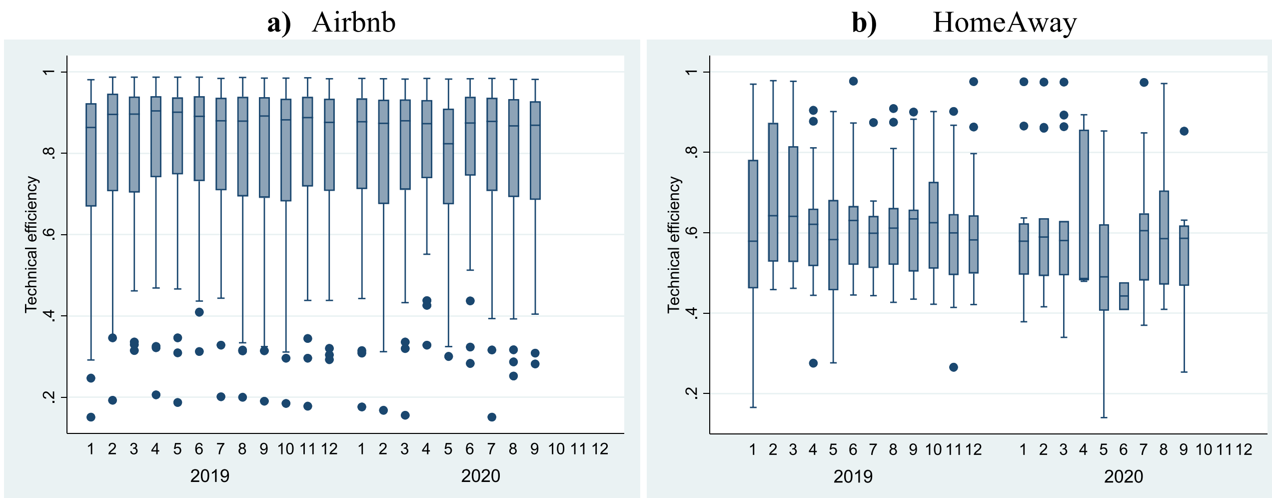

Fig. 2. Time path of distribution of estimated technical efficiencies over time.

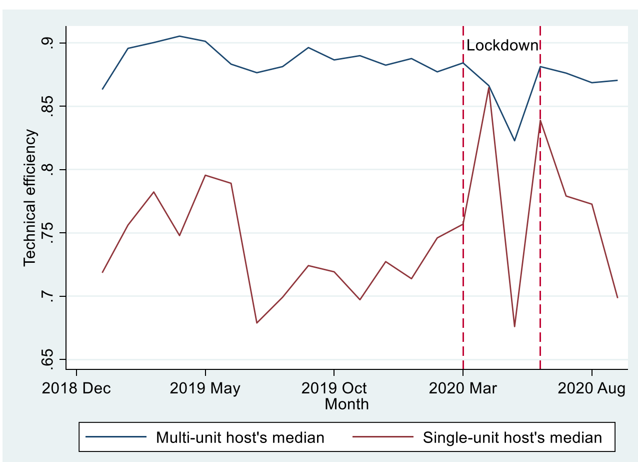

Fig. 3. Time-path of median technical efficiencies by month for listings managed by single- or multi-unit hosts.

industry in the Canary Islands finds that single-unit hosts are more efficient than multi-unit hosts (Pérez-Rodríguez and Hernández, 2022). In this regard, aside from non-including technological heterogeneity in the model formulation as we have considered in this paper, the model of Pérez-Rodríguez and Hernández (2022) takes revenue as the sole output. Then, the fact of including three non-monetary outputs (occupancy rate, number of bookings and rating) in our model substantially changes the most efficient type of host. The negative effect of guest room productivity (revenue/number of guest rooms) on efficiency also shows the key role of the non-monetary outputs in determining the most efficient listings. When considering both monetary and non-monetary outputs, our findings point to a better global performance of multi-unit hosts than microentrepreneurs managing just one single unit.

We observe that mean efficiency slightly decreased in the intra-COVID with respect to the pre-COVID period, also reducing the maximum efficiency (98% and 97%, respectively). It should also be highlighted that Airbnb show higher efficiency results than HomeAway over the whole period. One of the reasons of the lower efficiency scores for HomeAway is its lower occupancy rates and number of bookings. Moreover, after irruption of COVID-19, median efficiency scores for HomeAway show a time-varying decreasing pattern, due to the clear decrease in the occupancy rate and the difficulties to quickly adjust some inputs, such as the number of guest rooms. This is an interesting aspect which implies non-systematic management problems (low efficiency scores) during the lockdown period (March 2020 – June 2020).

5.2. Managerial implications

Our results show that Airbnb and HomeAway have, on average, high efficiency scores (78%). However, there is still room for improvement in management and the optimal allocation of resources in that 22%.

The efficiency scores of the P2P accommodation sector are lower than those obtained for the hotel sector in the Canary Islands, which is highly professionalised. For example, a recent study by Pérez-Rodríguez and Acosta-González (2021), using the metafrontier approach to account for hotel heterogeneity in the Canary Islands in the 2002–2015 period (mainly due to environmental characteristics such as size and ownership), found that, on average, efficiencies were above 90%. Recent papers have pointed out that P2P and hotels are substitute markets in this region (e.g., Jiménez et al., 2022; Suárez-Vega et al., 2022, among others). Therefore, listing managers can make efforts to increase the efficiency of their managed properties in order to improve competition of their properties with regard to hotels.

More specifically, listing managers can improve time-varying efficiency through several environmental variables. Some papers analysing other accommodation industries (e.g., hotels) have found that labour productivity was a relevant factor to explain cost inefficiencies in the hotel sector in the Canary Islands (Pérez-Rodríguez and Acosta-González, 2007). In our case, we used guest room productivity. However, the effect of this factor on efficiency is negative. Then, managers cannot take this variable into account if they want to improve global efficiency of properties, but others such as the market share of each listing in the P2P market. The larger the size of the property (in economic terms) is, the more the resources of the property are optimally managed. This result points to the existence of economies of scale in the P2P accommodation industry.

The global evolution of this sector shows a clear trend to management professionalisation. In this context, the results of this paper show that the optimum utilisation of resources and capabilities in terms of not only revenue but other non-monetary aspects, such as the occupancy rate and customer satisfaction, is obtained by means of a professionalized management. Therefore, microentrepreneurs or single-unit hosts can improve their efficiency by adopting more professionalized practices or letting their properties to be managed by more experienced multi-unit hosts.

Other more technical strategies to improve efficiency could be to adopt a benchmark management procedure in which managers compare their efficiency with the frontier of best practices, consider year-by-year changes in strategies for revenue and budget management, analyse the industry competition and/or create appropriate pricing strategies, or upgrade the quality of their management procedures to achieve greater efficiency, among other possibilities.

6. Conclusions

Until recently, the stochastic frontier models applied to tourism have commonly ignored heterogeneity. This paper contributes to this line of research by considering an explicit model for P2P accommodation heterogeneity using a multi-input and multi-output technology framework by modelling the input distance stochastic frontier model. To do this, we used the random parameters model of Greene (2005), which preserves the central feature of the stochastic frontier model and accommodates heterogeneity. The empirical analysis is based on data for Airbnb and HomeAway listings in the Canary Islands (Spain), which is a major sun-and-beach destination for European travellers. The analysis was conducted for before and after the lockdown of the Spanish economy due to the COVID-19 pandemic.

The results show evidence of technological heterogeneity and the presence of time-varying technical inefficiencies among the Canary Islands listings in the P2P market, which were more intense in the COVID-19 period. Therefore, tourism policies designed to increase P2P accommodation efficiency must take this technological heterogeneity into account.

The efficiency scores indicated that Airbnb and HomeAway listings in the Canary Islands had an average of 78% technical efficiency during the overall study period (January 2019 to September 2020). Consequently, it can be deduced that their operational activities are highly efficient. However, the median efficiency was high and not constant over the pre COVID-19 period, but decreased during the lockdown of the Spanish economy from March 2020 to June 2020, slightly for Airbnb and pronouncedly for the HomeAway platform. This implies that the operational activity was less efficient during the lockdown period, mainly due to a sudden decrease in the outputs (e.g., occupancy rate) combined with slow adjust of some inputs (e.g., number of guest rooms). This result is clearly corroborated by the model given that the coefficient for the variable representing the COVID-19 crisis period was positive, indicating an increase in the technical inefficiency of listings.

Certain limitations to the present study should be acknowledged. First, due to data limitations, the study period is not very long and the number of properties few. In future studies on P2P accommodation sector efficiency, it would be useful to expand not only the time interval, but also the number of listings. Second, it would be also helpful to analyse a random cost frontier model together with more listing-specific determinants in the analysis. They were not studied in this paper due to the lack of available data regarding prices of inputs and total operational costs. Third, if we focus on input orientation, we should address the endogeneity of inputs by developing a system approach considering a cost minimisation setup (Kumbhakar and Wang, 2006) and using data of prices. Finally, other econometric methods could be employed such as the Bayesian approach (Tsionas, 2002) or transient vs. persistent efficiency in P2P, in order to enrich the analysis and enhance the investigation.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

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