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A spatial stochastic frontier model at the P2P listing level

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ABSTRACT

This paper presents a novel approach to account for spatial effects in the estimation of the efficiency of peer-to-peer (P2P) accommodation units. Specifically, in a stochastic frontier approach, it analyses the correlation effects (spatial dependence of inputs and outputs) on the frontier itself, the noise term (e.g., unobserved but spatially correlated variables) and the inefficiency term (e.g., agglomeration or competition effects). To do so, a spatial efficiency model recently developed in the econometric literature is used. From this model, direct and indirect marginal effects on inefficiency for each listing can be calculated for the inputs and environmental factors. Geographical patterns of the spatial effects of the inputs and determinants among listings can thus be detected, providing researchers and practitioners with granular geographical information on the spatial heterogeneity of efficiency in the sample. The model was applied to the P2P lodging market in the Canary Islands, Spain.

1. Introduction

The analysis of the economic performance of the tourism industry has attracted the interest of scholars for the last two decades (Assaf & Tsionas, 2019). In this regard, the efficient use of resources in a firm can lead to benefits not only for the firm per se, but for other neighbouring firms through spillover effects. Several studies have revealed spatial effects in different aspects of the P2P industry, such as price fixation (Tang et al., 2019) and performance analyses (Yang & Mao, 2020). However, the previous literature on efficiency in the P2P lodging market has not taken into account spatial effects (e.g., Zekan et al., 2019; Alberca & Parte, 2020; Pérez-Rodríguez & Hernández, 2023a,b; among others), due mainly to the absence of meaningful spatial dimension in their data sources.

An exception is the study of Pérez-Rodríguez et al. (2024), which conducted an analysis of the determinants of efficiency from a spatial point of view. The study used a classical non-spatial efficiency estimation model and investigated the determinants of efficiency in a two-stage procedure using a spatial autoregressive model. However, when using a stochastic frontier (SF) approach, it is important to note that correlation effects (spatial dependence of inputs and outputs) can affect the frontier itself, as well as the noise term (e.g., unobserved but spatially correlated variables) and the inefficiency term (e.g., agglomeration effects). It is not enough to focus on spatial effects on determinants.

Given that the above aspects can affect the estimation of the efficiencies of listings, this paper employs a recent spatial stochastic frontier (SSF) model developed in the theoretical econometric literature on efficiency and applies it to the case of the P2P industry. This methodological innovation in tourism research has relevant theoretical and managerial implications, as described below.

Focusing on the methodological aspects, the main contribution of this paper is twofold. First, the use of a spatial panel data procedure is proposed to analyse the efficiency of P2P listings and its determinants in a one-step procedure. The model, which includes both frontier and error-based spatial cross-sectional dependence at the listing level (Galli, 2023a), constitutes an extension of the model proposed by Orea and Álvarez (2019) which introduced the spatial lag effect only in the error terms. Through this extension, the model additionally allows estimation of the spatial effects in the endogenous and exogenous variables as well as in the error terms. Second, the model allows the measurement of individual and aggregate direct and indirect (spatial spillover) marginal effects of the input factors and determinants of inefficiency. It should be noted that, unlike in spatial literature, we construct individual marginal effects to detect areas/elements where changes in inefficiency or outputs

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depend more on own characteristics and areas where neighbouring decisions are more influential. These effects, which have not been jointly analysed in efficiency studies until now, are geographically located and, in this way, hot and cold spots with higher and lower spatial effects, respectively, can be identified.

The integration of spatial spillovers in an efficiency analysis extends existing theories of firm performance and spatial competition in the field of tourism. Specifically, the paper contributes to competition theory and agglomeration effects in tourism (Canina et al., 2005; Marshall, 1920; McCann & Folta, 2009) as the spatial model allows for the detection of spillover effects of efficiency between neighbouring P2P listings, extending classical spillover effects (e.g., knowledge, technology diffusion and R&D) to those related to the efficient use of resources. Moreover, the model allows the quantification of external benefits or costs arising from proximity to other efficient or inefficient listings. This makes it possible to distinguish between positive (learning, shared reputation) and negative (saturation, price competition) spillovers on the efficiency of a firm, thereby refining the understanding of agglomeration effects.

This study also contributes to the resource-based view (RBV) theory of a firm (see Wernerfelt, 1984; Barney, 1991; Conner, 1991; for an overview), an underexplored area in tourism research (Kruesi & Bazelmans, 2023). In particular, the identification of spatial spillover effects on efficiency supports the extended RBV, which stresses the role of external resources in the competitive advantage of firms (Knoben, 2011). In this regard, the geographical location of a listing can be a source of competitive advantage, comprising a potentially valuable, rare, inimitable and/or non-substitutable resource.

The inclusion of spatial spillover effects in an efficiency analysis also has relevant managerial implications. The geographical information based on individual marginal effects can be used by investors, hosts, platform managers and policymakers to design location-based investment, management and regulation strategies. For example, knowledge of the spatial effects can be used to invest in lodgings located in so-called hot spots or high-efficiency areas and to redefine the product to take advantage of the positive and counteract the negative spillover effects in the area where the lodging is located. The spatial effects can also help to understand why some hosts are systematically more efficient than others, even with similar internal resources. Policymakers can use the spatial information for the implementation of zoning policies and promotion programs, as well as the design of market entry strategies based on areas with positive spillovers. Finally, such information could help regulators identify vulnerable or saturated areas, where negative spillovers affect the sustainability of the P2P model.

The empirical analysis focuses on the P2P accommodation market in the Canary Islands (Spain). The database contains monthly information on Airbnb listings operating on the islands during all months from January 2019 to September 2020. The proposed spatial panel data model is estimated with maximum likelihood (ML) estimators which are used to construct aggregated and individual marginal effects for input variables as well as environmental variables in the inefficiency equation.

The rest of this paper is organized as follows. Section 2 briefly reviews the relevant literature on efficiency in the P2P market and on spatial efficiency modelling. Section 3 describes the SSF model. In Section 4, the data and variables of the model are presented. Section 5 describes the empirical analysis and presents the results. Finally, Section 6 presents a discussion of the findings and the conclusions drawn from the study.

2. Literature review

This section starts with an overview of the methods that have been used to estimate P2P efficiency. Next, a review of how spatial effects have been included in tourism and hospitality contexts, both statistically and econometrically, is presented. The final subsection presents an overview of recent literature on SSF approaches and the gap this study intends to fill.

2.1. Efficiency in the P2P accommodation market

The academic literature on economic efficiency in the P2P accommodation sector is not very extensive, with differing results on P2P efficiency. The few studies conducted have essentially adopted two different approaches to efficiency estimation.

2.1.1. Non-parametric techniques

Firstly, the production frontier has been analysed using non-parametric data envelopment analysis (DEA) (e.g., Zekan et al., 2019; Zekan & Gunter, 2022) and robust non-parametric methods (Pérez-Rodríguez et al., 2024). In one of the first contributions, Zekan et al. (2019) examined the efficiency of listings in several European cities. The methodological strength of this article was in its application of interactive DEA modelling, allowing benchmark appearances of the results. Subsequently, Zekan and Gunter (2022) included hotel-related data in an efficiency analysis of 28 European cities using a non-parametric DEA method. They analysed efficiency for single- and multi-unit hosts (also called non-professional and professional hosts) and found listings managed by the former to be generally less efficient than those managed by the latter.

2.1.2. Parametric techniques

Efficiency in the P2P market has also been analysed using an SF approach, disentangling unobserved heterogeneity and time-varying efficiency in a panel data framework. For example, Pérez-Rodríguez and Hernández (2023a) used a parametric approach based on a panel data SF model to analyse the time-varying technical efficiency of P2P properties in the Canary Islands (Spain). The authors included several dummies representing different types of accommodation and levels of professionalism. In contrast to Zekan and Gunter (2022), their study found listings managed by professional hosts to be generally less efficient than those managed by non-professional hosts. In a further study, Pérez-Rodríguez and Hernández (2023b) analysed P2P efficiency considering technological heterogeneity. They used an input distance SF model with random coefficients to include both multi-input and multi-output technology and technological heterogeneity among listings. Through an empirical analysis based on monthly data from P2P listings in the Canary Islands (Spain) between 2019 and 2020, they found a negative dependence on productivity of technological heterogeneity between listings and time-varying inefficiency. In addition, type of accommodation and location, as well as other external determinants such as the degree of competitiveness, also negatively influenced technological heterogeneity. As in Zekan and Gunter (2022), in this case the authors also found professional hosts to be more efficient than non-professional ones.

2.2. Spatial effects in tourism and hospitality

Spatial effects in tourism and hospitality (e.g., tourism regions, hotels, P2P listings) have been studied using both statistical and econometric approaches.

2.2.1. Statistical approaches

Various statistical approaches have been used which involve the visualization and analysis of spatial patterns. These include, among others, exploratory spatial data analysis (ESDA), geographically weighted regression (GWR), and quadratic assignment procedure (QAP) regression analysis. For instance, Gutiérrez et al. (2017) employed an ESDA to explore the differences between the determinants of location for hotels and Airbnb listings in Barcelona city (Spain). Gyódi (2024) also studied the spatial patterns of Airbnb offers, hotels and attractions for various European cities using an ESDA. Lagonigro et al. (2020) used GWR to determine the effect of socioeconomic factors such as family income, education level and property size, when explaining the variation in the proportion of Airbnb short-term rentals in different districts of the city of Barcelona. More recently, Tan et al. (2024) and Liao et al. (2024) analysed spatial effects on efficiency using a QAP regression analysis. In the first of these two papers, both of which focused on China, the authors considered a possible spatial correlation with respect to tourism productivity among regions as well as structural characteristics. In the second, the authors considered the influencing factors of a spatial correlation network for tourism environmental efficiency.

2.2.2. Econometric approaches

Spatial econometric models are useful when spatial dependence exists in both the dependent variable and the independent variables. In other words, when a spatial and temporal dependence or interrelationship occurs between different units due to their location (i.e., spillover effects) not only in dependent variables but also in influencing factors. The main objective of the spatial analysis is to study both spatial patterns and determinant factors related to competition and agglomeration effects. The determining factors commonly used in empirical studies include, among others, the number of Airbnb or hotel beds, the employment rate, the number of attractions (e.g., shopping, natural or cultural attractions, etc.), per capita value-added growth rate, the labour force, international arrivals, and tourism territorial pressure.

An analysis of the literature shows that two types of econometric method have been used to date: classic econometric models and spatial econometric methods.

2.2.2.1. Classic econometric models. Classic econometric models include spatially-defined variables in the modelling or the use of statistical corrections which account for spatial dependence. Gan and Hernández (2013) considered potential agglomeration and spatial competition effects on hotels, using switching regression to model a price and occupancy rate equation. They found tacit collusion when hotels were clustered in Texas (USA), though the collusion did not hold when they were scattered. Balaguer and Pernías (2013) analysed the relationship between spatial agglomeration and both price level and price dispersion for businesses and tourism consumers in Madrid (Spain). They considered the spatial nature of the framework and took spatial heteroskedasticity and autocorrelation consistent (SHAC) estimations into consideration following Kelejian and Prucha (2007). They found lower average prices and less price variance with higher spatial agglomeration in hotels. Li et al. (2015) studied the spatial associations of urban tourism phenomena using a geographic information system (GIS) and logistic regression to examine the relationships between hotels and land use types, attractions, transportation facilities, and the economic variables of the tertiary planning units in which the hotels were located. Önder et al. (2019) studied spatial price dependencies between the traditional accommodation sector and the sharing economy using hedonic price regression models. Voltes-Dorta and Inchausti-Sintes (2021), with similar variables to those employed by Önder et al. (2019), used a log-linear specification to analyse the spatial and quality dimensions of the Airbnb market in the UK.

2.2.2.2. Spatial econometric methods. Spatial econometric methods include, for example, the spatial Durbin model (SDM), which considers the effect of the spatial lag on the dependent variable and the independent variables. The SDM can be considered a nesting model for other spatial regression models, such as the spatial autoregressive regression (SAR) (which only considers the effect of the spatial lag on the dependent variables) and the spatial error model (SEM) (see LeSage & Pace, 2009; for an overview). Note that these models can be extended to a dynamic framework by including time-lagged and spatially-lagged dependent variables. Numerous papers have investigated spatial effects in tourism and hospitality using such methods. For example, Zhang (2009) studied the spatial distribution of inbound tourism in China analysing several determinants of a region's international inbound tourism and the competition and complementarity between regions. Deng and Athanasopoulos (2011) modelled Australian domestic and international inbound travel using an SAR-based spatial-temporal approach. The authors allowed the strength of spatial autocorrelation to exhibit seasonal variations and allowed for the possibility of asymmetry between capital-city neighbours and non-capital-city neighbours. Yang and Wong (2012) modelled spillover effects in tourism flows in China considering a spatially-lagged dependent variable (SAR model). Liu (2020) analysed the effect of habit persistence and word-of-mouth (WOM) on tourism destination demand in Taiwan. Using a spatial dynamic panel data model and considering time-lagged and spatially-lagged dependent variables, the effect of WOM on Taiwan domestic tourism demand was found to be negative.

Chhetri et al. (2017) used spatial econometrics techniques (SEM) to model the spatial clustering of tourism and hospitality employment in Victoria (Australia). With respect to P2P accommodation, Eugenio-Martín et al. (2019) analysed the spatial distribution and location for Airbnb and hotels in the Canary Islands (Spain), considering sun and beach, nature-based and city tourism destinations. Using an SAR model, they found that hotel location was the best match for tourism attractions in sun and beach areas, but that the location of the Airbnb supply matched tourist attractions better in cities and nature-based tourism areas. In their analysis of Airbnb demand in New York City, Gunter et al. (2020) used a one-way fixed-effects SDM to estimate price and income elasticities, while Boto-García et al. (2021) considered spatial price mimicking on Airbnb, distinguishing between multi-host and single-hosts in Barcelona (Spain) using an SAR model. More recently, P2P accommodation demand was also studied by Suárez-Vega et al. (2023) using a dynamic SDM (D-SDM), in the Canary Islands (Spain), with a substitution effect found among neighbouring listings.

2.3. Spatial effects on efficiency

Spatial effects on efficiency have also been studied using spatial econometric methods. We distinguish between models based on non-parametric and parametric approaches.

2.3.1. Non-parametric approaches

Employing a non-parametric technique, Pérez-Rodríguez et al. (2024) applied a two-stage procedure to study several factors explaining the inefficiency of P2P accommodation units. They first estimated efficiency using an order-m robust non-parametric frontier analysis to detect superefficient, fully efficient, and inefficient properties. They then applied an SAR model to identify the spatial factors that influence the production efficiency. They found that competition and professionalization negatively influenced listing efficiency while agglomeration had a positive effect. Chiu et al. (2024) investigated the spatial effect of operational performance on China's regional tourism system using a panel data of 30 provincial-administrative regions. The authors first estimated the operating performance of each regional tourism system and its tourist stages using a slacks-based measure dynamic network DEA (SBM-DNDEA) model. They then investigated the spatial effect of regional tourism system operational performance and its influencing factors using the Tobit-SDM.

2.3.2. Parametric approaches

With respect to parametric approaches, and in particular SF models, it should be noted that numerous extensions of these models have been made in recent years to account for spatial dependence and spatial spillover effects on the efficiency of several industries. These include agriculture (Areal et al., 2012; Druska & Horrace, 2004; Schmidt et al., 2009), banks (Kutlu, 2022), chemical firms (Kutlu et al., 2020) and wineries (Vidoli et al., 2016). Other specific non-industrial topics have also been considered, such as the capital investment model in Taiwan (Wang & Ho, 2010) and Spanish provinces (Gude et al., 2018), among others (see Orea & Álvarez, 2019, for a general review).

Some authors have proposed methodologies that relate spatial econometrics with SF analyses to construct SSF models. For example, Glass et al. (2016) built a spatial Durbin stochastic frontier model (SDSFM) which included both global and local spatial dependence, Tsukamoto (2019) used an SAR model including both the spatial lag of endogenous variables and a model for the determinants of the efficiency of firms, while Kutlu et al. (2020) considered endogenous frontier and environmental variables in an SSF model. However, a new SF model which differed from the previous ones was developed by Orea and Álvarez (2019). In their paper, the SEM structure is adopted in the form of a spatial moving average (SMA) model, allowing for spatial correlation in both the noise and inefficiency terms. This novel model can be straightforwardly estimated through ML and non-linear least squares methods. More recently, Galli (2023a) extended the Orea and Álvarez (2019) approach by modelling the frontier function or the inefficiency error term through the introduction of spatial components. This paper combined the SDM and SMA approaches, obtaining a full and comprehensive specification that introduces different sources of spatial cross-sectional dependence affecting outputs, inputs, and the idiosyncratic and inefficiency errors in the model. Most notably, the model allows the capture of global and local spatial spillover effects while controlling for spatial correlation related to listing unit efficiency and to unobserved but spatially correlated variables.

To our knowledge, only one paper has been published investigating spatial efficiency and employing an SF approach. Using a Cobb-Douglas model, Galli (2023b) applied the SDM approach with spatial spillovers in efficiency to the Italian accommodation sector to estimate spatial efficiency, reporting the relevance of the model in capturing labour productivity and knowledge spillover effects. The model was similar to that proposed in Galli (2023a) but without considering spatial lags for the error terms. In this case, to model the spatial effects on the errors associated with inefficiency, the author proposed a spatial lag model on the determinants rather than an autoregressive model. The model revealed that geographic proximity enhances efficiency, especially through labour productivity and shared experience.

The main limitation of many of the above cited papers conducting efficiency analyses is that they do not allow for spatial dependence and spatial spillover effects in the estimation of the efficiency of accommodation units. The inclusion of these spatial effects would avoid biased estimates of efficiency and its determinants, which, for example, could not be avoided using two-step procedures (Orea & Álvarez, 2019). In this regard, our paper fills an existing gap in the literature, analysing the spillover effects in the P2P accommodation sector using an SSF-based analysis of efficiency. We therefore assume that emulation behaviour due to spatial proximity (Areal et al., 2012) can be present in the P2P market in terms of efficiency, both in the stochastic frontier and technical inefficiency.

3. Spatial efficiency stochastic frontier (SF) model

In this section, we describe the spatial lags SF model developed by Galli (2023a) that generalizes the Orea and Álvarez (2019) SSF model which accommodates spatially-correlated inefficiency and noise terms. Then, we distinguish the aggregated and individual marginal effects from this model to construct direct and indirect effects on the stochastic frontier and also inefficiency.

First, we briefly explain the parametric spatial stochastic production frontier model based on the Cobb-Douglas production function.

3.1. The spatial stochastic frontier (SSF) production model

SF models are used to measure the efficiency of productive units and, for a given unit i and a period t, follow the general form:

$$y_{it} = f(X_{it}, \beta) + \widetilde{v}_{it} - \widetilde{u}_{it} \quad [1]$$

where f is a production function relating the inputs used, X_{it}, with the outputs, y_{it}, generated, and β, a vector of parameters. The error in this model has two components, the random component, $\widetilde{v}_{it}$, captures random variations that are beyond the control of the productive unit, and the technical inefficiency, $\widetilde{u}_{it}$, which represents the inefficiency of the productive unit, indicating how much it deviates from the efficient production frontier.

The Cobb-Douglas function:

$$f(X_{it}, \beta) = \beta_0 \prod_{j=1}^{k} x_{j,it}^{\beta_j}, \quad [2]$$

and the translog function:

$$\log(f(X_{it}, \beta)) = \beta_0 + \sum_{j=1}^{k} \beta_j \log(x_{j,it}) + \frac{1}{2} \sum_{j=1}^{k} \sum_{l=1}^{k} \beta_{jl} \log(x_{j,it}) \log(x_{l,it}), \quad [3]$$

are the most common production functions used in SF models. While the translog function is the most flexible because it allows for interactions between inputs, the Cobb-Douglas function is more widely used due to its simplicity, ease of interpretation and the greater efficiency of its estimation (Yao & Liu, 1998).[1]

The general log-linear specification for the Cobb-Douglas production model incorporating the Hicksian neutral technological progress, expressed by the linear trend (t) and a squared time trend (t^2), can be written as follows:

$$\log(f(X_{it}, \beta)) = \beta_0 + \sum_{j=1}^{k} \beta_j \log(x_{j,it}) + \kappa_1 t + \kappa_2 t^2. \quad [4]$$

To model spatial dependence for the outputs and the spatial interactions among inputs for the different units, model [4] can be extended to the following SDM:

$$\log y_{it} = \rho W_i^t \log y_{.t} + \sum_{k=1}^{K} \beta_k \log x_{k,it} + \sum_{k=1}^{K} \theta_k W_i^t \log x_{k,it} + \kappa_1 t + \kappa_2 t^2 \quad [5]$$

where $y_{.t}$ is the outputs vector, ρ is the spatial autocorrelation coefficient for the dependent variable reflecting the effect on the output of the current listings of the neighbours (if $\rho = 0$, the contemporaneous endogenous interaction effects are excluded), θ is the coefficient for the spatial lag for the inputs (if $\theta = 0$ exogenous interaction effects are excluded), and W_i^t is the i-th cross-sectional weight vector reflecting the influence of the neighbouring units over unit i. Elements W_{ij}^t represent the spatial relationship existing, at period t, between the features i and j (e.g., Airbnb properties) verifying that $W_{ij}^t > 0$ for the neighbouring Airbnb listings ($i \neq j$) and elements $W_{ii}^t = 0$.

Then, the SF model using the spatial production function [5] can be written as:

$$\log y_{it} = \rho W_i^t \log y_{.t} + \sum_{k=1}^{K} \beta_k \log x_{k,it} + \sum_{k=1}^{K} \theta_k W_i^t \log x_{k,it} + \kappa_1 t + \kappa_2 t^2 + \widetilde{v}_{it} - \widetilde{u}_{it} \quad [6]$$

Galli (2023a) modified [6] to capture the spatial correlation of the random error and inefficiency terms. Moreover, it can measure global and local spatial spillovers that influence the frontier function. This panel data production SF model can be written including spatial lags in

[1] Note that using the translog production function involves high complexity in calculating marginal effects and estimating, for example, standard errors, as there are no standard econometric software tools available for these computations.

the error terms in the following way:

$$\widetilde{v}_{it} = v_{it} + \gamma W_i^t \widetilde{v}_{.t}$$

$$\widetilde{u}_{it} = u_{it} + \tau W_i^t \widetilde{u}_{.t} \quad [7]$$

where v_{it} is a random variable normally distributed with null mean and constant variance, σ_v^2, γ measures the degree of cross-sectional correlation between the noise term of listings, u_{it} is a random variable normally distributed with null mean and constant variance, σ_u^2, and τ measures the degree of cross-sectional correlation between the inefficiency term of listings.

Orea and Álvarez (2019) pointed out that "while the spatial specification of the noise terms is likely capturing an environmentally induced correlation, the spatial specification of the inefficiency term will likely capture a behavioural correlation" (Orea & Álvarez, 2019, p. 556). In this sense, inefficiency error terms [6] at unit i can be expressed as $u_{it} = h(Z'_{it}\delta)u_t^*$ where Z'_{it} is a vector of variables affecting the inefficiency of unit i, $h(Z'_{it}\delta)$ is a scaling function which models the effects of the determinants Z'_{it} on the inefficiency, δ is an unknown parameter vector reflecting the influence of the inefficiency determinants, and u_t^* is a non-negative random variable following the distribution $N^+(0, \sigma_u^2)$, where σ_u^2 is the constant variance.

In this case, the scaling function $h(Z'_{it}\delta) = \sqrt{\exp(Z'_{it}\delta)}$ proposed by Du et al. (2024) can be used.

Note that, as pointed out in Galli (2023a), using an SF model in a production sector for which the cross-sectional independence fails can lead to either biased estimates for both the model coefficients and the technical efficiencies or to less efficient models due to the ignoring of spatial dependence in the error term. So, when spatial structure exists (for the output, inputs or the error decomposition), a spatial stochastic frontier (SSF) production model is preferable because it both improves the statistical validity of the model and adds analytical value by identifying spatial interrelationships and distinguishing between direct and indirect effects.

A more detailed explanation regarding estimation of the coefficients of the SSF model and calculation of the marginal effects can be found in Appendix A1. Note that the general form considered in the appendix allows the use of different weight matrices for input, output, inefficiency determinants and the idiosyncratic error terms, but for simplicity the same matrix is used in this paper. The same choice was considered in Galli (2023a, 2023b) and Orea and Álvarez (2019) in their applications to different productive sectors.

3.2. Marginal effects for the spatial stochastic frontier production model

3.2.1. Aggregated marginal effects

As Galli (2023a) notes, given that the coefficient of explanatory variables cannot be interpreted as marginal effects because of the spatial lag of the endogenous variable, the marginal effects for explanatory variables can be obtained for both the stochastic frontier specification and the inefficiency term.

3.2.1.1. Marginal effects in the stochastic frontier specification. For a given period t, the marginal effects of input k of unit j over the output i are stored in a $N \times N$ matrix, $M = (m_{ij}) = \left(\frac{\partial y_{it}}{\partial X_{jk}^t}\right)$ (see Appendix A1 for details). For a given unit i, the ith element in the diagonal of M represents the direct effect of input k (effect on output of unit i of changing input k in i) and the non-diagonal elements of row i are the indirect effects of the rest of the units on unit i (effects on outputs of unit i of changing input k on the neighbours). The spatial structure of the marginal effects is independent from the inputs (see formula [A1.4] in Appendix A1). Then, the spatial structure for the individual direct effects is similar for all inputs, even though numerically they are different. The same observation applies to the indirect effects, as the spatial weight matrix is row standardized.

To quantify both direct and indirect effects in these models, the measures proposed by LeSage and Pace (2009) are commonly used. They proposed aggregate measures for the whole sample based on the averages of the individual effects. They defined the aggregated direct effect for regressor k as the average direct effects among the different units (mean diagonal element in M, $DE_k = \frac{1}{N}\sum_{i=1}^N m_{ii}$), and as aggregated indirect effect they proposed the average of the sum of indirect effects for each sample unit (the mean row sum of the non-diagonal elements in M, $IE_k = \frac{1}{N}\sum_{i=1}^N \sum_{j=1, j\neq i}^N m_{ij}$). As can be inferred from the definitions, these are aggregate measures that aim to measure the effects at the global level, ignoring the local effects on each unit. Note that the marginal effects matrix M is independent from period t and the aggregated measures obtained for all the periods coincide with the measurement obtained for a single period.

3.2.1.2. Marginal effects for inefficiency errors. For the inefficiency errors, and assuming the scaling function $h(Z'_{it}\delta) = \sqrt{\exp(Z'_{it}\delta)}$ proposed by Du et al. (2024), the marginal effects for the k determinant of the inefficiency at i, at period t, is given by the $N \times N$ matrix $M^t = \left(m_{ij}^t\right) = \left(\frac{\partial \widetilde{u}_{it}}{\partial Z_{jk}^t}\right)$ (see calculation details in [A1.5] in Appendix A1). Both individual and aggregated direct and indirect effects for the inefficiency regressors for period t, as LeSage and Pace (2009) defined, can be deduced from M^t. In this case, the marginal effects matrix depends on the period t and must be calculated for each period. Similarly, in the case of the marginal effects of the input factors, the spatial structure for the individual direct and indirect effects of the environmental factors depends on the spatial weight matrix, the spatial autocorrelation and the inefficiency autocorrelation terms, but not on the specific estimates of the coefficients.

3.2.2. Individual marginal effects

As mentioned above, the measures of effects used in the literature are considered from a global point of view, not allowing to distinguish different behaviours along the study area. In order to bring the analysis down to the local level, an individualization of the measures of direct and indirect effects is proposed. To do so, for a given unit i, the ith element in the diagonal in M ($DEX_k^i = m_{ii}$) is proposed as individual direct effect for the *k-th* input, and the sum of the non-diagonal elements in row i in M ($IEX_k^i = \sum_{j=1, j\neq i}^N m_{ij}$) as individual indirect effect. Individual direct and indirect marginal effects for the determinants of the inefficiency are calculated similarly using M^t. The individual direct effect for the k inefficiency determinant is defined as $DEZ_k^i = \frac{1}{T}\sum_{t=1}^T m_{ii}^t$ and the individual indirect effect is $IEZ_k^i = \frac{1}{T}\sum_{t=1}^T \sum_{j=1, j\neq i}^N m_{ij}^t$. These new measures make it possible to identify individuals and areas where inefficiency depends mainly on own characteristics, and areas where the effect of neighbouring characteristics is more influential.

4. Data and variables

The data used in the empirical study correspond to the P2P accommodation market in the Canary Islands, one of the most important destinations for European tourists visiting Spain. The tourism supply includes sun and beach tourism and, more recently, urban and rural tourism as well. The P2P hosting sector has increased considerably since its beginnings around the first decade of the 20th century. According to the official statistical database records (ISTAC, 2025), the maximum number of P2P properties offered in the Canary Islands in 2019 was 40, 633 with a capacity of 179,991 beds, representing 45.91 % of the total bed supply in the archipelago.

The Airbnb property data in the Canary Islands were collected monthly from January 2019 to September 2020. A balanced panel considering only those properties with available data for all the months in the period of study was then built. For homogeneity, only listings labelled as 'Housing/complete flat' were considered and, among these, the seven most frequent subtypes (Apartments, Houses, Villas, Cottages, Condominium, Bungalows and Townhouses) were considered, representing more than 90 % of the sample. In order to use natural logarithms for the inputs used to estimate efficiencies, houses with zero values for any of these variables were excluded. The final database contains N = 534 Airbnb listings for T = 21 months, making a total of N × T = 11,214 observations. A situation map and the sample distribution, along with the average revenue (in euros) in the study period, are shown in Fig. 1.

In this paper, the production efficiency of Airbnb properties according to the ability of the listing to obtain revenues derived from the services offered during the reporting period is investigated. In general, the inputs and outputs employed have been used in previous empirical studies on sharing accommodation efficiency. Table 1 presents the list of variables and their definitions.

Following other papers in the empirical literature on efficiency, four inputs and one output were used (e.g., Gunter & Önder, 2018; Zekan et al., 2019; Pérez-Rodríguez and Hernández, 2022; Pérez-Rodríguez & Hernández, 2023a; among others). The inputs are the number of bedrooms (as proxy for fixed capital), the maximum number of guests (as proxy for the size of Airbnb listings), the minimum number of nights to represent the minimum length of stay of guests in the property (and therefore a minimum revenue obtained per reservation) and, finally, the number of photos (as a measure of the public information about the listing). This final input represents the host's service to customers, providing them with useful information relative to the property's facilities. As output, the revenue of the listing was selected. This is an indicator of monetary success in the production of services. It is measured as the total monthly listing revenue in euros and includes cleaning fees but no other additional fees.

As environmental variables affecting listing inefficiency, some determinants proposed by Pérez-Rodríguez et al. (2024) for analysing the spatial effects on inefficiency of Airbnb listings in the Canary Islands were considered. They were generally extracted and estimated from the official statistics database (ISTAC, 2025) and data provided by AirDNA, supported by a geographic information system (GIS) and classified in three groups (managerial, market and socioeconomic factors). First, the managerial factors are Available days and Blocked days (as a measure of the business operation), and Relative professionalism (as a measure of the level of professionality in the surroundings of the focal listing). The common definition of professional host, one managing multiple listings (two or more), was adopted (Pérez-Rodríguez & Hernández, 2023a).[2] Second, the market factors include variables representing market competition in the surroundings of the focal listing (Suárez-Vega et al., 2023). These are Market share (as an indicator of the market concentration), mean monthly Hotel ADR (average daily rate) (as an indicator of the substitution effect), Airbnb listings (as a measure of agglomeration or competition), and Employment competition (as a measure of the competition among listings to hire employees). We also consider the Covid-19 variable to account for the period where the Spanish economy was in lockdown (=1 for the period March 2020–June 2020; = 0, otherwise). Finally, the variables that represent the socioeconomic characteristics of the visitors are included, namely weighted average real gross domestic product (WARGDP) (Liao et al., 2024; Pérez-Rodríguez et al., 2024) and Hospitality employees. Quarterly GDP data was extracted from Eurostat (2021) and evenly allocated for each month. The missing visitor data for April 2020 was assumed to be the same as April 2019.

Table 2 shows the descriptive statistics of the variables used, considering the pooled data, once the records with zeros in the guest rooms, photos and minimum number of nights variables had been removed in order to apply natural logs. The result is a balanced panel with 11,214 observations, corresponding to 534 listings with monthly data ranging from January 2019 to September 2020 (21 months).

As Table 2 shows, the average listing has two rooms, with a capacity of 4 guests and a minimum stay of 3–4 nights. The advertisements are usually well documented with plenty of photos (33 on average). On average, 39.1 % of the listings in the surrounding area (within 10 kms) are managed by hosts who manage more listings (i.e., more professional) than the host who manages the focal listing. In addition, the average market share for the listings within 10 km is around 7.3 %, suggesting that, in general, there is not a high market concentration in the surroundings, although there are some isolated areas where only one listing exists (the maximum market share is one). The average ADR for the hotel beds in the municipalities where the listing is located is 75 euros. Each listing has a mean of 116.8 competing Airbnb listings in the surrounding 10 km. In average terms, there is almost one employee for each tourist bed in the municipalities (0.954), indicating strong competition in a region where employees in the tourism sector account for around 27.2 % of the workforce (IMPACTUR, 2020).

5. Empirical analysis

In this section, the empirical results are presented. First, cross-dependence tests are conducted, second, the SSF panel data model is estimated using ML. Input variables used were transformed to natural logarithms, together with the environmental variable WARGDP. All the tests and estimations presented in this paper were done using the STATA v.16 statistical and econometric software package.

5.1. *Spatial dependence tests*

This section provides the Moran's index (Moran's I; Moran, 1950) which is an independence test to assess the spatial autocorrelation and, therefore, to assess the pertinence of the spatial autocorrelation regression. Results of the test for the variables used in the study appear in Table 3 for the first and last months in the analysis (January 2019 and September 2020).

As can be observed, the results of the Moran's I test present a positive spatial autocorrelation in all cases and the null hypothesis of spatial random distribution is rejected at 5 % significance level in most cases (p-value <0.05). The existence of positive spatial autocorrelations implies the clustering of similar values suggesting spatial dependency and supporting the use of spatial regression models.

5.2. *Spatial panel data results*

In this section, we present estimation results for the SSF panel data model which are based on the proposed spatial efficiency stochastic frontier considering the stochastic Cobb-Douglas production function. We estimate two approaches for the listings data of our study period. On the one hand, we estimate the traditional SF model of Battese and Coelli (1995) (SFM-BC), which allows inefficiency to depend on determinants in a panel data framework, and which is estimated for comparative purposes (Eq. [6–7] with $\gamma = \tau = 0$). On the other hand, we estimate the SSF model defined by Eq. [6–7], which distinguishes between direct, indirect and total marginal effects.

Table 4 contains information related to both models which were estimated using STATA v.16 software econometric package. In

[2] Following the empirical literature, we define professionals as those who manage two or more properties (called multi-unit hosts) and behave similar to business operators, while non-professionals refer to those who manage a single property (called single-unit host) (see, for example, Xie et al., 2021; among others).

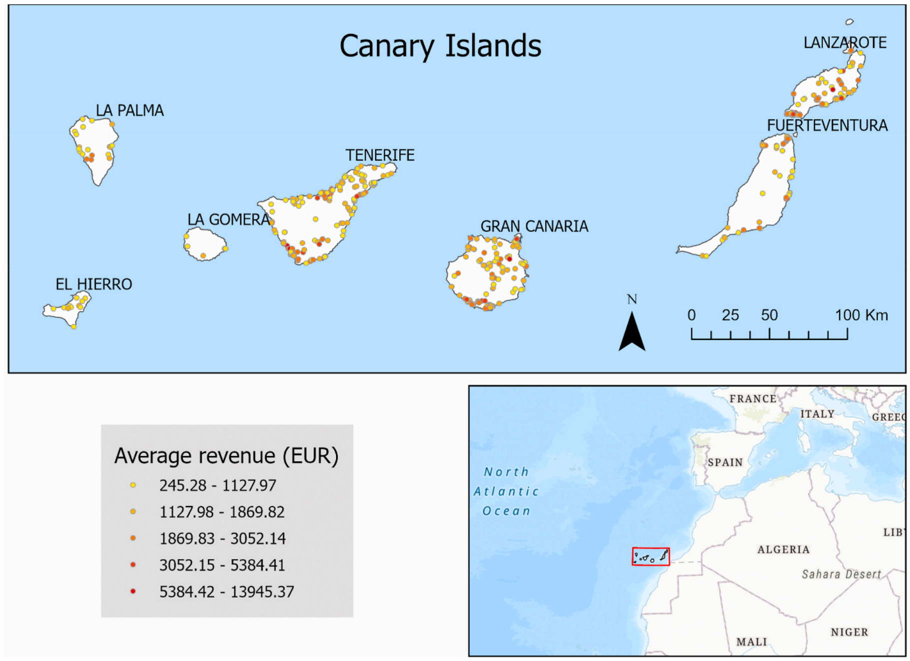

Fig. 1. Spatial distribution and monthly average revenue of the sample considered in the study period.

particular, the SSF model was estimated using the *xtsfsp* procedure developed by Du et al. (2024).

Regarding the SFM-BC results, we observe that most of the estimated frontier and inefficiency parameters are statistically significant, but additionally the standard deviations for the inefficient term (σ_u), noise (σ_v), and their quotient ($\lambda = \sigma_u/\sigma_v$) are also statistically significant at any level, indicating the pertinence of this approach. However, the pertinence of a spatial approach can be investigated based on the residual and efficiency estimates in the SFM-BC model. The results are shown below.

On the one hand, the pooled estimated coefficient of technical efficiency has an absolute mean of 0.619 and presents a positive spatial autocorrelation as shown by the Moran indices at the beginning and the end of the period analysed (I = 0.059 and I = 0.026, with p-values 0.000 and 0.061, respectively). On the other hand, the residuals for the first and last months in the analysis also present positive spatial autocorrelation (I = 0.069 and I = 0.041, with p-values 0.000). Therefore, both results suggest the existence of a spatial component that must be modelled by a spatial variant of the SF model, namely the SSF.

As a complement to the analysis, Fig. 2 shows the spatial distribution of the technical efficiencies obtained by means of the SFM-BC model. More specifically, Fig. 2 (upper half) shows the spatial distribution of the average (along periods) technical efficiencies across the study area, while Fig. 2 (lower half) shows clusters for the average technical efficiency inferred from the local Moran index. In the calculation of these clusters, a row-standardized spatial weight matrix is considered, where weights are inversely proportional to the distance between listings. Fig. 2 (lower half) shows the geographical locations where technical efficiency is high and therefore a promising area to invest. As can be observed, although most of the listings do not show any significant spatial pattern, clusters of properties with high efficiency can be detected in the most populated islands (north and south of Tenerife and south of Gran Canaria). Some low efficiency clusters in the central part of Gran Canaria, east of Tenerife, El Hierro and parts of La Palma, Fuerteventura and Lanzarote are also present.

Regarding the SSF model, there are several technical issues which should be acknowledged in the spatial econometric approach. First, the spatial autocorrelation for the inefficiency error term is the only one considered because the spatial autocorrelation for the idiosyncratic error gave convergence problems in the estimations. Second, an inverse distance row-standardized weight matrix is used to model the spatial interactions between listings. The coefficients for variables "*W* number of guest rooms", "*W* guest capacity", "*W* number of photos" and "*W* minimum stay" represent the spatial Durbin terms associated to the corresponding inefficiency determinants (in natural logs). Third, parameters ρ and τ represent the spatial lag parameters associated to the output (revenue) and the inefficiency determinants, respectively. Both parameters (ρ and τ) are significant, showing that revenues and inefficiencies are spatially correlated.

The existence of significant spatial parameters in the SSF model suggests that the SF model would tend to be inefficient and produce biased estimates, so the spatial version would be the most convenient for our analysis. In this case, marginal effects cannot be interpreted directly from the model coefficients (as in the SF model) but rather from direct effects (resulting from changes in the own listing) and the indirect effects (as a consequence of variations in the neighbouring properties). This means that, in this case, the SF model tends to overestimate the direct effects by implicitly including part of the spillover effects.

Next, we comment on the spatial econometric results. As shown in the first block of Table 4, the effect of the input or production factors can be divided into direct and indirect effects, and the total effects are the aggregate of both partial effects. Number of guest rooms shows larger direct than indirect effects of the inputs, indicating that this is the key factor to be managed by hosts to obtain high revenues. In contrast, Minimum stay shows significantly larger indirect than direct effects, which indicates that the effect of being surrounded by properties with large minimum stay is more relevant to obtain revenues than managing own minimum stay.

The inefficiency determinants can also be analysed through direct, indirect and total effects. In general, total effects are statistically significant at 1 % for all the variables except for log WARGDP. The interpretation of the estimations depends on the specific variable and sign. For example, the negative direct effect coefficient for Market share indicates that a property with higher market share has a lower inefficiency score or, in other words, it is more efficient. The coefficient for the indirect effect of market share is also negative, which indicates that if a focal listing is surrounded by neighbours that increase its market share in a radius of 10 km, then it would also reduce its inefficiency. The

Table 1
Output, inputs and environmental factors in P2P efficiency analysis.

Variables	Description	Authors
Panel A: Output		
Revenue (€)	Revenues derived from the services offered during the reporting period in euros.	Gunter and Önder (2018), Zekan et al. (2019), Pérez-Rodríguez and Hernández (2023a)
Panel B: Inputs		
Number of guest rooms	Proxy of the fixed capital.	All inputs were used by Gunter and Önder (2018) and Zekan et al. (2019), among others.
Guest capacity	Proxy for the size of Airbnb listings.	
Number of photos	Measure of public information about the listing.	
Minimum stay	Represents the minimum length of stay of guests in the property.	
Panel C: Environmental factors		
Managerial factors		
Available days	The number of days classified as available during the reporting month.	All managerial factors were used by Pérez-Rodríguez and Hernández (2023a) and Pérez-Rodríguez et al. (2024)
Blocked days	The number of days classified as blocked during the reporting month.	
Relative professionalism	The percentage of hosts that manage more listings than the focal listing's host in a radius of 10 km.	
Market factors		
Market share	The ratio between revenue obtained by the focal listing and the total revenue earned by listings located within 10 km.	All considered market factors were used by Pérez-Rodríguez et al. (2024)
Hotel ADR (€)	The mean monthly ADR for hotels located in the municipality where the focal listing is located.	
Airbnb listings	Number of Airbnb listings within 10 km of the focal listing.	
Employment competition	The number of tourists beds divided by the number of employees in the tourism sector in the municipality where the focal listing is located.	
Socioeconomic factors		
Weighted average real GDP (WARGDP, million €)	The weighted average real GDP of the top seven tourist origin countries[a] over the number of tourists visiting the islands.	Liao et al. (2024), Pérez-Rodríguez et al. (2024)
Hospitality employees	The number of employees in the hospitality industry in the municipality where the focal listing is located.	Pérez-Rodríguez et al. (2024)

Notes:
[a] UK, Germany, Spain, Sweden, Netherlands, Belgium and Denmark – accounting for 77.31 % of visitors according to ISTAC (2025).

reason for the positive spillover effects of market share may be the expected high attractiveness of the area where listings with higher market shares are located.

The indirect effects represent the spatial spillover effects of the environmental factors in a certain area. Thus, the number of Airbnb listings in a radius of 10 km of a focal listing also has a positive indirect effect on efficiency, as is the case of market share. In general, direct marginal effects are greater than indirect effects in absolute terms, indicating that the own-listing effects are more relevant than the spatial spillover effects on inefficiency.

Table 2
Descriptive statistics.

Variable	Mean	Standard deviation	Min	Max
Panel A: Output				
Revenue (€)	1,634.494	1,542.946	0.684	18,737.778
Panel B: Inputs				
Number of guest rooms	2.047	1.076	1	6
Guest capacity	4.685	2.235	1	16
Number of photos	33.228	19.444	6	184
Minimum stay	3.592	7.863	1	180
Panel C: Environmental variables				
Available days	9.546	7.925	0	30
Blocked days	3.715	6.303	0	30
Relative professionalism	0.391	0.255	0.000	0.889
Market share	0.073	0.121	0.000	1.000
Hotel ADR (€)	75.0	19.074	28.170	121.220
Airbnb listings	116,810	64,550	2,000	252,000
Employment competition	0.954	4.444	0.001	108.704
Hospitality employees	5,034.899	5,572.987	24.000	19,316.000
WARGDP (million €)	141,791.500	24,761.680	80,618.230	203,332.500

Table 3
Results of the Moran's I test for the first and last months of the analysed period.

Variables	January 2019		September 2020	
	Moran's I	p-value	Moran's I	p-value
Revenue (log)	0.084	0.00	0.043	0.01
Number of guest rooms (log)	0.096	0.00	0.096	0.00
Guest capacity (log)	0.114	0.00	0.114	0.00
Number of photos (log)	0.068	0.00	0.068	0.00
Minimum stay	0.140	0.00	0.140	0.00
Available days	0.104	0.00	0.129	0.00
Blocked days	0.033	0.03	0.027	0.06
Relative professionalism	0.040	0.01	0.042	0.01
Market share	0.112	0.00	0.104	0.00
Hotel ADR	0.505	0.00	0.507	0.00
Airbnb listings	0.506	0.00	0.506	0.00
Employment competition	0.554	0.00	0.145	0.00
Hospitality employees	0.608	0.00	0.609	0.00
WARGDP (log)	0.785	0.00	0.662	0.00

However, the coefficients of the direct and indirect effects of Relative professionalism are positive, which indicate that inefficiency is larger in areas where the percentage of professional hosts increases. This also occurs with Blocked days. Negative spillover effects on efficiency are detected when the mean blocked days of listings surrounding a focal property increases. The reason for this result may be the confluence of blocked days for many hosts in certain months during the year. In fact, the average number of blocked days in August 2020 (5.26) is more than double the lowest average blocked days, recorded in April 2019 (2.21). Due to their location near the traditional beach areas in the islands, many listings are blocked by owners to enjoy their vacation periods.

5.3. Spatial distribution of inputs and determinants of inefficiency

To complement the previous analysis, this section conducts an analysis of the spatial distribution of the individual effects of both the input variables belonging to the stochastic frontier and the determinants of inefficiency. By means of this analysis, geographic patterns of influence between listings in terms of production factors and determinants of efficiency can be found.

Some descriptive statistics for these effects are presented in Appendix

Table 4
Panel data estimates with covariates of mean inefficiency for the Cobb Douglas stochastic production frontier model. Balanced panel data (January 2019–September 2020).

Variables	Battese and Coelli (1995) model (SFM-BC)		Spatial stochastic frontier (SSF) model							
	Coeff.	Standard error	Coeff.	Standard error	Direct effect	Standard error	Indirect effect	Standard error	Total effect	Standard error
Panel A: Frontier										
Number of guest rooms (log)	0.397***	0.0163	0.2972***	0.0145	0.306***	0.0157	0.302***	0.0970	0.609***	0.1018
Guest capacity (log)	0.271***	0.0182	0.2588***	0.0163	0.263***	0.0172	0.137	0.1113	0.400***	0.1158
Number of photos (log)	0.114***	0.0072	0.0583***	0.0066	0.064***	0.0067	0.190***	0.0411	0.254***	0.0427
Minimum stay (log)	0.067***	0.0087	0.0786***	0.0076	0.089***	0.0077	0.354***	0.0604	0.443***	0.0627
time	−0.012***	0.0031	−0.0093***	0.0032	–	–	–	–	–	–
$time^2$	0.001***	0.0003	0.0011***	0.0003	–	–	–	–	–	–
W Number of guest rooms	–	–	−0.0595	0.0422	–	–	–	–	–	–
W Guest capacity	–	–	−0.1026**	0.0470	–	–	–	–	–	–
W Number of photos	–	–	0.0408 *	0.0178	–	–	–	–	–	–
W Minimum stay	–	–	0.0945***	0.0246	–	–	–	–	–	–
Constant	6.907***	0.0384	2.4070	0.1308	–	–	–	–	–	–
Panel B: Inefficiency determinants										
Covid-19	0.092***	0.0225	0.0813	0.7867	0.032	0.2969	0.019	0.1757	0.050	0.4722
Available days	−0.004***	0.0005	0.1538***	0.0033	0.060***	0.0009	0.035***	0.0025	0.095***	0.0027
Blocked days	0.124***	0.0023	0.1581***	0.0033	0.062***	0.0010	0.036***	0.0026	0.098***	0.0028
Relative professionalism	0.127***	0.0024	0.2151***	0.0316	0.084***	0.0125	0.049***	0.0078	0.003***	0.0012
Market share	−1.867***	0.1760	−14.8628***	0.7915	−5.799***	0.2927	−3.379***	0.3429	−9.179***	0.5894
Hotel ADR	0.290***	0.0312	−0.0027***	0.0007	−0.001***	0.0003	−0.001***	0.0002	−0.002***	0.0004
Airbnb listings	0.002	0.0020	−0.0053***	0.0002	−0.002***	0.0001	−0.001***	0.0005	−0.003***	0.0002
Employment competition	−0.00001***	0.0000	0.0051**	0.0019	0.002***	0.0008	0.001***	0.0005	0.003***	0.0012
Hospitality employees	−0.003***	0.0002	−0.000005**	0.0000	−0.000002**	0.0000	−0.000001**	0.0000	−0.000003**	0.0000
WARGDP (log)	−0.081	0.0518	−0.032	0.0676	−0.012	0.0256	−0.007	0.0149	−0.020	0.0405
Constant	0.200	0.6030	−1.283	0.8671	–	–	–	–	–	–
σ_u	0.335***	0.0103	–	–	–	–	–	–	–	–
σ_v	0.421***	0.0045	–	–	–	–	–	–	–	–
λ	0.797***	0.0134	–	–	–	–	–	–	–	–
ρ	–	–	0.610***	0.0129	–	–	–	–	–	–
τ	–	–	−0.559***	0.0155	–	–	–	–	–	–
Log likelihood	−7572.861		−6190.381							
Observations	11,214		11,214							
Number of listings	534		534							

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors were computed using the Monte Carlo method (500 iterations) over the log likelihood function. p-values were computed using normal distribution.

A2. In this section, a description is provided of the cluster analysis carried out using the Getis-Ord G index. This measure allows us to determine the existence of areas with high (hot) or low (cold) influence of direct and indirect effects. The spatial interaction among listings was modelled by a weight matrix obtained considering the neighbours in a radius of 5 km. In our case, for each listing, the average effects in the 5 km radii surrounding area are compared with the global average and detect if it is located in a hot spot (zone with higher values than the mean) or a cold one (values lower than the mean). Listing in a hot spot for direct effects reflects zones where own decisions are important for own efficiency or revenue, while hot spots for indirect effects reflect zones where neighbour decisions have strong effects on own listings.

As pointed out in section 3.1, the geographical distribution of the direct and indirect effects for the inputs throughout the sample exclusively depends on the weight matrix *W* moderated by the spatial autocorrelation coefficient of the revenue ρ. In the case study, each element in *W* is defined as the inverse distance among listings, and so represents the geographical proximity between listings. Thus, the clustering of effects does not depend on the specific input variable but on the geographical disposition of the listings. Therefore, it is expected that zones with high accumulation of listings have similar large marginal effects, whereas zones with dispersed listings have similar low marginal effects of the inputs.

Fig. 3 represents spatial clustering for the direct and indirect effects of the input factors for the listing in the sample on production (revenue). As can be observed in Fig. 3 (upper half), there are several areas where an accumulation of high direct effects is produced. This is the case for some parts in the north of Tenerife, western La Gomera and the centre of Gran Canaria. In these areas, the effect of input factors on revenue of the listings would be higher than in the rest of the listings.

The indirect effects show several areas with large values (hot spots) and other areas with lower values (cold spots). Most of the hot spots correspond to urban tourist areas in the most populated islands. In these zones, the higher the input factor in the neighbouring listings, the larger the listing revenue is. Thus, Fig. 3 (lower half) exhibits locations where spatial spillover effects of input factors on listing revenue are presented. The cold spots correspond to rural zones in the less populated western islands. In these areas, low spatial spillover effects on efficiency are presented. As expected, the results show a relationship between the density of listings in an area and marginal effects of the inputs.

Fig. 4 presents the spatial distribution of the marginal effects of the inefficiency determinants. As noted in section 3.2, the geographical

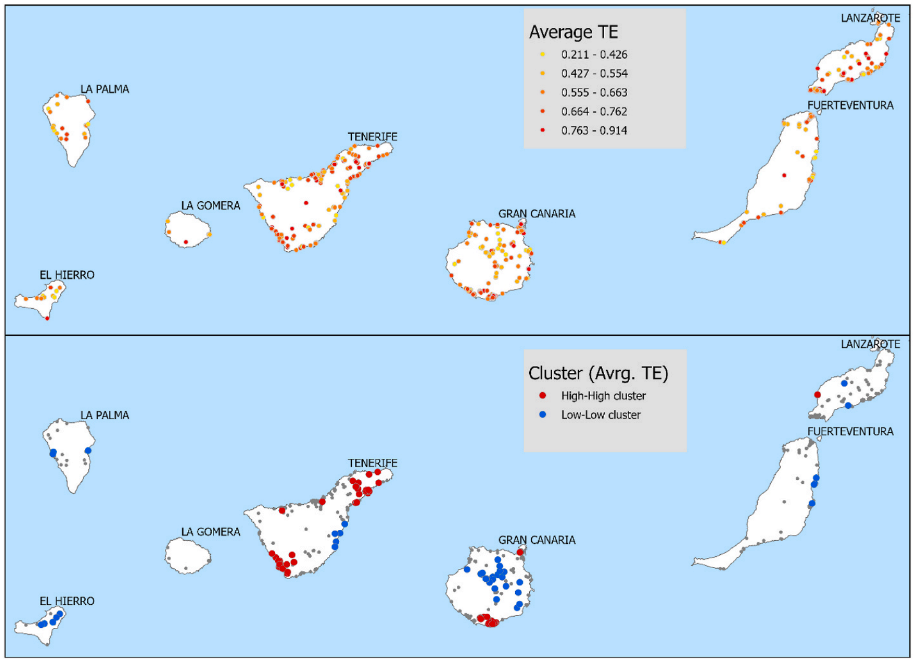

Fig. 2. Spatial distribution of the average of the technical efficiencies obtained by the SFM-BC model: average technical efficiencies (upper half) and clusters (lower half).

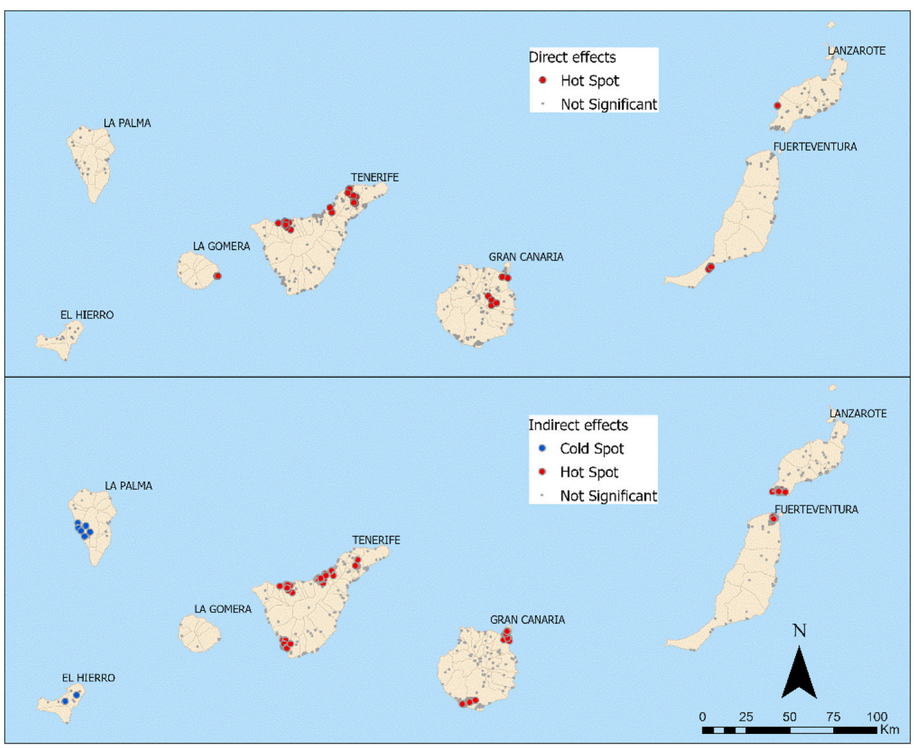

Fig. 3. Spatial clustering for the effect of the input factors on revenue: direct (upper half) and indirect effects (lower half).

distribution of these effects also depends on the weight matrix W, moderated by the spatial autocorrelation of the revenue ρ and the degree of cross-sectional correlation between listing inefficiency τ. Then, the accumulation of high values of the marginal effects corresponds to hot spots, which represent areas with a high listing density in combination with a high inefficiency level.

In the empirical sample, the most prominent direct effects of the determinants are presented in the centre of Gran Canaria and some areas in Lanzarote, whereas the hot spots of the indirect effects are more widespread, but mostly in Gran Canaria. Depending on the sign of the marginal effect of the determinant (Table 4), the hot spots indicate areas with a high positive or negative effect on inefficiency. For example, the increase in blocked days conducted by neighbouring listings in some parts of central and coastal Gran Canaria has a large negative effect on the inefficiency of a listing (or, in other words, a positive effect on efficiency).

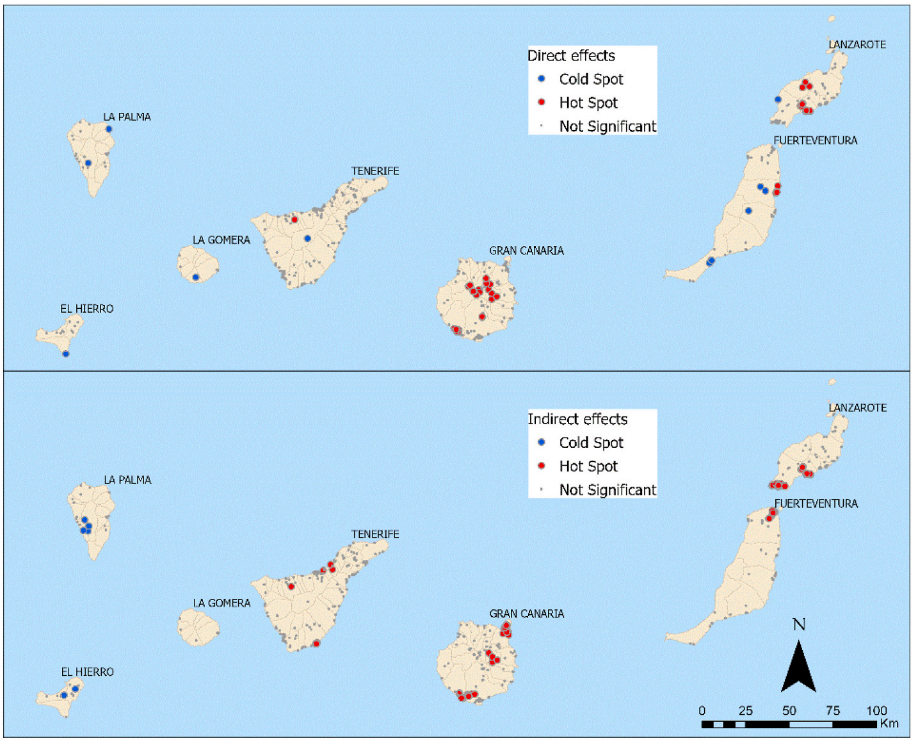

Fig. 4. Spatial clustering for the effect of environmental variables on inefficiency: direct effects (upper half) and indirect effects (lower half).

The cold spots show areas with low effects of the determinants on inefficiency and are presented where listings are dispersed and with high levels of efficiency (areas in the western islands of La Palmas and El Hierro), as expected.

6. Discussion and implications

6.1. Discussion

This paper applies an SF panel data model that captures the geographic heterogeneity of the efficiency of P2P listings. The case study focuses on the sharing accommodation market in the Canary Islands, an important tourist destination in Spain. The findings indicate that the spatial correlation effects are statistically significant in the frontier specification (for both output and input variables) as well as in the inefficiency terms.

The model serves to investigate agglomeration economies and other spatial spillover effects in the efficiency of the accommodation sector. In accordance with the traditional economic theory (Marshall, 1920), a positive relationship between agglomeration and efficiency in the general tourism industry has been found in previous studies (Li and Liu, 2022). The general results in this paper agree with these previous findings and point to a positive effect of agglomeration of the sharing accommodation units on their economic efficiency. Areas with high concentration of listings take more advantage of the direct positive effects of the input factors, such as the guest capacity and number of photos, than other areas where listings are more dispersed. This high-intensive effect occurs not only in urban and high listing density areas, but also in other places where a certain accumulation of highly inefficient listings is produced. Then, the combination of listing density and low efficiency values of closely located listings determines areas with high-intensive marginal effects of the environmental determinants.

The results also provide information about the spillover effects of market factors other than the concentration of neighbouring listings on the efficiency of a P2P listing. For example, the increase in the number of tourism employees per accommodation bed has a positive effect on the efficiency of a listing. This result also points to the existence of agglomeration economies, as also found in previous studies for the hotel sector (Bernini & Guizzardi, 2016). However, the negative effect of the number of employees in the surrounding area and the positive effect of increasing market share on the efficiency of a listing leads to the opposite conclusion. These partial findings agree with some previous studies, which showed that competition effects prevail over agglomeration effects in neighbouring listings (Suárez-Vega et al., 2023).

Other findings can be extracted from the effect of other environmental factors. For example, the spillover effect of some managerial factors, such as the number of blocked days, illustrates the high interdependence among hosts managing neighbouring listings. According to the results, the efficiency of a listing is negatively influenced by an increase in the number of blocked days conducted by its neighbouring listings. This finding points to a voluntary (or involuntary) confluence in the period of blocked days between hosts which reduces the efficiency of the listing in these areas.

Negative spillover effects of professionalism on efficiency can also be extracted from the results, in line with previous studies (Suárez-Vega et al., 2023). Although professional hosts usually obtain higher returns from the listings than non-professionals (Xie & Mao, 2017), they also convey some other costs and a lower efficiency use of their resources, such as guest capacity, photos and minimum stay.

6.2. Theoretical significance

This study contributes to efficiency theory not only in the P2P sector, but in the accommodation sector in general. Furthermore, it also contributes to competition/agglomeration and RBV theories in tourism.

First, the method proposed in this paper allows the inclusion of spatial effects in the efficiency estimation on outputs, inputs and error terms (efficiency methodology). The empirical findings support the convenience of the joint analysis of these effects. In general, it can be concluded that spatial correlation is a key factor in modelling not only the specification of the frontier but also the inefficiency of the P2P listings.

Second, the model serves to investigate agglomeration economies and other spatial spillover effects in the efficiency of the accommodation sector. In particular, spillover effects of the input factors among neighbouring listings (indirect effects) in the production frontier analysis can be detected. This approach extends other methods which analyse spatial spillover effects for other economic performance indicators. For example, Kim et al. (2021) analysed spillover effects in productivity in the context of a temporarily lagged spatial Durbin panel model and Tan et al. (2024) combined DEA-Malmquist with a vector autoregressive Granger causality test to create a social network among units and thereby identifying spillover effects using social network analysis tools. The production frontier analysis followed in this paper allows study of the spatial effects of the production factors on economic efficiency by splitting the marginal effects of inputs into direct and indirect effects.

Finally, the model in this paper refines previous methods by allowing the geographical representation of areas where not only inputs but also environmental effects on inefficiency are more intense than in others. In other words, the method detects the spatially heterogeneous distribution of the marginal effects of the input and determinants, highlighting those areas with larger effects of these variables. Therefore, some geographical patterns of the spatial effects of the inputs and determinants among listings can be detected, providing researchers with granular geographical information on the spatial heterogeneity of efficiency in the sample. This opens up the possibility of exploring how geographic location affects access to strategic resources and how such access is reflected in the positioning along the efficiency frontier. The efficiency analysis proposed in this paper therefore contributes to the RBV of the P2P accommodation sector, showing how internal and external resources, including spatial ones, can shape performance outcomes and provide competitive advantage to listings.

6.3. Practical implications

The spatial method to study efficiency in P2P listings allows useful information to be obtained for P2P investors, hosts, platform managers and policymakers. The spatial distribution of the spillover effects can be used by these actors to design strategies adapted to different areas in the destination.

First, P2P investors can focus on inputs and locations with higher production of direct and indirect spatial effects. The inputs related to a listing's capacity are those which have a higher marginal direct effect. Thus, the selection of larger-sized properties seems to be a good choice when seeking high efficiency. Moreover, investors can take advantage of neighbouring management practices by selecting listings in areas where large minimum stays and the use of photos are common practice in the local P2P industry. Regarding specific geographical areas, those with a high listing density, situated for example in the north of Tenerife and coastal areas of Gran Canaria, Lanzarote and Fuerteventura, are good locations for new investment. In these specific places, investors could be favoured by own management practices and spillover effects, as well as the efficient use of resources by neighbours.

The spatial distribution of the environmental effects also provides information about the most favourable locations for investment. In our empirical study, these locations have lower relative professionalism values, high listing densities and low numbers of blocked days during the year, among other factors. When managed in the right direction (e.g., low number of blocked days and high minimum stay), some parts of central Gran Canaria and Lanzarote are the most appropriate locations for increasing efficiency. Other coastal areas of the islands present higher indirect effects of environmental variables. Thus, to be positively influenced by the spillover effects, investors need to previously study the common practices regarding these factors (professionalism, listing density and mean number of blocked days, among others) in these areas before deciding the investment location.

Second, although P2P hosts of existing listings cannot choose the location of the property, they can take advantage of the information on spillover effects of the input and environmental variables in their marketing and new investment strategies. Hosts managing properties in urban and high-density areas, such as the north of Tenerife and north-east of Gran Canaria are clearly favoured by own and spillover effects in input and environmental factors, so investment actions, such as structural renovation or marketing promotions, are expected to be more efficient in these locations than in other low-density areas, such as the case of some parts of La Palma and El Hierro. In the latter islands, the incorporation of new non-professional hosts would favour the efficient use of resources, while increasing the competition effect as well.

Other recommendations for current P2P hosts can be extracted from the findings. In the empirical sample, efficiencies are approximately 73 % on average for all listings, indicating there is room for the better allocation of resources. Apart from the increase of some flexible inputs for each individual host, such as the number of photos and minimum stay, the coordination of managers in a certain area for some determinants is a key factor to enhance the efficiency of listings. For example, an agreement about the period of blocked days for the listings located in hot spots could lessen the negative spillover effect of this managerial factor on efficiency, maintaining an attractive and varied supply throughout the year.

Third, platform managers can also use the geographic information of the spillover effects to design location-based marketing strategies and recommendations to hosts for improving the economic performance of their listings. For example, the negative influence of the number of blocked days on the technical efficiency of listings is clear. The platforms can recommend to hosts the most appropriate period for closing the listing to avoid the undesirable simultaneity of blocked days and the consequent reduction of the supply. They can also promote low rates of professionalism in certain areas with overload of this managerial practice, in order to increase the economic efficiency of the listings. They can also design the specific promotion of areas where high direct and indirect effects are detected in order to increase demand and favour the profitability of high-efficiency listings.

Finally, policymakers can also use the spatial distribution of efficiency to promote areas where more efficient practices are observed and implement policies to improve efficiency in those areas with lower scores. For example, they can take advantage of the spillover effects of inputs by applying zoning policies, incentivizing investors to locate in specific areas. In the sample, this is the case of some coastal areas in the north of Tenerife and Gran Canaria. Other regulatory measures aiming to avoid the negative effect of some environmental variables can also be implemented. For example, policies aimed at limiting high relative professionalism (see Table 1 for definition) in areas with high listing densities. The facilitation of coordination among listings in these areas could also be a measure to improve the efficient behaviour of managers in a destination. Such policy measures can be combined with incentives to invest in locations with an intensive effect of these environmental variables. In the empirical sample, this is the case of many parts of the islands of Gran Canaria and Lanzarote. The combination of regulatory policies and the promotion of investment in areas with high environmental indirect effects will help new investors and managers to make correct decisions and use resources more efficiently.

6.4. Limitations and future research

Certain limitations should be acknowledged. First, the methodological approach assumes that the marginal effect of each input factor depends exclusively on the spatial disposition of the units. The same occurs with environmental factors. New approaches could address this issue and make the marginal effect depend not only on the spatial interrelationship of the units but also on the factor itself. Second, the estimations are based on a balanced panel data because, although the proposed method allows use of an unbalanced panel data, this implies a considerable increase in computational times. Third, data limitations prevented conducting a cost efficiency analysis, which would add new information about the efficiency of a listing. Finally, one notable limitation of this study is the potential distortion of efficiency dynamics caused by the Covid-19 pandemic. This effect was included using a dummy variable, but it was not found to be significant. This is problematic because it seems clear that during this period there were significant changes on the part of both property managers and consumers. For example, the irruption of Covid-19 largely distorted price and income elasticities (Suárez-Vega et al., 2023). These anomalies challenge the generalizability of results derived from pre- or early-pandemic data to more stable market conditions.

Future research can follow several specific avenues. The method employed could be applied across different tourism segments (e.g., hotels, tour operators, travel agencies, or even destination management organizations). Basically, segment-specific dynamics could be studied investigating whether spatial dependencies and efficiency determinants differ across segments due to variations in service delivery, customer interaction, and operational scale. Also, benchmarking across sectors could be done by comparing efficiency frontiers between segments to identify best practices and cross-sectoral learning opportunities.

Another line of future work could be to incorporate temporal variability through time-dependent spatial weight matrices in order to better analyse the temporal dynamics of the factors that determine efficiencies. Furthermore, it would be interesting to use more flexible production functions than Cobb-Douglas (e.g. the translog) and estimate the marginal effects and their standard errors under these conditions.

Finally, another interesting line of future research could be to use post-pandemic datasets to identify long-term structural changes in tourism behaviour. Thus, studies could incorporate data from after 2020 that reflect changes in consumer preferences, the rise of remote work and digital adoption, travel restrictions, and resilience strategies. This would address the limitations of generalizability associated with pre-pandemic or early pandemic data. Additionally, the application of time-varying spatial matrices could also facilitate the identification of spatial dependencies in competitive dynamics, offering a more robust understanding of tourism efficiency in the post-Covid-19 era. These analyses could be relevant for policy, particularly for destination planning and resource allocation, by highlighting spatial clusters that have emerged or disappeared due to the pandemic.

CRediT authorship contribution statement

Jorge V. Pérez-Rodríguez: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Rafael Suárez-Vega:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Juan M. Hernández:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition.

Impact statement

In this paper, an innovative method to account for direct and indirect effects in the estimation of the efficiency of sharing accommodation units is presented. The method combines the analysis of the spatial correlation effects on the stochastic frontier, the noise and the inefficiency term. This approach allows for the calculation of direct and indirect effects of the inputs on revenues and of the environmental factors on inefficiency. The method was applied to the peer-to-peer market in the Canary Islands. Relevant theoretical and practical implications are drawn from the results.

Declaration of competing interest

None.

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Appendix

A1. Spatial efficiency stochastic frontier model

In this section, we first describe the spatial lags stochastic frontier model developed by Galli (2023a) that generalizes the Orea and Álvarez (2019) spatial stochastic frontier model which accommodates spatially-correlated inefficiency and noise terms. Then, we distinguish the aggregated and individual marginal effects from this model to construct direct and indirect effects on the stochastic frontier and also inefficiency.

The model

The Galli (2023a) model captures the spatial correlation of the random error and inefficiency terms by means of a spatial Durbin process. Moreover, it can measure global and local spatial spillovers that influence the frontier function.

Following Galli (2023a), the panel data production stochastic frontier model can be written as:

$$y_{it} = \rho W_i^{yt} y_{.t} + X_{it}\beta + W_i^{xt} X_{.t}\theta + \widetilde{v}_{it} - \widetilde{u}_{it}, i = 1, 2, ..., N \quad \text{[A1.1]}$$

where, for the instant t, y_{it} is the value for the output variable for the i-th unit, $X_{.t}$ is the $N \times K$ inputs matrix for that instant, X_{it} is the i-row of $X_{.t}$, representing the inputs for unit i, and $y_{.t} = (y_{1t}, ..., y_{Nt})'$ is the N-component outputs vector. Given W^{yt} and W^{xt}, two $N \times N$ spatial weight matrixes, $W_i^{yt} = (W_{i1}^{yt}, ..., W_{iN}^{yt})$ and $W_i^{xt} = (W_{i1}^{xt}, ..., W_{iN}^{xt})$, are the i-th cross-sectional weight vectors. Matrixes W represent the spatial relationship existing among the features (e.g., Airbnb properties) in the data, verifying that $W_{ij} > 0$ for the neighbouring Airbnb listings ($i \neq j$) and its diagonal elements $W_{ii} = 0$.

Orea and Álvarez (2019) pointed out that "while the spatial specification of the noise terms is likely capturing an environmentally-induced correlation, the spatial specification of the inefficiency term will likely capture a behavioural correlation" (Orea & Álvarez, 2019, p. 556). In this sense, the idiosyncratic and inefficiency error terms can be expressed in a spatial autoregressive (SAR) specification as follows, respectively:

$$\widetilde{v}_{it} = v_{it} + \gamma W_i^{vt} \widetilde{v}_{.t}$$

$$\widetilde{u}_{it} = u_{it} + \tau W_i^{ut} \widetilde{u}_{.t} \quad [A1.2]$$

where $W_i^{yt} = (W_{i1}^{yt}, ..., W_{iN}^{yt})$ and $W_i^{ut} = (W_{i1}^{ut}, ..., W_{iN}^{ut})$ are two known $1 \times N$ cross-sectional weight vectors (i-rows of matrixes W^{vt} and W^{ut}) representing the structure of the cross-sectional relationship for idiosyncratic noise and inefficiency terms, respectively, v_{it} is a random variable normally distributed with null mean and constant variance, σ_v^2 and $\widetilde{v}_{.t} = (\widetilde{v}_{1t}, ..., \widetilde{v}_{Nt})'$, $u_{it} = h(Z_{it}'\delta)u_t^*$ and $\widetilde{u}_{.t} = (\widetilde{u}_{1t}, ..., \widetilde{u}_{Nt})'$, $h(Z_{it}'\delta)$ is the scaling function where Z_{it}' is a $1 \times K_Z$ vector of variables affecting the inefficiency of individual units, δ is an unknown parameter vector, and u_t^* is a non-negative random variable following the distribution $N^+(0, \sigma_u^2)$, where σ_u^2 is the constant variance. Note that the spatial moving average (SMA) model can also be modelled (see Orea & Álvarez, 2019).

The parameters and restrictions involved in the model defined in Eqs. [A1.1] and [A1.2] are as follows:

- ρ is the spatial autocorrelation coefficient for the dependent variable, or in other words the effect on the output of the current listings of the neighbours. If $\rho = 0$, the contemporaneous endogenous interaction effects are excluded.
- β is the vector of coefficients associated to the inputs.
- θ is the coefficient for the spatial lag for the inputs. If $\theta = 0$ exogenous interaction effects are excluded.
- γ measures the degree of cross-sectional correlation between the noise term of listings.
- τ measures the degree of cross-sectional correlation between the inefficiency term of listings.

We parameterize ρ, γ, and τ following Gude et al. (2018) to ensure regularity conditions for the spatial autoregressive model.

For example, $\rho = \left(\frac{1}{r_{\min}}\right)(1-p) + \left(\frac{1}{r_{\max}}\right)p, 0 \le p = \frac{\exp(\delta_0)}{1+\exp(\delta_0)} \le 1$, where $r_{\max}$ and $r_{\min}$ are the maximum and minimum characteristic roots of the corresponding spatial weight matrix, W^{yt}. The same conditions are applied to the γ, and τ coefficients.

The estimation procedure is based on the ML estimator. The log-likelihood function for period t ($\log L_t$) can be written as follows:

$$\log L_t = \log|I_N - \rho W^{yt}| - \frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\Pi| - \frac{1}{2}\widetilde{\varepsilon}_{.t}\Pi^{-1}\widetilde{\varepsilon}_{.t} + \frac{1}{2}\left(\frac{\mu_*^2}{\sigma_*^2}\right)$$
$$+\log\left(\sigma_*\Phi\left(\frac{\mu_*^2}{\sigma_*^2}\right)\right) - \log\left(\frac{1}{2}\sigma_u\right)$$

where $\Pi = \sigma_v^2(I_N - \rho W^{yt})^{-1}\left[(I_N - \rho W^{yt})^{-1}\right]'$; $\mu_* = \left(-\widetilde{\varepsilon}'_{.t}\Pi^{-1}\widetilde{h}_{.t}\right)/\left(\widetilde{h}'_{.t}\Pi^{-1}\widetilde{h}_{.t} + 1/\sigma_u^2\right)$; $\sigma_*^2 = 1/\left(\widetilde{h}'_{.t}\Pi^{-1}\widetilde{h}_{.t} + 1/\sigma_u^2\right)$; $\widetilde{h}_{.t} = (I_N - \tau W^{ut})h(Z_{.t}\delta)$ with $Z_{.t} = (Z_{1t}, ..., Z_{Nt})'$; Φ is the cumulative distribution function of the standard normal distribution; $\widetilde{\varepsilon}_{.t} = (\widetilde{\varepsilon}_{1t}, ..., \widetilde{\varepsilon}_{Nt})'$ where the composed error term in Eq. [A1.1] can be written as: $\widetilde{\varepsilon}_{it} = y_{it} - \rho W_i^{yt} y_{.t} - X_{it}\beta - W_i^{xt} X_{.t}\theta$. Note that consistent parameter estimates can be obtained by maximizing the final loglikelihood function using a numerical constrained maximization algorithm (Galli, 2023a).

Technical efficiency scores are calculated as in Galli (2023a), following Orea and Álvarez (2019). See Orea and Álvarez (2019) and Galli (2023a) for more details.

Marginal effects

As Galli (2023a) notes, given that the coefficient of explanatory variables cannot be interpreted as marginal effects because of the spatial lag of the endogenous variable, the marginal effects for explanatory variables can be obtained for both the stochastic frontier specification and the inefficiency term.

For the stochastic frontier, we follow Elhorst (2012), who finds that for a given period t the variation for the vector of dependent variable, $y_{.t} = (y_{1t}, ..., y_{Nt})'$, with respect to the k-th regressor ($k = 1, ..., K_X$) is given by:

$$\frac{\partial(y_{1t}, ..., y_{Nt})}{\partial(X_{1k}^t, X_{2k}^t, ..., X_{Nk}^t)} = \begin{bmatrix} \frac{\partial Y_1^t}{\partial X_{1k}^t} & \frac{\partial Y_1^t}{\partial X_{2k}^t} & \cdots & \frac{\partial Y_1^t}{\partial X_{Nk}^t} \\ \frac{\partial Y_2^t}{\partial X_{1k}^t} & \frac{\partial Y_2^t}{\partial X_{2k}^t} & \cdots & \frac{\partial Y_1^t}{\partial X_{Nk}^t} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Y_N^t}{\partial X_{1k}^t} & \frac{\partial Y_N^t}{\partial X_{2k}^t} & \cdots & \frac{\partial Y_N^t}{\partial X_{Nk}^t} \end{bmatrix} = (I - \rho W^{yt})^{-1}(\beta_k I + \theta_k W^{xt}), \quad [A1.4]$$

with X_{ik}^t the (i,k) element in $X_{.t}$. This is an $N \times N$ matrix where, for a given unit i, the element in the diagonal represents the direct effect of input k (effect on output of unit i of changing input k in i) and the non-diagonal elements of the row i are the indirect effects of the rest of the units on unit i (effects on outputs of unit i of changing input k on the neighbours).

The spatial structure of the marginal effects in Eq. [A1.4] is dominated by the matrix $(I - \rho W^{yt})^{-1}$, which is independent from the inputs. Then, the spatial structure for the individual direct effects is similar for all inputs, even though numerically they are different. The same observation applies to the indirect effects, as the spatial weight matrix is row-standardized.

To quantify both direct and indirect effects in these models, the measures proposed by LeSage and Pace (2009) are commonly used. They proposed aggregate measures for the whole sample based on the averages of the individual effects. If the matrix of Eq. [A1.4] is denoted as $M = (m_{ij})_{N\times N}$, they suggested as the aggregated direct effect for regressor k the average direct effects among the different units (mean diagonal element in the matrix of Eq. [A1.4], $DE_k = \frac{1}{N}\sum_{i=1}^N m_{ii}$), and as aggregated indirect effect they proposed the average of the sum of indirect effects for each sample unit (the mean row sum of the non-diagonal elements in the matrix of Eq. [A1.4], $IE_k = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N} m_{ij}$). As can be inferred from the definitions, these are aggregate measures that aim to measure the effects at the global level, ignoring the local effects on each unit. Note that the marginal effects matrix of Eq. [A1.4] is independent from period t and the aggregated measures obtained for all the periods coincide with the measurement obtained for a single period.

For the inefficiency regressors, and assuming the scaling function $h(Z_{it}'\delta) = \sqrt{\exp(Z_{it}'\delta)}$ proposed by Du et al. (2024), the marginal effects for regressor k ($k = 1, \dots, K_Z$) at period t is given by the following $N \times N$ matrix:

$$\frac{\partial(\tilde{u}_{1t}, \dots, \tilde{u}_{Nt})}{\partial(Z_{1k}^t, Z_{2k}^t, \dots, Z_{Nk}^t)} = \frac{1}{2}\delta_k (I - \rho W^{yt})^{-1}(I - \tau W^{ut}) diag\left(\exp\left(\frac{1}{2}Z_{1t}'\delta\right), \dots, \exp\left(\frac{1}{2}Z_{Nt}'\delta\right)\right), \quad [A1.5]$$

with Z_{ik}^t the value for the k inefficiency factor for unit i, with $i = 1, \dots, N$ and $k = 1, \dots, K_Z$, for period t. Both individual and aggregated direct and indirect effects for the inefficiency regressors for period t, as LeSage and Pace (2009) defined, can be deduced from [A1.5]. In this case, the marginal effects matrix depends on the period t and must be calculated for each period.

Similarly to the case of the marginal effects of the input factors, the spatial structure for the individual direct and indirect effects of the environmental factors is dominated by the matrix $(I - \rho W^{yt})^{-1}(I - \tau W^{ut})$, which depends on the spatial weight matrix, the spatial autocorrelation and the inefficiency autocorrelation terms, but not on the specific estimates of the coefficients.

As mentioned, the measures of effects used in the literature are considered from a global point of view, not allowing to distinguish different behaviours along the study area. In order to bring the analysis down to the local level, an individualization of the measures of direct and indirect effects is proposed. To do so, for a given unit i, the ith element in the diagonal in [A1.4] ($DEX_k^i = m_{ii}$) is proposed as individual direct effect for the k-th input, and as individual indirect effect, the sum of the non-diagonal elements in row i in [A1.4] ($IEX_k^i = \sum_{j=1,j\neq i}^{N} m_{ij}$). Individual direct and indirect marginal effects for the determinants of the inefficiency are calculated similarly using [A1.5]. Noting the matrix of Eq. [A1.5], for a given t, as $M^t = \left(m_{ij}^t\right)_{N\times N}$, the individual direct effect for the k inefficiency determinant is defined as $DEZ_k^i = \frac{1}{T}\sum_{t=1}^{T} m_{ii}^t$ and the individual indirect effect is $IEZ_k^i = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1,j\neq i}^{N} m_{ij}^t$. These new measures will make it possible to identify individuals and areas where inefficiency depends mainly on their own characteristics, and areas where the effect of neighbouring characteristics is more influential.

A2. Some empirical results

Table A2.1 shows the descriptive statistics for the individual effects for the inputs, the individual direct effects (DEX_k^i) and the individual indirect effects (IEX_k^i) for all the listings considered in the study. It should be noted that the variability of the indirect effects is much greater than that of the direct effects, with market share being the input with the highest effects. The direct effect for the number of photos presents the lowest variability along the listings.

Table A2.1
Descriptives for the individual direct and indirect effects of the inputs.

	Mean	Median	SD	IQR	Min.	Max.	Skewness	Kurtosis
Panel A: Direct effects								
No. guest rooms	0.306	0.301	0.018	0.007	0.297	0.415	4.273	20.053
Guest capacity	0.263	0.260	0.008	0.003	0.259	0.312	4.273	20.053
No. photos	0.064	0.061	0.011	0.004	0.058	0.132	4.273	20.053
Min. stay	0.089	0.083	0.021	0.008	0.079	0.217	4.273	20.053
Panel B: Indirect effects								
No. guest rooms	0.302	0.269	0.167	0.172	0.074	1.411	2.516	10.774
Guest capacity	0.137	0.122	0.076	0.078	0.034	0.639	2.516	10.774
No. photos	0.190	0.169	0.105	0.108	0.047	0.885	2.516	10.774

Table A2.2 shows the individual direct and indirect effects for the inefficiency determinants, DEZ_k^i and IEZ_k^i, respectively. The variability of the effects is lower, except for the market share variable, which has significantly higher values than the rest.

Table A2.2
Descriptives for the individual direct and indirect effects of the inefficiency determinants.

	Mean	Median	SD	IQR	Min.	Max.	Skewness	Kurtosis
Panel A: Direct effects								
Hotel ADR	−0.001	−0.001	0.0004	0.001	−0.003	−0.0000007	−0.523	0.596
Available days	0.061	0.058	0.025	0.032	0.00004	0.16	0.523	0.596
Blocked days	0.062	0.059	0.026	0.033	0.00004	0.164	0.523	0.596
Market share	−5.866	−5.558	2.435	3.096	−15.421	−0.004	−0.523	0.596
Relative professionalism	0.085	0.08	0.035	0.045	0.0001	0.223	0.523	0.596
Employment competition	0.002	0.002	0.001	0.001	0.000001	0.005	0.523	0.596
Hospitality employees	0	0	0	0	−0.000005	−0.0000000	−0.523	0.596
Airbnb listings	−0.002	−0.002	0.001	0.001	−0.005	−0.000001	−0.523	0.596
GDP	−0.013	−0.012	0.005	0.007	−0.033	0	−0.523	0.596
Panel B: Indirect effects								
Hotel ADR	−0.001	−0.001	0.0004	0.0004	−0.003	−0.0000001	−1.584	4.399
Available days	0.035	0.031	0.023	0.025	0.000007	0.169	1.584	4.399

(continued on next page)

Table A2.2 (*continued*)

	Mean	Median	SD	IQR	Min.	Max.	Skewness	Kurtosis
Blocked days	0.036	0.032	0.024	0.026	0.000007	0.174	1.584	4.399
Market share	−3.418	−3.015	2.256	2.427	−16.312	−0.001	−1.584	4.399
Relative professionalism	0.049	0.044	0.033	0.035	0.000009	0.236	1.584	4.399
Employment competition	0.001	0.001	0.001	0.001	0.0000002	0.006	1.584	4.399
Hospitality employees	−0.0000009	−0.000001	0.0000007	0.0000007	−0.000005	−0.0000000	−1.584	4.399
Airbnb listings	−0.001	−0.001	0.001	0.001	−0.006	−0.0000002	−1.584	4.399
GDP	−0.007	−0.006	0.005	0.005	−0.035	−0.000001	−1.584	4.399

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