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Substitution among hotels and P2P accommodation in the COVID era: a spatial dynamic panel data model at the listing level

Rafael Suárez-Vega [a,b], Jorge V. Pérez-Rodríguez [a] and Juan M. Hernández [a,b]

[a]Department of Quantitative Methods for Economics and Management, Universidad de Las Palmas de Gran Canaria, Las Palmas de Gran Canaria, Spain; [b]Institute of Tourism and Sustainable Economic Development (Tides), Universidad de Las Palmas de Gran Canaria, Las Palmas de Gran Canaria, Spain

ABSTRACT
This paper analyses whether peer-to-peer (P2P) accommodation substitutes traditional accommodation, taking into account dynamic and spatial spillover effects. We also analyse the impact of the COVID-19 pandemic crisis on the demand and substitution effect. To do this, we use a spatial dynamic panel data demand model for occupancy rates related to prices of P2P accommodation units, prices of competitors (hotels and apartments) and income. Its dynamic component allows estimation of the short- and long-term effects of prices and income on P2P accommodation demand. The model was applied to the P2P accommodation demand in the Canary Islands, Spain. The results indicate that, in the pre-pandemic period, occupancy rates were positively autocorrelated, demand was own-price elastic and substitution with hotels was significant in the short-term. This substitution effect and consumer sensitivity to prices and substitution increase in the long term. However, the irruption of COVID-19 largely distorted price and income-elasticities.

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Demand modelling; Airbnb listings; spatial dynamic panel data Durbin model; substitution effect; spatial spillover effects

1. Introduction

The emergence of peer-to-peer (P2P) accommodation in the last decade has transformed the accommodation industry worldwide. Sharing accommodation platforms, such as Airbnb, were perceived as a disruptive innovation in the accommodation sector, characterized by offering an initially cheaper and simpler product supported by internet technologies (Guttentag, 2015). In a second phase, the new accommodation sector began to attract new customers by including further differentiating characteristics with the hotel sector, such as supply variety (Dolničar, 2018), immersive experiences (Paulauskaite et al., 2017), and social interactions (Tussyadiah, 2015). All these new services have allowed P2P accommodation to satisfy the needs of upper-level customers that would possibly be hosted in hotels as an alternative (Destefanis et al., 2020).

In parallel to the growing popularity of Airbnb, tourism researchers have addressed the following question: Is P2P accommodation a substitute for traditional accommodations? The answer to this question has theoretical relevance, since it serves as a test for the suitability of the application of the disruption innovation theory in this context, showing whether sharing accommodation has or has not colonized part of the hotel demand. A positive answer would also support the argument of hoteliers who claim that P2P lodging hosts, with lower fixed costs than hoteliers, should have similar regulatory standards to those imposed on them. Moreover, it would also have practical consequences, since managers from both types of accommodation would need to implement policies to

CONTACT Rafael Suárez-Vega rafael.suarez@ulpgc.es

adapt their supply to the new circumstances, offering products and services based on observed strategies from the other sector, in order to compete and gain market share.

However, studies about the substitution effect between P2P and incumbent actors conducted to date have shown mixed results. Some papers claim the existence of this substitution effect, evidenced by the negative impact of P2P on hotel revenues (Dogru et al., 2020; Zervas et al., 2017) and occupancy rates (Gunter et al., 2020), as well as by an increase in price elasticity (Chen et al., 2021) and the synchronization of occupancy rate series in P2P and hotels (Sainaghi & Baggio, 2020). However, other studies do not find any substitution effect, evidenced for example by a null influence of P2P on hotel revenues (Blal et al., 2018). One of the reasons used to justify the absence of a relationship between the two accommodation products is location. For example, exploratory analyses found different location patterns of Airbnb listings and hotels in major cities, such as Paris, indicating an insignificant competition effect between them (Heo et al., 2019).

This paper contributes to answering the question above by including new aspects that have been disregarded in previous analyses. Specifically, we consider the role of consumer habits in the substitution effect between P2P accommodation and hotels. Although some previous studies have looked at the importance of habit persistence in tourism demand (Fleissig, 2021; Song et al., 2010), its effect in terms of substitution between accommodations units is still unexplored. Habit persistence is included in tourism demand models by means of a lagged dependent variable and allows estimating the own – and cross-price elasticities in the short and long term. Cross-price elasticities reveal the relationships (substitutive or complementary) between the two products. While previous studies have adopted a static framework for calculation of the substitution effect, an analysis of habit persistence would show a dynamic estimation of this effect by splitting the elasticities into the short and the long term.

Then, we propose a novel spatial dynamic panel data model to quantify own-price, cross-price and income elasticities of Airbnb demand. The model includes dynamic effects in combination with spatial spillover effects. The latter have been considered in other previous demand models for P2P accommodation, although in isolation from the dynamic effects (Gunter et al., 2020). In the model presented here, the dynamic part evaluates habit persistence, while the spatial part evaluates the current and lagged spatial spillover effect. In this way, it is possible to study direct (related to own-listing effects), indirect (representing cross-listing spillovers) and total marginal effects on tourism demand, both in the short and long term. In other words, the model allows the analysis of habit persistence in tourism demand including spatial effects.

Our motivation to include the habit persistence effect in the demand model is to find a finer estimation of the substitution effect by means of a double focus (dynamic and spatial). The economic theory argues that, in general, demand elasticities are expected to be lower in the short than in the long term. Applied to the case of cross-elasticities, this theoretical hypothesis points to an increase in the substitution effect over time. The empirical estimation conducted in this paper could be used to test the validity of this hypothesis in the context of P2P and traditional accommodation market.

The estimations obtained with the model also have relevant practical implications. The findings obtained should allow policy makers and managers to be able to analyse in advance the short – and long-term effect of certain policies to deal with potential competition with the other types of accommodation. The spatial effects results would also provide information about the secondary effects of these policies for actors in a given geographical area. All this information can be used to implement the most suitable actions accordingly.

As a case study, the model was applied to the accommodation market in the Canary Islands (Spain). The database comprises information from a balanced panel data for Airbnb listings in the Islands from January 2018 to December 2020 on a monthly basis. This time span allows a study of the effect of the COVID-19 period on the demand of Airbnb listings and the substitution effect with hotels. The econometric method used is a first-order spatial panel data model with one-way fixed effects (Belotti et al., 2017; Elhorst, 2012), which is estimated using maximum likelihood estimators. Then, we analyse whether P2P is a substitute or complement of traditional accommodations such as hotels and apartments in the Canary Islands.

2. Literature review

2.1. Dynamic demand models

Dynamic tourism demand models have been used to estimate short – and long-term price and income elasticities. They are represented within the set of explanatory factors as the coefficient of a time lagged dependent variable. Generally, the literature considers that the lagged dependent variable describes, from the demand side, habit persistence and the word-of-mouth effect in travel preferences (Peng et al., 2015; Song et al., 2010), but it can also reflect supply constraints, limiting rapid increase in tourism flow (Witt & Witt, 1995).

Many papers on tourism demand modelling have traditionally included lagged demand as an explanatory variable in a panel data framework (e.g. Garín-Muñoz, 2006; Garín-Muñoz & Montero-Martín, 2007; Ledesma-Rodríguez et al., 2001). In general, the most widely used dependent variable representing tourism demand is tourism arrivals (e.g. Garín-Muñoz, 2006; Naudé & Saayman, 2005; Seetaram, 2010). Other authors have analysed tourism expenditure (e.g. Li et al., 2004; Lyssiotou, 2000; Wu et al., 2012) and occupancy rates (Jiménez et al., 2021).

The results obtained for coefficients of lagged variables in the empirical studies are mixed. Some studies have found them to be highly significant and positive (Song & Witt, 2003), revealing a strong positive disposition to repeat visits and/or a high word-of-mouth effect. Nevertheless, other authors have reported negative values of the lagged dependent value (Naudé & Saayman, 2005). This can be interpreted as a negative disposition to repeat visits. Other studies even indicate the lagged dependent variable to be the main determinant of tourism demand (Song et al., 2010; Song & Witt, 2003).

To our knowledge, Jiménez et al. (2021) are the only authors who have analysed the habit persistence effect in the P2P accommodation sector. They used a dynamic panel data model at the Spanish city level (period 2014-2017) to analyse the effects of Airbnb on the size of local tourism markets. They took Airbnb occupancy rates and hotel overnight stays as dependent variables in order to analyze the causal relationship between them. Their findings showed a positive habit persistence effect for this type of accommodation.

2.2. Spatial demand models

The literature on panel data models in tourism demand research is extensive (also including the case for dynamic frameworks, as we have seen). There has been growing interest in recent years in research into spatial effects. The incorporation of the spatial dimension allows analysis of not only the factors determining tourism demand of units (regions, destinations, accommodation units) over time, but also the interrelationships that are produced between different units due to their locations. The basic principle of these models is the existence of spatial spillover effects, in other words, close units are more mutually influent than those that are farther apart.

Papers using spatial econometric methods have focused their analysis on tourism demand, studying several types of variables including, for example, inbound tourism, prices and supply. Some papers have analysed inbound tourism in China (e.g. Ma et al., 2015; Yang & Wong, 2012; Yang & Zhang, 2019; Zhang, 2009) and Australia (Deng & Athanasopoulos, 2011). Regarding P2P accommodation such as Airbnb, some papers have studied price determinants in UK (Voltes-Dorta & Inchausti-Sintes, 2021), Estonia (Önder et al., 2019) and Spain (Adamiak et al., 2019; Boto-garcía et al., 2021; Eugenio-Martin et al., 2019; Gutiérrez et al., 2017). To our knowledge, Gunter et al. (2020) is the only study of Airbnb demand that used occupancy rates as a dependent variable in a spatial econometric model. They showed that Airbnb demand in New York City is price inelastic and that the city's traditional accommodation industries, as well as neighbouring Airbnb listings, are substitutes for the analysed Airbnb listings.

Some of the studies above have reported insights about the influence of location on Airbnb demand and its substitution effect with hotels. For example, Gutiérrez et al. (2017) compared spatial patterns of hotels and P2P accommodation in Barcelona. The study was done based on geo-located photos shared in a web app. They found that the factors determining the location of hotels and Airbnb listings are not the same. For instance, Airbnb listings use to be closer to the city centre and benefit more than hotels from their proximity to tourist attractions. Eugenio-Martin et al. (2019) also explored the Airbnb accommodation spatial distribution using geo-located photos. They used a spatial autoregressive model to estimate the relationship between hotels and Airbnb listings located in three kinds of local tourism destinations in the Canary Islands (Spain): sun and beach, nature-based and city. The authors found that the location of the Airbnb supply fits better tourist attractions in cities and nature tourism areas, whereas the location of hotels fits better the attractions in sun and beach areas. Voltes-Dorta and Inchausti-Sintes (2021) explored the spatial and quality dimensions of local Airbnb markets in the UK. To do this, they employed standard regression techniques to study prices considering structural variables (number of bathrooms or bedrooms), value variables (value and quality of the house) and spatial variables (distances to the city centre, to the nearest bus/train station, to points of interest, or number of competing listings). As a novelty, they concluded that the area where competing listings exert a negative effect is reduced when the listing quality increases.

However, the papers above did not consider the habit persistence effect (or the partial adjustment mechanism) in the tourist demand including spatial spillover effects. In this sense, Liu (2020) recently analysed tourism demand for attractions in Taiwan using a spatial dynamic panel model to account for habit persistence and word-of-mouth effect separately. The former is estimated by the time-lagged dependent variable and the latter by the spatially lagged dependent variable. This interpretation is questionable in the sense that the word-of-mouth effect could also be presented in the time-lagged dependent variable. Moreover, the current spatial autocorrelation is not estimated with the model.

To our knowledge, price and income elasticities of tourism demand in P2P accommodation, in the short and long term, have not been investigated yet using a spatial dynamic panel data model.

3. Data and variables

The data for the empirical study corresponds to tourism in the Canary Islands, one of the most important destinations for European tourists who visit Spain, and where, at this moment, an important traditional accommodation industry (hotels and apartments) with an emergent P2P accommodation market coexist. The traditional industry is mostly oriented to sun and beach tourism, although urban and rural tourism have increased their share in the last decade. The first P2P accommodation units appeared at the beginning of the last decade and their number has grown sharply since then. In the year prior to the pandemic (2019), the accommodation industry in the Islands included 1,602 hotels and apartments, with a total of 395,016 beds and hosting more than 15 million visitors (ISTAC, 2021). According to data provided by AirDNA (https://www.airdna.co/), the official entity that manages information on properties advertised on Airbnb, there were 73,150 registered P2P properties in 2019 in the Canary Islands, accommodating 9.2% of the total number of visitors.

The database presents a monthly structure, from January 2018 to December 2020, in which Airbnb listings in the Canary Islands are the units of observation. To have a balanced panel, only those listings with available data for all the months in the period of study were considered. For homogeneity, only facilities labelled as 'Entire home/apt' were considered in the sample. From this category, only the seven most frequent subtypes were considered: Apartment (37.21%), House (25.58%), Villa (17.94%), Cottage (12.29%), Condominium (3.66%), Bungalow (1.33%) and Townhouse (1.99%). After this filtering process, a database with $N = 301$ Airbnb listings for $T = 36$ months, meaning a total of N×T = 10,836 observations, was obtained. A situation map and the sample distribution are presented in Figure 1.

Figure 2 shows the distribution of hotels and apartments in the Canary Islands in 2020. In contrast to the Airbnb listing, this type of facility is concentrated in traditional touristic areas, such as beach zones and the main cities of the islands. The Airbnb offer expanded the accommodation possibilities to new areas, such as rural areas in the interior of the islands (especially evident in the islands of Gran Canaria and Lanzarote).

The demand analysis will be carried out based on the monthly occupancy rate (OCR) of the Airbnb listings. For each property, we consider the surrounding alternative supply, which corresponds to both neighbouring Airbnb listings and hotels in the vicinity. Finally, gross domestic product (GDP) is considered a proxy for tourist income. The variables involved in the model are:

- OCR: This is the monthly occupancy rate (used as a demand variable) for each Airbnb listing. It is provided by AirDNA. This variable varies monthly (in time) and depends on the geographical coordinates of the Airbnb listing (in space).
- RADR: This is the relative average daily rate (ADR) of the property. It is calculated as the proportion of its ADR with respect to the average ADR for the Airbnb listings located within a ten km radius.[1] Accommodations with an RADR lower (higher) than one indicate an ADR lower (higher) than the average ADR in their surroundings. Therefore, this variable varies monthly and depends on the geographical location of each listing.
- HADR: This is the average monthly ADR (in Euros) for the hotels and apartments located in the municipality where the Airbnb accommodation is sited. The monthly HADR by municipality was taken from the *Instituto Canario de Estadística* (ISTAC, 2021), the official provider of statistical data for the Canary Islands. Therefore, this variable varies monthly (in time) and by municipality (in space).
- GDP: This is the weighted average real GDP of the top seven European tourist origin countries[2] related to the number of tourists visiting the islands. Tourists from these countries accounted for 77.31% of the total number of visitors to the islands during the study period (ISTAC, 2021).[3]

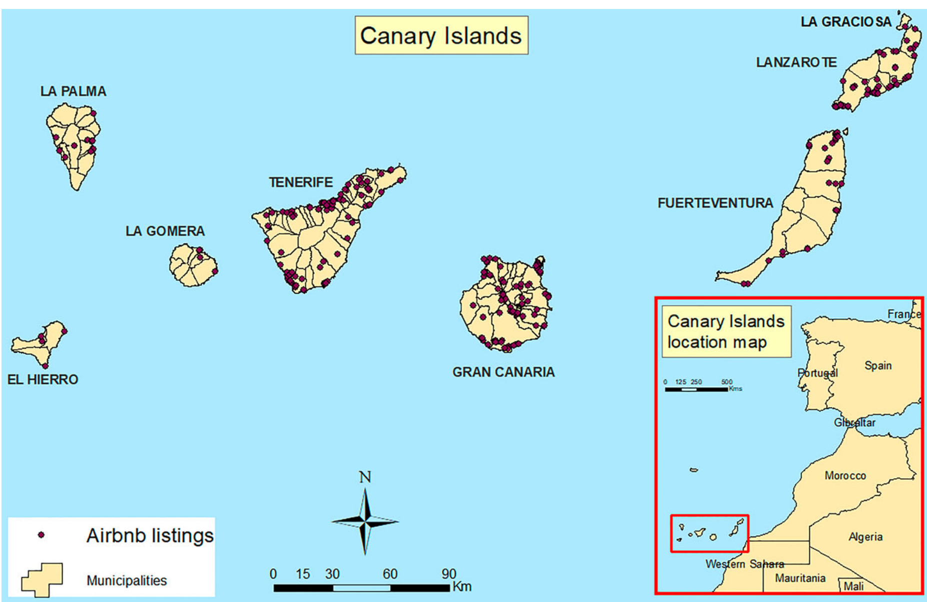

Figure 1. Spatial location of the sample of Airbnb listings in the Canary Islands in the period January 2018–December 2020.

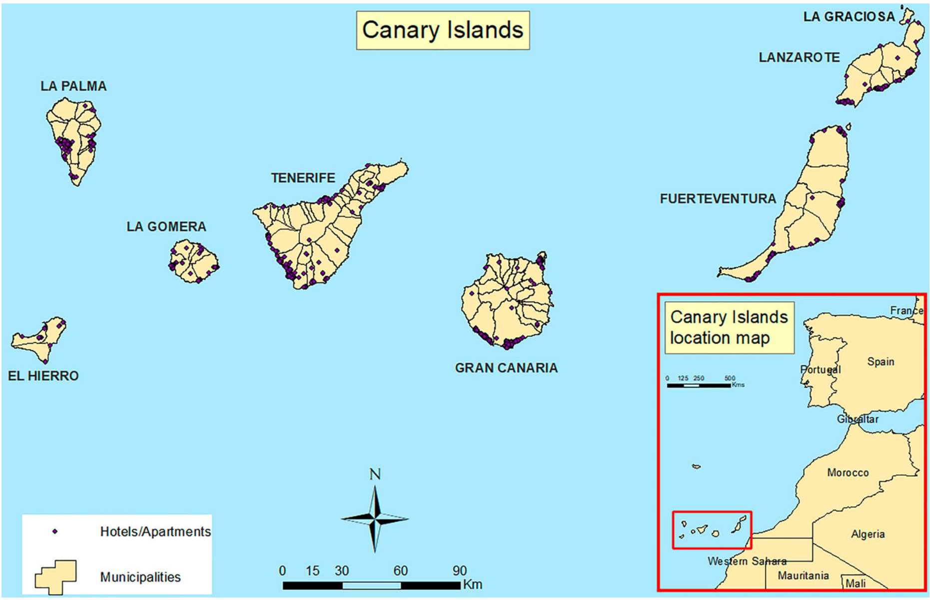

Figure 2. Spatial location of all hotels and apartments in the Canary Islands in 2020.

The quarterly series of real GDP (in millions of Euros) for these countries was obtained from EUROSTAT (2021) and divided by three to approximate the monthly values. All these figures were restated taking year 2017 as base and using the corresponding Harmonised Index of Consumer Prices (HICP). This variable adopts values in time (month) and space (island).[4]

4. Methodology

In this Section, we propose a dynamic spatial demand model (DSDM) that generalizes several simpler models in the literature. This model allows that dependent variables may be affected by both temporal and spatial lags. In particular, we use the dynamic spatial Durbin model (Debarsy et al., 2012; Elhorst, 2012) which introduces both time-lagged and spatially lagged dependent variables, but here we also include in the formulation the contemporaneous spatial spillover effect of the dependent variable and other spatially lagged regressors, which have not been considered before. The model can be written as:

$$y_t = \tau y_{t-1} + \rho W y_t + \psi W y_{t-1} + X_t \beta + D Z_t \theta + \mu + u_t \tag{1}$$

where, for an instant t, y_t is the vector for the dependent variable (e.g. log OCR), X_t represents the matrix containing the regressors, and Z_t is the matrix formed by the spatially lagged regressors. The term u_t is a disturbance term normally distributed with null mean and constant variance, σ_u^2, and is not correlated with the regressors.

$W$is the spatial weight matrix, included in the autoregressive component and D the spatial matrix, included in the spatially lagged regressors (in this work, the same spatial matrices are considered, that is $D = W$). Matrix Wrepresents the spatial relationship existing among the features (Airbnb listings) in the data verifying that $w_{ij} > 0$ for the neighbouring Airbnb listings ($i \neq j$) and its diagonal elements $w_{ij} = 0$. In this case, a row-standardized matrix is used where terms $w_{ij}$are calculated by means of the inverse distance between the geographical coordinates of the properties.

The parameters and restrictions involved in the one-way fixed DSDM defined in equation (1) are as follows:

- τ is the scalar reflecting time lag effect for the dependent variable, or in other words the effect on the OCR of its previous value. The stationarity in time requires the conditions $|\tau| < 1 - \rho r_{\max}$, $\rho \geq 0$ and $|\tau| < 1 - \rho r_{\min}$, $\rho < 0$ ($r_{\max}$and $r_{\min}$are the maximum and minimum characteristic roots of W). Otherwise, the model is nonstationary in time. These conditions show a trade-off between the serial and spatial autocorrelation coefficients (Elhorst, 2012).
- ρ is the spatial autocorrelation coefficient for the dependent variable, or in other words the effect on the OCR of the current neighbours' OCR. If $\rho = 0$, the contemporaneous endogenous interaction effects are excluded.
- ψ represents the coefficient for the spatial lag and time autocorrelation dependent variable, or in other words the effect of the neighbours' OCR in the previous period on the current OCR. If $\psi = 0$, lagged endogenous interaction effects are excluded. Also, following Elhorst (2012), ψ is equal to $-\tau\rho$.
- β is the vector of coefficients associated to the regressors.
- θ is the coefficient for the spatial lag for the regressors. If $\theta = 0$ exogenous interaction effects are excluded.
- μ is the vector of fixed effects. These estimated coefficients represent an unobservable individual effect that is considered constant over time.

Three methods to estimate models including mixed dynamics in both space and time have been proposed: (1) the quasi-maximum likelihood (QML) estimator, (2) the generalized method of moments, and (3) the Bayesian Markov Chain Monte Carlo approach. In this paper, we use the QML estimator which has implemented the bias-corrected maximum likelihood proposed by Yu et al. (2008).

The DSDM takes into consideration both spatial dependence between units and interactions in time. Then, an explanatory variable's change for a specific unit will affect the unit itself (direct effect) and possibly the rest of units indirectly (indirect effect) (Belotti et al., 2017), and these effects can be reported both in the short and long term. The total effects are the sum of the direct and indirect effects. As these effects vary along the different units in the sample, LeSage and Pace (2009) proposed two measures for reporting them. The direct effect of one regressor is given by the average direct effects among the different units; and the indirect effect is reported by the average of the sum of indirect effects for each sample unit. Table 1 shows the expression for the direct and indirect effects, both in the short and long term. More details about the DSDM can be found in Elhorst (2012) and Debarsy et al. (2012).

5. Empirical analysis

In this section, we focus on the results of our analysis. First, we conduct cross-dependence tests and, second, we estimate the spatial dynamic panel data model using maximum likelihood.

All variables used were transformed to natural logarithms. This transformation enables interpretation of the regression coefficients as price elasticity of demand (RADR), price elasticity for substitute accommodation in the destination (HADR), and income elasticities (GDP).

All the tests and estimations presented in this paper were done using STATA 14.[5]

Table 1. Direct and indirect effects for the k-th explanatory variable in DSDM.

	Direct effects	Indirect effects
Short-term	$\{(I - \rho W)^{-1}(\beta_k I + \theta_k W)\}^{\bar{d}}$	$\{(I - \rho W)^{-1}(\beta_k I + \theta_k W)\}^{\overline{rsum}}$
Long-term	$\{((1 - \tau)I - (\rho + \psi)W)^{-1}(\beta_k I + \theta_k W)\}^{\bar{d}}$	$\{((1 - \tau)I - (\rho + \psi)W)^{-1}(\beta_k I + \theta_k W)\}^{\overline{rsum}}$

Note: k represents the coefficient for the k-th variable in the corresponding parameter vector. $\bar{d}$ represents the operator that calculates the mean diagonal element of a matrix, and $\overline{rsum}$ denotes the operator that calculates the mean row sum of the non-diagonal elements. *Source*: Adapted from Elhorst (2012).

5.1. Spatial dependence tests

Some pre-test analyses were done in order to justify the use of a spatial data panel regression model. The Wooldridge test (Wooldridge, 2002) for temporal autocorrelations in panel data rejects the null hypothesis (F-statistic test equal to 150.6, p-value < 0.01) of no temporal autocorrelation in the error terms. The convenience of a pooled regression model is rejected according to the Breusch–Pagan-Lagrangian multiplier test for random effects (Breusch & Pagan, 1980) with chi-squared statistic equal to 4467.08 and p-value < 0.01. Additionally, the Hausman test confirms the preferability of a fixed-effects model over a random-effects one (chi-squared statistic test equal to 226.98, p-value < 0.01).

The Pesaran test of cross-sectional independence (Pesaran, 2004) reflects a high cross-sectional dependence in the error terms (rejecting the null of weak cross-sectional dependence (CD) with statistic test equal to 97.551 and p-value < 0.01). This fact reduces the efficiency of traditional panel data regression models and suggests that other alternatives such as spatial regression may improve the results. In this line, variables involved in the regression present spatial autocorrelation as reflected by their Moran Index (Moran, 1950) during the period of study. Table 2 shows the results of the Moran test for the variables and residuals in the cross-section regression at the beginning and the end of the period analysed. The table also presents the mean of the Moran Index for the 36 months and the percentage of months for which the variables present spatial autocorrelation. The presence of spatial autocorrelation is another aspect in favour of the use of spatial regression models.

5.2. Spatial dynamic panel data results

5.2.1. Global results

The DSDM defined by equation (1) was estimated considering all listings in the study period and both dynamic in time and in space. Table 3 contains information related to estimated coefficients of the dynamic model (distinguishing between main coefficients and coefficients for variables affecting the W matrix – denoted by Wx), number of listings used in the panel, R^2 and mean of fixed effects.

The dynamic in space was not statistically significant and the model finally implemented includes dynamic in time exclusively. Table 3 shows that the spatial autocorrelation coefficient and the variance of the error term (σ_u^2) are positive and statistically significant at a significance level of 1%, indicating that the spatial dynamic model is relevant. Additionally, the coefficient for time-lagged OCR is positive and statistically significant, indicating a positive autocorrelation and the existence of a possible partial adjustment mechanism for occupancy rates in time. A similar result was also found by Jiménez et al. (2021) for Spanish cities in the 2014–2017 period.

Moreover, the own-price, cross-price and income elasticities can be analysed through direct, indirect and total effects as follows:

(1) Direct marginal effects – that is, the own-listing effects.
    (a) The coefficients for the RADR of Airbnb based on a radius of 10 km (own-price elasticity) are negative and significant in both the short and long term. More specifically, a 1% increase in the ADR of listings reduces occupancy rates by 0.584% in the short term and 0.843% in the

Table 2. Results for the Moran test at the beginning and the end of the study period.

Time	log OCR	log RADR	log HADR	log GDP	Residuals
Jan. 2018	I = 0.077***	I = 0.124***	I = 0.529***	I = 0.784***	I = 0.083***
Dec. 2020	I = 0.123***	I = 0.107***	I = 0.460***	I = 0.762***	I = 0.118***
Mean	I = 0.101	I = 0.127	I = 0.530	I = 0.726	I = 0.096
Correlated months	80.6%	100%	100%	100%	83.3%

Note: ***, p-value < 0.01.

Table 3. DSDM estimates considering all the period (January 2018–December 2020).

	Coefficients		Marginal effects					
			Short-term			Long-term		
Variables	Main	*Wx*	Direct	Indirect	Total	Direct	Indirect	Total
Time-lag log OCR (τ)	0.305***							
log RADR	−0.584***	0.155***	−0.584***	0.050	−0.534***	−0.843***	−0.017	−0.860***
log HADR	0.417***		0.423***	0.099***	0.551***	0.521***	0.613***	0.840***
log GDP	0.085**		0.084**	0.019**	0.103**	0.121**	0.045**	0.166**
Spatial-lag (ρ)	0.194***							
σ_u^2	0.233***							
Number of listings	301							
R^2	0.114							
Mean of fixed effects	−3.139							

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

long term. These results indicate that Airbnb demand to the Canary Islands is price-inelastic, more in the short term than in the long term. Therefore, an increase in listing price will result in a less than proportionate decrease in demand and consequently total listing revenue will fall. Moreover, the significant coefficient for neighbouring Airbnb listings (0.155) shows the existence of competition within Airbnb accommodation units.

(b) The direct marginal effects of HADR in the Canary Islands (cross-price elasticity) are positive and statistically significant in both the short and long term. In this case, a 1% increase in the ADR of the hotels increases occupancy rates by 0.423% in the short term and 0.521% in the long term, indicating that Airbnb properties are substitutes of hotels in the destination.

(c) The direct marginal effect for GDP (income elasticity) is positive and statistically significant, for both short-term and long-term direct effects. These results show that demand for P2P lodgings in the Canary Islands is affected by the economic situation in the origin country of tourists and, therefore, a rise/fall in income in the origin country affects P2P demand in the Canary Islands in the same way.

(2) Indirect effects – that is, the spatial spillover effect.

(a) In this case, RADR does not present significant indirect effects in either the short or long term, meaning that the prices of nearby P2P properties do not significantly influence occupation rates in this period.

(b) The indirect effect for the HADR is significant both in the short and long term, being higher in the long term. This result means that an increase in hotel prices in neighbouring municipalities produces an increase in occupancy rates in P2P accommodation. This indirect effect is more important in the long term, even exceeding the direct marginal effect.

(c) The indirect effect for GDP is also significant and positive, but the figures are lower in contrast with the direct effect. That is, the occupancy of P2P accommodation of an island is also positively influenced when the GDP of the countries of the origin of visitors to the other islands increases.

(3) Total effects – which represent the aggregate effect summing the direct and indirect effects. These effects are significant for all the variables.

5.2.2. The effect of COVID-19

In order to analyse the possible effect of the restrictions imposed as a result of the pandemic, the model was estimated considering both pre-COVID (January 2018–February 2020) and intra-COVID (March 2020–December 2020) scenarios. The results are presented in Tables 4 and 5. It should be noted that the number of periods for the second sample is small (10 months). Consequently, conclusions extracted from the estimation in this period must be taken with caution. Nevertheless, as a general observation, the spatial dynamic panel data model is supported in both subperiods (e.g.

Table 4. DSDM estimates considering the pre-COVID period (January 2018–February 2020).

	Coefficients		Marginal effects					
			Short-term			Long-term		
Variables	Main	*Wx*	Direct	Indirect	Total	Direct	Indirect	Total
Time-lag log OCR (τ)	0.250***							
log RADR	−0.325**	0.263***	−0.321***	0.246***	−0.048	−0.426***	0.320***	−0.106
log HADR	0.519***		0.526***	0.093***	0.619***	0.704***	0.175***	0.879***
log GDP	0.263***		0.264***	0.047***	0.311***	0.354***	0.088***	0.442**
Spatial lag (ρ)	0.153***							
σ_u^2	0.158***							
Number of listings	301							
R^2	0.103							
Mean of fixed effects	−5.659							

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

coefficients for spatial autocorrelation, variance of error and one-lagged OCR are statistically significant and positive).

It is interesting to note the remarkable pattern for direct marginal effects of own prices (RADR) in the two subperiods. In the pre-COVID period demand is price inelastic in the short and long term, whereas in contrast in the intra-COVID period it is price elastic. With regard to indirect effects, there are also some differences. In the pre-COVID period, significant negative indirect effects can be observed (both in the short and long term), but they are no longer significant in the intra-COVID period, meaning that in this period variations in neighbour (competitor) prices do not affect occupancy rates in either the short or long term. The balance between the direct and indirect effects in the pre-COVID period results in non-significant total effects, whereas in the intra-COVID period total effects are dominated by the direct effects.

The effects for cross prices (HADR) are positive and statistically significant in the two periods, replicating the results obtained for the entire panel, both in the short and long term. Results in both periods also show that the occupancy rate is price inelastic with respect to hotel ADR, both in the short and long term. Then, hotels are substitute goods for Airbnb listings in the pre – and intra-COVID period. Indirect (spatial) cross-price effects are also significant in the two periods.

Income elasticity (GDP) is positive and statistically significant before COVID, suggesting that the demand for P2P accommodation in the Canary Islands in this period is sensitive to changes in the GDP in the origin country and, therefore, a rise/fall in income in the origin country could affect tourism demand in the Canary Islands. However, the GDP effects are negative in the intra-COVID period, which does not fit the economic theory.

Table 5. DSDM estimates considering the intra-COVID period (March 2020 – December 2020).

	Coefficients		Marginal effects					
			Short-term			Long-term		
Variables	Main	*Wx*	Direct	Indirect	Total	Direct	Indirect	Total
Time-lag log OCR (τ)	0.268***							
log RADR	−1.233***	0. 131	−1.237***	−0.036	−1.273***	−1.694***	−0.152	−1.845***
log HADR	0.447***		0.453***	0.068***	0.521***	0.621***	0.134***	0.755***
log GDP	−0.710***		−0.717***	−0.108***	−0.825***	−0.982***	−0.214***	−1.196***
Spatial lag (ρ)	0.132***							
σ_u^2	0.375***							
Number of listings	301							
R^2	0.056							
Mean of fixed effects	5.815							

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2.3. Robustness analysis

In order to test the robustness of the model, results were obtained considering three time horizons: 2017–2020, 2018–2020 and 2019–2020. Because the method requires a balanced panel, increasing the time horizon significantly reduces the number of dwellings in the panel data. Thus, the samples we have contain 112, 301 and 917 properties for the four-, three – and two-year periods. This issue mainly influences the number of nearby listings and therefore the calculation of the RADR, so that the fewer competing listings there are in the neighbourhood the less information this variable provides.

The summary of the estimation results is shown in Table 6.

We can say the following regarding variables.

RADR: The model seems sensitive to the sample size, because it is small and this variable uses fewer properties and, therefore, could imply less information. In fact, the effect in *Wx* disappears when increasing the number of years, and then reducing sample size.

HADR: The behaviour is stable over the different sample sizes, indicating the substitution effect between hotels and P2P is robust across estimations.

GDP: The behaviour of this variable is only distorted in the intra-COVID period. Results show that the longer the time horizon, the less influence the intra-COVID period has and the results tend to be more in line with expectations (positive effect of origin income on demand).

6. Discussion and conclusions

In this paper, we analysed the demand of Airbnb listings in a tourist area in Spain to obtain evidence of the degree of substitution with respect to traditional accommodation such as hotels and apartments, which are the most important accommodation types in the destination. To do this, we proposed a spatial dynamic panel data model which allows the inclusion of spatial effects and a possible partial adjustment mechanism or habit persistence for tourists.

6.1. Theoretical implications

The model contributes new insights into the dynamic and spatial nature of the substitution effect between P2P and traditional accommodation. The empirical section covers a time horizon that includes the outbreak of the pandemic, allowing the estimation of the effect of COVID-19 on P2P demand and on the substitution between sharing accommodation and hotels/apartments.

Regarding P2P demand, the results show an increase in own-price elasticity and therefore a higher sensitivity to price changes in the long term. This novel finding agrees with the general predictions from the economic theory and previous estimations of tourism demand (Peng et al., 2015). In general, economic theory suggests that price elasticity tends to increase in the long term because consumers have more time to adjust their behaviour and adapt to substitute goods. According to this principle, tourism demand negatively reacts to price increases in P2P more in the long than in the short term, as obtained in the empirical estimation.

Moreover, the estimation results reveal changes in own-price effect on demand between the pre – and intra-COVID period. Whereas own-price elasticities in the pre-COVID period are inelastic, agreeing with previous findings for P2P accommodation (Gunter et al., 2020), they change to elastic in the intra-COVID time. That is, tourism demand is more price-sensitive in the intra-COVID period. In addition, it is not influenced by indirect (spillover) effects, but exclusively by own price. Varied own-price elasticities across destinations and time periods have been long observed in tourism (e.g. Peng et al., 2015). Smeral (2017) provides several economic reasons of why tourism demand elasticities vary. One of them is the phase of the business cycle. In bad economic situations, consumers expect an income decrease, leading them to adopt a precautionary behaviour in terms of expenses, making them more price sensitive than in economic upswing periods. In the case analysed

Table 6. Estimates for the DSDM applied to different time horizons.

	2017–2020			2018–2020			2019–2020		
	All	pre-C	intra-C	All	pre-C	intra -C	All	pre-C	intra -C
Time-lag log OCR	0.316***	0.228***	0.307***	0.305***	0.250***	0.268***	0.292***	0.239***	0.243***
log RADR	−0.497***	−0.305***	−0.615***	−0.584***	−0.325***	−1.233***	−0.661***	−0.470***	−0.977***
Wx	−0.055	−0.237	0.020	0.155*	0.263***	0.131	0.296***	0.376***	0.323***
ST-Total effects	−0.691***	−0.642**	−0.790***	−0.534***	−0.075	−1.273***	−0.518***	−0.133	−0.863***
LT-Total effects	−1.142***	−0.878**	−1.278***	−0.860***	−0.106	−1.845***	−0.886***	−0.200	−1.269***
log HADR	0.378***	0.543***	0.391**	0.417***	0.519***	0.447***	0.309***	0.349***	0.321***
ST-Total effects	0.477***	0.651***	0.491***	0.521***	0.619***	0.521***	0.440***	0.491***	0.426***
LT-Total effects	0.789***	0.891***	0.794***	0.840***	0.879***	0.755***	0.752***	0.735***	0.626***
log GDP	0.196***	0.132	0.152**	0.085**	0.263***	−0.243**	0.001	0.184***	−0.479***
ST-Total effects	0.242***	0.155	0.184**	0.103**	0.311***	−0.405**	−0.002	0.255***	−0.634***
LT-Total effects	0.399***	0.212	0.298**	0.166**	0.442***	−0.654**	−0.005	0.382***	−0.933***
Spatial (ρ)	0.200***	0.151***	0.194***	0.194***	0.153***	0.132***	0.295***	0.281***	0.241***
σ_u^2	0.194***	0.107***	0.226***	0.233***	0.158***	0.375***	0.257***	0.170***	0.345***
Mean of fixed-effects	−4.226	−4.209	−3.811	−3.139	−5.659	5.815	−1.617	−3.931	3.776
Number of listings	112	112	112	301	301	301	917	917	917
R-squared	0.148	0.092	0.132	0.114	0.103	0.056	0.087	0.082	0.045
Log-likelihood	−3119.495	−397.232	−2458.	−7167.776	−3611.969	−2402.112	−1.53E+04	−6024.298	−6987.042
AIC	6247.675	795.865	4923.183	14,330.97	7215.336	4766.001	30493.61	11947.65	13832.09
BIC	6293.656	832.849	4966.688	14,381.81	7263.818	4807.332	30549.31	11999.35	13881.22

Notes: pre-C is pre-COVID and intra-C is intra-COVID period. ST is short term and LT is long-term. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in this paper, the economic uncertainty derived from the pandemic would make tourists adopt this precautionary behaviour with a consequent increase in own-price elasticities, as observed in our sample.

The results also show a robust substitution effect between P2P and hotels/apartments in the analyzed period, agreeing with some previous empirical findings (Gunter et al., 2020; Zervas et al., 2017) and disagreeing with others (Blal et al., 2018; Heo et al., 2019). The outcome reached in this paper can be explained by the spatial characteristics of the case study. The Canary Islands is a geographically limited, traditional sun-and-sand destination where accommodation units are mainly located near the main attractions (beach and more recently urban areas). Although sharing accommodation is more spatially dispersed than traditional accommodation (mainly in two of the seven islands), most P2P units in the archipelago are located in the same areas as previous hotels and apartments. Given that there are no differences in terms of distance to the main attractions (e.g. beach) between the units of the two types of accommodation, we expect a significant substitution effect between them. In other large destinations, such as Paris or other cities, the two types of accommodation are located in separated spatial clusters, inducing a low substitution effect between them (Heo et al., 2019).

Moreover, the results also reveal that the substitution effect is larger in the long than in the short term, as was observed for own-price elasticities. Similar reasons given for the dynamic effect of own-price elasticity (i.e. delay of consumer adaptation to price changes) can be applied to the dynamic effect of cross-price elasticities.

Regarding the pandemic effect, the study reveals that COVID-19 has been accompanied by a decrease in substitution between the two types of accommodation. Several explanations can be given for this outcome. One is the increased health risk perception after the pandemic outbreak, which made tourists adopt coping strategies, for example avoiding exposure to risky situations (Zheng et al., 2021). In this regard, although some studies find that the perception of risk in P2P users has increased during the COVID-19 crisis, it is also true that sharing accommodation is perceived as safer than hotels due to its lower physical contact (Lee & Deale, 2021). This perception is confirmed by the preference for entire rather than shared lodgings during the pandemic (Bresciani et al., 2021) and by the fact that higher economic performance indicators in the intra-COVID period have been reported for P2P than for hotels in several destinations (Medeiros et al., 2022). Then, if one type of accommodation is perceived as being more risky than the other in the period of pandemic (hotels vs. P2P), we would expect a decrease in substitution between the two products, as has also been revealed in previous empirical findings applied to substitute destinations (Eilat & Einav, 2004).

The estimation of income elasticity in the pre – and intra-COVID periods also gave some interesting results. In the first period (pre-COVID), the income effect is positive and significant for all marginal values, as expected. This result is in concurrence with the empirical literature where a positive and less than unity effect is generally found, indicating that tourism is a normal good (e.g. Gunter and Smeral (2016) reported that tourism has been a necessity in the recent past). An exception is the study by Gunter et al. (2020), who found that income elasticity was higher than unity for Airbnb demand in New York City, indicating that it is a luxury good.

However, income elasticity was found in this study to be negative for the intra-COVID period, which does not agree with the economic theory. Various factors related to the irruption of the pandemic, such as the restrictions imposed on visiting the destination, may help to explain this odd finding. In fact, Spanish visitors had fewer travelling restrictions than foreigners in the period analysed, and the percentage of Spanish tourists with respect to total tourists significantly increased in the intra-COVID period, passing from an average of 27.12% to 32.10%.

6.2. Practical implications

This paper analysed the case of tourism demand for P2P accommodation in the Canary Islands, a major tourist destination in Spain. The findings provide some new clues for implementing policies adapted to real circumstances. Although the practical implications are applied to the case study, they could be generalized to other destinations where the application of the method obtains similar results.

First, the existence of habit persistence justifies differentiating policy and marketing strategies in the short and long term. For example, the results reveal that own-price elasticities for Airbnb in the intra-COVID period experience a high increase in the long term. Then, the efficiency of renovation investments in the destination would be higher in economic growth periods than in stagnation or recession periods, as has also been reported by other authors (Fleissig, 2021).

Second, the substitutability between P2P accommodation and hotels/apartments also has relevant policy implications. Although moderated by the COVID-19 crisis, results also show that the substitution effect with traditional accommodation increases in the long term. Therefore, long-term strategies to compete for customers from other types of accommodation, such as major investments to re-define the product, are more recommendable than focusing exclusively on other short-term strategies, like temporary promotions or discounts.

Third, the spatial spillover effect of the substitution between the two accommodation sectors justifies the application of global policies to deal with this issue, rather than local or individual ones. For example, it is recommendable that policy makers design regional policies involving both types of accommodation, instead of local actions or specific regulations with respect to one of the accommodation sectors without taking into account the effect of these policies on the other sector. Moreover, it is recommendable that hotel managers coordinate their actions to compete with P2P accommodation from a regional perspective, instead of applying individual strategies or coordination at the municipality level.

6.3. Limitations and future research

Certain limitations to the present study should be acknowledged. First, the endogeneity of some regressors such as income or prices used in the spatial dynamic panel data model cannot be treated at this stage. The reason is because, to our knowledge, there are no instrumental variable methods implemented in this type of spatial model. Second, the analysis was conducted using a balanced panel data. It would be interesting to repeat the analysis using a unbalanced panel data, since the estimations depend on this assumption. Third, the robustness analysis reveals that own-price elasticities are sensitive to sample size, so findings regarding this factor should be taken with caution. Finally, a plausible economic interpretation of spatial coefficients for lagged spatial variables is still open to debate. Liu (2020) offers an interesting approach to this issue, but we strongly believe that more effort is required to separate persistence from word-of-mouth effects.

Notes

1. 1, 3, 5 and 10 km radii were considered as alternatives. The 10 km radius was the one with the best performance.
2. By order of number of visitors: Great Britain, Spain, Germany, Sweden, Netherlands, Belgium and Denmark.
3. Islands were chosen as the level of aggregation because the municipal level series lacked data, mainly in lock-down periods due to COVID-19. However, historically, differences in the predominant nationalities of tourists have been observed across islands.
4. Due to the COVID-19 restrictions, no visitor data are available for the islands, and so the proportions of visitors for the same month in 2019 were considered.
5. The DSDM is estimated using the *xsmle* STATA package (Belotti et al., 2017).

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ORCID

Rafael Suárez-Vega http://orcid.org/0000-0002-1926-3121
Jorge V. Pérez-Rodríguez http://orcid.org/0000-0002-6738-9191
Juan M. Hernández http://orcid.org/0000-0001-6897-5179

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