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COVID-19 and Guests' Preferences in Short-Term Rentals: Evidence from Madrid

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Abstract

This paper investigates how guests' preferences in peer-to-peer accommodations changed during the COVID-19 summer season. To this end, we adopt a semi-parametric hedonic pricing model and test the importance of attributes that better allow for social distancing. We take the city of Madrid as a compelling case study of an important tourist destination severely hit by the crisis. We show that guests' marginal willingness to pay for social distancing characteristics has changed from August 2019 to August 2020. In particular, we find that whereas those listings that have kitchen amenities have a premium price of around 20.4% in August 2020, which represents a 15.2 percentage point increase with respect to the previous year, the marginal willingness to pay for size-related characteristics decreased in 2.7 percentage points. Results are robust to sample and time composition.

Keywords: Hedonic modelling, Peer-to-peer accommodation, COVID-19 pandemic, Generalized Additive Models.

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1 Introduction

COVID-19 has severely hit the hospitality sector on a global scale. The UNWTO estimates an 80% drop in the number of international tourists for the 2020 summer season (UNWTO, 2020). In Spain, the drop stands at 80% and 25% in international and national tourism, respectively, with a 72% decrease in hotel occupancy (INE, 2020a). Travel restrictions, uncertainty and worries about health and safety all have contributed to a drastic reduction in numbers of trips and travelers. The inherent uncertainties surrounding COVID-19 make it hard to predict the effect on guest booking behavior. Previous experience from SARS outbreaks has shown how travelers prefer avoiding personal contacts, and they opt out of group tours (Wen et al., 2005). Similar findings have been reported lately after COVID-19 outbreaks. For instance, Hong et al. (2020) show that guests' satisfaction about B&B in China is influenced by the availability of single, more spacious rooms, and by the existence of self-service management. The possibility of minimizing physical contact through contactless transactions and interactions has also been highlighted as an important determinant of guests' perceived health safety (Kim et al., 2020; Shin and Kang, 2020; Rahimizhian and Irani, 2020). Eventually, concerns about social distancing were extended to leisure-related activities like eating out (Byrd et al., 2020; Parady et al., 2020; Wen et al., 2020), extending the impact of the COVID-19 crisis to the leisure sector (Eichenbaum et al., 2020).

The necessity of preserving social distance when traveling may have led to a shift in accommodation choices. In this line, a recent report by DuBois and Sanford (2020) shows that hotels experienced steeper declines in revenues *per* available room during the first wave of COVID-19, although they usually show higher occupancy rates than peer-review accommodations. One possible explanation is that short-term rental units help maintain social distancing. Borko et al. (2020) claim that the overperformance of short-term rental units during the crisis may be explained by the greater privacy and independence that the latter offer. It has also been pointed out that this kind of accommodation may provide for a safer environment while avoiding talking with receptionists or meeting other people in common areas (The Economist, 2020). Finally, the possibility of having a kitchen available to avoid eating out for meals has been highlighted as yet another attribute that favors social distancing (Glusac, 2020).

Against this background, this contribution aims to test whether and how guests' preferences indeed shifted towards social distancing attributes when they chose short-term rentals in the first COVID-19 summer season. For our purpose, we make use of a semi-parametric hedonic modeling framework to check whether the implicit prices of what we identify as social distancing attributes changed between August 2019 and August 2020 in the city of Madrid. We find that guests preferred smaller, well-equipped listings to preserve social distancing during this time. Listings that have kitchen amenities had a premium price of around 20.4% in August 2020, up 15.2 percentage points compared with August 2019. Moreover, the implicit price for size-related variables decreased 2.7 percentage points, which indicates a preference for smaller accommodations. However, we do not have statistical evidence that guests are less willing to pay for shared and private rooms after COVID-19. Ultimately, we consider that Madrid is a suitable setting to study the effect of COVID-19 on the change of guests' preferences, since it is a major tourist destination that has been severely affected by the COVID-19 outbreak.

To answer our research question, we adopt a Generalized Additive Model (GAM) that allows controlling for non-linearities in both price determinants and spatial dependence of the error term. As demonstrated by previous literature (Geniaux and Napoléone, 2008), GAMs are suitable for detecting the non-linear relationship between prices and the urban environment, as the latter strongly influences accommodation prices.

Our results are robust under different model specifications, including simple OLS. Additionally, we rule out the possibility that results depend on time and geography by performing several robustness checks. First, we reproduce our analysis on a different time frame, comparing August 2019 and August 2018, and we do not find any specific change in how social distancing attributes had been priced. Then, we show that results are similar if we choose a different case study by replicating the analysis for Barcelona, a city that, like Madrid, is of touristic interest and was an epicenter of the outbreak.

To the best of our knowledge, this is the first contribution that provides evidence of a shift in guests' tastes for attributes that help preserve social distancing in the aftermath of the COVID-19 crisis. We argue that our findings are relevant well beyond the evolution of the ongoing pandemic, since we may reasonably expect long-lasting effects after a re-organization of travel patterns to better cope with future pandemics (Chang et al., 2020; Santos et al., 2020).

The rest of the paper is organized as follows. Section 2 provides a brief review of previous literature. Section 3 and Section 4 describe the data and methodology, respectively. Section 5 presents the results, and we draw our conclusions in Section 6.

2 Literature review

We adopt a hedonic pricing framework, according to which the total price of a good can be represented as the sum of implicit prices for its individual characteristics (Lancaster, 1966; Rosen, 1974). As Teubner et al. (2017) pointed out, short-term rental business is an ideal setting for studying price formation because of the relative homogeneity in listings information, the non-professional role of most hosts, and the competitive environment of the sector.

In this study, we rely mainly on price determinants that have been proposed in previous literature (Chica-Olmo et al., 2020; Deboosere et al., 2019; Lladós-Masllorens et al., 2020; Perez-Sanchez et al., 2018; Tang et al., 2019). Most authors consider price determinants: i) structural Airbnb characteristics (i.e., number of bedrooms, beds, amenities, whether the listing is offered as shared/private versus the entire apartment); ii) quality and host covariates (number of reviews, overall star rating, Superhost badge, rental policy, host experience, number of listings managed by the host), and iii) environmental and location variables (i.e., distance to the center, distance to the nearest point of interest, number of nearby hotel properties, population and Airbnb listing density).

Structural characteristics like size-related attributes, the provision of certain amenities (internet connection, air conditioning, kitchen) and the room type of the listing (entire apartment versus shared/private room) have a positive and significant effect on the price (Chen and Xie, 2017; Gibbs et al., 2018; Gunter and Önder, 2018; Voltes-Dorta and Sánchez-Medina, 2020; Wang and Nicolau, 2017). On the other hand, location variables like distance to the center, distance to the nearest point of interest, and population density all are expected to have a negative impact on prices (Chica-

Olmo et al., 2020; Deboosere et al., 2019; Lawani et al., 2019; Perez-Sanchez et al., 2018; Tang et al., 2019; Gunter and Önder, 2018; Voltes-Dorta and Sánchez-Medina, 2020), whereas the number of other nearby listings is likely to be associated with a higher price (Cai et al., 2019; Lladós-Masllorens et al., 2020; Tang et al., 2019). As for quality and host covariates, previous research has found that the number of reviews seems to have a negative correlation with the price of a listing, possibly because many tourists prefer cheaper accommodations. Knowing that approximately 70% of guests left a review (Fradkin et al., 2018), one expects low-price accommodations to have higher occupancy rates and more reviews (Lorde et al., 2019; Teubner et al., 2017; Wang and Nicolau, 2017). Finally, there are certain price determinants whose sign and significance vary across studies like the availability of the so-called *Superhost* badge or the overall rating score of the listing (Cai et al., 2019; Chen and Xie, 2017; Ert et al., 2016; Teubner et al., 2017; Wang and Nicolau, 2017; Zhang et al., 2017). In this respect, mixed results may be explained by specific sample selection and country-specific characteristics (Benítez-Aurioles, 2018; Gibbs et al., 2018).

Previous studies that use hedonic regression models focus mainly on Western countries because of the availability of data aggregators like AirDNA and Inside Airbnb.[1] Also, data availability is clearly oriented to analyses of urban areas, whereas only a few papers analyze rural areas (Dudás et al., 2020; Falk et al., 2019).

Previous hedonic pricing models of peer-to-peer accommodations have been estimated using simple linear regressions (Benítez-Aurioles, 2018; Cai et al., 2019; Chen and Xie, 2017; Perez-Sanchez et al., 2018; Gibbs et al., 2018; Teubner et al., 2017). Only recently, quantile regression models (Dudás et al., 2020; Perez-Sanchez et al., 2018; Gunter and Önder, 2018) and machine learning algorithms (Chattopadhyay and Mitra, 2019) have been proposed. However, spatial dependence is an important element to consider in the hospitality sector, and is especially important in the case of Airbnb listings (Gutiérrez et al., 2017). Most previous contributions solve the problem of spatial autocorrelation by assuming that spatial dependence is known *ex-ante*[2]. Many papers have tried to solve the problem of spatial autocorrelation in the error

[1]For a complete list of the contributions in this field, please refer to Table AI in the Appendix.

[2]To solve the issue, multiple techniques have been used, including Geographically Weighted Regression (GWR), Spatial Autocorrelation Regression (SAR), Spatial Error Model (SEM) and Multilevel models (Chica-Olmo et al., 2020; Deboosere et al., 2019; Suárez-Vega and Hernández, 2020; Tang et al., 2019; Voltes-Dorta and Sánchez-Medina, 2020; Zhang et al., 2017).

term by assuming that the spatial dependence is known, and therefore, it can be estimated parametrically. However, no paper has tackled the potential non-linearities in the price determinants except for Chattopadhyay and Mitra (2019), who apply random forest and conditional decision trees to explain the variability in Airbnb prices. Unfortunately, even if they measure the importance of each attribute by calculating the increase in the model's prediction error after permuting each feature, they do not retrieve any coefficient, which would reveal the implicit price of that attribute.

Against this background, we adopt GAM as a suitable technique for detecting the potential non-linear effects of the continuous predictors, whether they are geographic coordinates or attributes of short-term rental units. For example, if we included distance to the city center as a linear term in the regression equation, like Voltes-Dorta and Sánchez-Medina (2020) and Tong and Gunter (2020), we would not capture the actual urban sprawl. As a semi-parametric estimator, GAM does not make any *ex-ante* assumption on the structure of spatial autocorrelation. As Von Graevenitz and Panduro (2015) pointed out, the inclusion of coordinates as a bivariate smooth term in the equation can be seen as a sort of flexible fixed effect. This procedure goes by the name of *Geoadditive Models* (Kammann and Wand, 2003). We believe a GAM is preferable to just including controls for a large range of spatial predictors (Chica-Olmo et al., 2020; Deboosere et al., 2019; Suárez-Vega and Hernández, 2020; Lawani et al., 2019; Perez-Sanchez et al., 2018; Tang et al., 2019; Voltes-Dorta and Sánchez-Medina, 2020) since, as argued by Geniaux and Napoléone (2008), the specification can suffer from quasi-collinearity.

In sum, a GAM can be seen as a halfway technique between highly interpretable models like linear regression (OLS) and black-box machine learning methods (i.e., SVM, neural nets, random forest), while assuming that there is a linear and non-linear component of coefficients, therefore preserving interpretability. To the best of our knowledge, the use of a GAM is novel in the sharing economy hedonic price model literature. The GAM has already been applied to study real estate in Pace (1995, 1998) and Mason and Quigley (1996). The semi-parametric approach for estimating hedonic pricing models has been improved after the development of the geoadditive models (Kammann and Wand, 2003). Since then, several authors have highlighted the benefit of using a semi-parametric approach in hedonic price estimation. Geniaux and Napoléone (2008) and

Cajias and Ertl (2018) showed how GAMs outperform Geographically Weighted Regression models in terms of goodness of fit. More recently, Panduro and Veie (2013) and Von Graevenitz and Panduro (2015) analyzed the performance of this semiparametric technique with the use of more standard spatial econometrics methods like Spatial Error Models or spatial fixed effects. Following the same approach of these last papers, Montero et al. (2018) studied the out-sample performance of several parametric and semi-parametric spatial hedonic models, highlighting the importance of including a spatial drift (smooth coordinates interaction) term to improve the predictive power of the model.

3 Data

For our purposes, we consider Airbnb Madrid listings in August 2019 and in August 2020. We collect data from the platform Inside Airbnb. We select the same summer month before and after the COVID-19 crisis to minimize the differences in tourist demand composition due to the seasonality of the arrivals by origin. We choose the city of Madrid as a compelling case study since it is one of the largest destinations in Europe by number of Airbnb listings (Statista, 2019) and it is the most visited city in Spain (INE, 2020b). In fact, Spain was one of the most affected countries during the first wave of the COVID-19 crisis with 498,989 confirmed cases as of September 7, 2020 (WHO, 2020). Specifically, Madrid has become one of the epicenters of the COVID-19 crisis in Europe. As in Deboosere et al. (2019), Suárez-Vega and Hernández (2020) and Wang and Nicolau (2017), we restrict our sample to listings that have at least one review in the last six months because price rates of inactive listings could be misleading.

Our choice of price determinants is driven by the review of previous literature. In our sample, we include: i) structural characteristics, i.e., the size of the listings measured as the first dimension of a Principal Component Analysis (PCA) for the number of rooms, beds and the capacity of the listings; ii) whether the accommodation has a fully equipped kitchen (oven, dishwasher and refrigerator); iii) whether the listing is offered as an entire unit or a shared/private room; iv) quality and host attributes, i.e., the number of different listings that the host manages, the number of years the listing has appeared on the platform, the number of reviews and their valence; v) geographic location of the accommodation.

In particular, our main variables of interest are accommodation size, the presence of a fully equipped kitchen, and room type as proxies of the capacity of the listing to allow social distancing. As for size, we expect that a reduction in the size of travel groups may lead to a shift in guests' preferences towards smaller listings. Besides, the availability of kitchen amenities may help to make for a more pleasant stay without the risk of eating out. Eventually, even though the size and the type of room are invariant, we observe that the kitchen-related amenities change slightly in the period we consider. Therefore, to remove any capitalization effect due to the addition of new attributes in August 2020, we restrict our sample to observations that did not change the number of kitchen amenities in the period of study. In this way, changes in implicit prices better reflect shifts in preferences.

Table I

	Whole sample	**Restricted sample**
Variable	N = 14,420	N = 3,190
Average price, 2019	76.45	77.92
Average price, 2020	57.75	56.77
Aggregate price variation	-.24	-.27
Supply, August 2019	11,423	1,595
Supply, August 2020	2,997	1,595
Supply variation	0.73	-

The Whole sample includes all active listings in the platform either in August 2019 or August 2020 whereas restricted sample only listings that are active on the platform in both years.

Table I: Sample descriptive statistics for active Airbnb listings, city of Madrid, August 2019 and August 2020.

In Table I, we report descriptive statistics on changes in both the number of peer-to-peer accommodations in Madrid and their average prices between August 2019 and August 2020. The change in Airbnb listing supply has been much greater than the variation in price. The number of active listings has decreased 73%, whereas the average price has fallen 24%. To rule out potential composition effects in the Airbnb supply, we make our results robust by restricting ourselves to a subsample of listings that were active in both periods. Notably, only 13.9% of the Madrid Airbnb supply in August 2019 remained active after one year. A description of price determinants for the restricted sample is provided in Table II.

Variable	Description	Mean	SD
	Structural Airbnb characteristics		
Accommodates	Max nº of people in each listing	3.89	1.95
Bedrooms	Nº of bedrooms in each listing	1.53	.84
Beds	Nº of beds in each listing	2.24	1.32
Social distancing size	First dimension of PCA for accommodates, bedrooms and beds variables.	-	-
Shared room	1 if it is a shared room, 0 otherwise	.002	.05
Private room	1 if it is a private room, 0 otherwise	.20	.40
Entire unit	1 if it is an entire apartment, 0 otherwise	.80	.40
Social distancing room type	1 if it is a private or shared room, 0 otherwise	.20	.5
Oven	1 if the listing has an oven	.49	.50
Dishwasher	1 if the listing has a dishwasher	.37	.48
Refrigerator	1 if the listing has a refrigerator	.77	.42
Social distancing kitchen	1 if the listing has an oven, a dishwasher and a refrigerator.	.29	.46
	Quality and host attributes		
Host listings count	Nº of listings owned/managed by the host	11.87	24.9
Age	Nº of years the listing has been on the platform	2.5	1.72
Number of reviews	Nº of reviews in each listing	100.03	97.59
Review scores rating	Average score in each listing (0-100)	93.41	5.36
	Environmental and location variables		
Longitude and latitude	Approximate longitude and latitude coordinates of each listing	-	-

Table II: Variable description for active Airbnb listings in the restricted sample, city of Madrid, August 2019 and August 2020.

4 Empirical strategy

4.1 The Generalized Additive Method

Our baseline choice is a Generalized Additive Model as introduced by Hastie and Tibshirani (1987, 1990) and extended by Wood (2003, 2017), where linear predictors can be specified as the sum of smooth functions of regressors. Formally, a GAM model can be written as:

$$g(\mu_i) = A_i\beta + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + ... \tag{1}$$

where $g(.)$ is the link function, $\mu_i \equiv E(Y_i)$ is the expectation of Y, $Y_i \sim EF(\mu_i, \phi)$ is a response variable distributed according to an exponential family distribution with mean μ_i and shape parameter ϕ, A_i is a row of the model matrix for the parametric model components with β the corresponding parameter vector, and any f_j is a smooth function of a non-linear covariate. Each smooth function f_j can be represented by the sum of K basis functions $(b_{j,k})$ times their respective coefficients $(\beta_{j,k})$

$$f_j(x_j) = \sum_{k=1}^{K} \beta_{j,k} b_{j,k}(x_j) \tag{2}$$

Intuitively, a basis is a set of functions that span the space of the smooth component with the goal of containing the true functional form $f(x_j)$ or an approximation of it. For instance, a polynomial of degree 3 can be seen as an example of basis expansion which is composed of 4 basis functions: $b_{j,1}(x_j) = 1, b_{j,2}(x_j) = x_j, b_{j,3}(x_j) = x_j^2, b_{j,4}(x_j) = x_j^3$. Several basis functions have been proposed including cubic splines, B-splines and thin-plate regression splines. A spline is a special function defined piecewise by polynomials that are joined together at some specific locations also known as *knots*. They are usually joined in such a way that a certain degree of smoothness is granted. To avoid discretionality on knot placement, low-rank thin-plate regression splines have been developed (Wood, 2003). Finally, $f_3(x_{3i}, x_{4i})$ is a bivariate smoothing function of the coordinates to catch most sophisticated spatial settings (Kammann and Wand, 2003). The bivariate smooth term is estimated by isotropic smoothing splines given that the interaction of both variables is on the same unit scale.

To avoid overfitting, we estimate the model by a penalized maximum likelihood in the following way:

$$l_p(\beta) = l(\beta) - \frac{1}{2} \sum_j \lambda_j \beta^{\mathrm{T}} S_j \beta \quad where \quad \beta^T \mathbf{S} \beta = \int_R [f'']^2 \tag{3}$$

where $l(\beta)$ is a GLM likelihood function, and λ_j is a penalty term which controls how wiggly the $j-th$ smooth function is. As $\lambda \to \infty$, the result is a linear fit because any wiggliness will add too much to the loss function. As $\lambda \to 0$, we have the opposite effect, where any wiggliness is incorporated into the model. The correct value of λ is found by optimization methods such as Generalized Cross Validation (GCV) or Restricted Maximun Likelihood (REML). The basic idea of a penalized likelihood is to account for wiggliness while avoiding overfitting. This is why the second derivatives of smooth functions, S_j, are considered in the second term. It is up to the researcher to choose the number of basis functions to include in each smooth term. The basis should be large enough to contain the true unknown function or an approximation of it. Its number partially determines the number of degrees of freedom in the model. This is because of the term λ, which penalizes the wiggly basis functions. That is why a more accurate measure is the effective degrees of freedom, i.e., the proportion of the original weight of a basis function that is retained after the penalization. Those basis functions correspond to the number of knots used to estimate the variables. Therefore, the choice of k depends on the model setting and it has an impact on the model complexity.

4.2 Specification

The aim of this study is to test how guests' preferences for short rentals change after COVID-19. In particular, we focus on the implicit prices for a selection of social distancing attributes from the following semi-parametric model:

$$log(P_{i,t}) = \alpha + \beta X_i + \rho Aug2020_t + \gamma(Aug2020_t \times X_i) + f(Z^k_{i,t}) + f(long_i, lat_i) + \epsilon_{i,t} \tag{4}$$

where i is the listing, t is the selected month (August 2019, August 2020), $Aug2020$ is a time dummy variable equal to 1 for observations in August 2020, X contains the three social distancing variables, Z includes non-linear predictors, and the term $f(long, lat)$ is a bivariate smooth term of the spatial coordinates from each listing. We assume the error term $\epsilon_{i,t}$ is normally distributed. By including interactions between the time dummy and our variables of interest X, we let the change on social distancing attributes vary after the first COVID-19 summer.[3]

In our specification, all dichotomous attributes are included in a parametric way as belonging to the linear component, whereas continuous attributes are included as being potentially non-linear, with the exception of size-related variables for purposes of comparison.

[3] We use the *mgcv* R package (Wood, 2016). MGCV stands for Mixed GAM Computational vehicle. For a more complete review of all splines functions in R, please refer to Perperoglou et al. (2019). To draw partial plots, we use the Gratia package, developed by Gavin L. Simpson.

For the sake of comparison, in our analysis we also consider a standard linear regression model

$$\log(\mathrm{P}_{i,t}) = \alpha + \rho Aug2020_t + \beta X_i + \gamma(Aug2020_t \times X_i) + \theta Z_{i,t} + Zipcode_i + \epsilon_{i,t} \tag{5}$$

where the only difference with respect to the semi-parametric model is that the continuous variables enter as linear terms Z_i, and the spatial dependence is modeled using zip code fixed effects. As in Von Graevenitz and Panduro (2015), the reason for including spatial fixed effects is to control for the omitted variable problem, which may cause the errors to be spatially autocorrelated. By using zip codes, we assume that the latter catch time-invariant characteristics of the accommodation within a city district.

5 Results

Table III summarizes the main findings. The first and the second columns of Table III display first the GAM estimates for the linear coefficients, and then the number of effective degrees of freedom used in each smooth term. The third and last columns show results of the simpler linear regressions. With respect to the smooth terms of the GAM model, the greater the effective degrees of freedom, the more wiggly the variables are. To interpret the effect of those variables on the conditional mean, we make use of the partial plots in Figure I. Those graphs capture the partial effect of each smooth term when all the continuous variables are fixed at their means and the categorical variables are set to their modes. To estimate the intercept term, the smooth components have imposed the following identification constraint: $\sum_i f(z_i) = 0$.

Linear terms	Whole sample, GAM	Restricted sample, GAM	Whole sample, linear	Restricted sample linear
(Intercept)	4.295^{***}	4.302^{***}	4.087^{***}	3.413^{***}
	(0.005)	(0.012)	(0.092)	(0.109)
Social distancing size	0.153^{***}	0.151^{***}	0.151^{***}	0.150^{***}
	(0.003)	(0.006)	(0.006)	(0.008)
Social distancing kitchen	0.065^{***}	0.051^{*}	0.076^{***}	0.051
	(0.010)	(0.021)	(0.012)	(0.032)
Social distancing room type	-0.623^{***}	-0.727^{***}	-0.619^{***}	-0.720^{***}
	(0.010)	(0.025)	(0.021)	(0.045)
Aug2020	-0.356^{***}	-0.338^{***}	-0.345^{***}	-0.343^{***}
	(0.012)	(0.018)	(0.030)	(0.035)
Aug2020×Social distancing size	$\mathbf{-0.028}^{***}$	$\mathbf{-0.027}^{**}$	$\mathbf{-0.026}^{***}$	$\mathbf{-0.026}^{***}$
	(0.006)	(0.009)	(0.007)	(0.007)
Aug2020×Social distancing kitchen	$\mathbf{0.123}^{***}$	$\mathbf{0.135}^{***}$	$\mathbf{0.116}^{***}$	$\mathbf{0.133}^{**}$
	(0.019)	(0.028)	(0.027)	(0.043)
Aug2020×Social distancing room type	**−0.034**	**0.061**	**−0.033**	**0.062**
	(0.022)	(0.034)	(0.041)	(0.068)
Number of reviews			-0.001^{***}	-0.001^{***}
			(0.000)	(0.000)
Review scores rating			0.005^{***}	0.012^{***}
			(0.001)	(0.001)
Age			0.000^{*}	0.023^{**}
			(0.000)	(0.007)
Host listings count			−0.000	0.000
			(0.000)	(0.000)
			(0.041)	(0.068)
Smooth terms				
EDF: f(Longitude,Latitude)	49.988^{***}	37.789^{***}		
	(55.272)	(46.056)		
EDF: f(Number of reviews)	5.814^{***}	3.320^{***}		
	(6.811)	(4.160)		
EDF: f(Review scores rating)	5.823^{***}	4.800^{***}		
	(6.759)	(5.694)		
EDF: f(Age)	2.736^{***}	4.803^{***}		
	(3.464)	(5.922)		
EDF: s(Host listings count)	6.469^{***}	3.300^{**}		
	(7.339)	(3.942)		
R^2	0.625	0.685	0.604	0.671
Num. obs.	14421	3190	14421	3190

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Zip code fixed effects are included but not shown for linear specifications. Errors are clustered by zip code. EDF stands for *Estimated Degrees of Freedom.* They capture the level of wiggliness in the variable. The significance of the smooth terms is a test of deviation from a flat or null function that is constant at 0 over all observed Z_i. The first dimension of the PCA for the size-related variables,*Social distancing size*, account for nearly 85% of the explained variance.

Table III: Whole and restricted sample hedonic models, Madrid, August 2019 and 2020.

At first glance, it is worth noticing that the results do not crucially depend on the selected model. Our main variables of interest are the interactions between the COVID-19 summer season, $Aug2020$, and the social distancing attributes. We do find a change in implicit prices for both size and kitchen equipment. We do not find any statistically significant change in prices across room types. Using the restricted sample as a reference, listings that have the select kitchen equipment amenities have a premium price of around 20.4%. Interestingly, the previous premium price for kitchen amenities was 5.2%; therefore, we register an average rise of 15.2 percentage points. In the same period, the premium price of larger listings fell 2.7 percentage points. The lack of significance across different room types may be explained by a combination of reasons. On the demand side, potential guests may prefer to book entire units to avoid social contact, even though they are traveling with smaller groups. On the supply side, hosts of private and shared rooms may charge a positive risk premium for sharing their residences. In particular, Hu and Lee (2020) found for the case of London that the price of private rooms was reduced less than entire homes during the COVID-19 aftermath. Finally, their supply was reduced by a greater amount (10% more compared with entire apartments). Overall, the results are in line with the hypothesis that guests' tastes change in times of a pandemic in favor of listings that better allow for social distancing.

Regarding other price determinants, our findings are in line with previous studies. The number of reviews is negatively related to the price, whereas the number of months the listing has been on the platform seems to have a positive effect on the price. Those findings hold no matter the inclusion of the variable as a linear or smooth term. However, the overall score rating and the number of listings that the host manages presents a different picture whenever one includes them as smooth terms. As we can see in Figure I, the valence of the reviews impacts on the average price positively from at a certain score rating. In particular, it seems that the turning point is around 80. From this level, the implicit price increases. The number of listings managed by the host, as a proxy for the level of professionalization, seems to have a positive and significant effect on price. However, by including this variable as a linear term and not considering the potential non-linear effect, the coefficient in the linear specification is not significant. As can be seen in the partial plots, this is because of the presence of a group of outliers who own over 100 listings and whose effects are not significant as the point wise confidence interval contains the zero line for the upper range of the covariate values. This result is in line with previous studies which have also found a positive effect on prices for commercial providers (Li et al., 2016; Gibbs et al., 2018; Gunter et al., 2020).

Lastly, the spatial dependence between Airbnb listings depicts a strong non-linear effect as it shows the higher degrees of freedom needed to estimate the spatial structure. Therefore, the zip code fixed effects do not capture the omitted spatial process. First, spatial dependencies between peer-to-peer accommodation units are clearly non-linear as the smooth interaction term of the coordinates is significant at 1%. This validates the hypothesis that the coordinates deviate from a flat or null function. Second, by

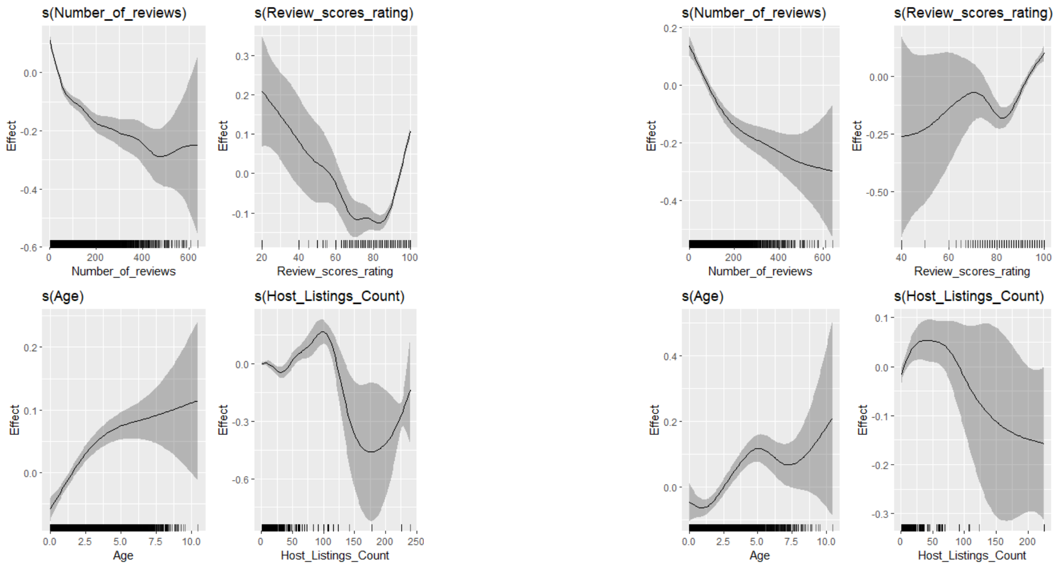

Figure I: Partial plots for the whole (on the left) and restricted GAM sample (on the right). The response variable is (log of) price. Each component function is vertically centered around zero. Shaded regions indicate 95% pointwise confidence intervals. Tick marks indicate values of predictors.

using the zip code as a fixed spatial effect, we assume that this is the right geographical entity for capturing the omitted spatial process, which might not be the case as the zip code simply represents the administrative organization of the official postal service.

5.1 Robustness checks

Findings are robust to alternative measures for capturing social distancing attributes. For instance, we check that our main tenets are still there after we take size-related measures one by one in our specification. Also, we get similar results when we define kitchen amenities as a sum of different attributes (oven, dishwasher and refrigerator). Finally, we make our results robust by running separate regressions for August 2020 and August 2019.[4] Notably, differences in the implicit prices for social distancing variables are similar in magnitude to our baseline specifications.

In particular, to check whether our results depend on the peculiar case study or on the month of the year we picked, we replicate our exercise for the restricted sample on

[4]See Table AII, Table AIII, Table AIV and Figure II in the Appendix.

different periods and for the case of Barcelona. In the first case, we compare September 2019 and September 2020, as we are still in summer but tourist demand composition may be different. In fact, international and national mobility restrictions are similar in either case. As from the first column of Table IV, we still find results in magnitude and significance that are similar to the baseline.

In the second case, we discard the possibility of an unobserved trend from previous years, replicating the same specification by comparing August 2019 and August 2018. We argue that if observed changes are, as expected driven by the pandemic, we should not find statistical significance when we check one year back. This is the case of the second column of Table IV.

Linear terms	Robustness check 1	Robustness check 2	Robustness check 3
	Sep 2020 - Sep 2019	Aug 2019 - Aug 2018	Barcelona, Aug 2020 - Aug 2019
(Intercept)	4.326^{***}	4.256^{***}	4.611^{***}
	(0.013)	(0.012)	(0.017)
Social distancing size	0.154^{***}	0.152^{***}	0.138^{***}
	(0.007)	(0.006)	(0.009)
Social distancing kitchen	0.065^{**}	0.109^{***}	0.017
	(0.021)	(0.022)	(0.025)
Social distancing room type	-0.706^{***}	-0.694^{***}	-0.656^{***}
	(0.027)	(0.027)	(0.031)
Time*	-0.286^{***}	0.046^{**}	-0.335^{***}
	(0.019)	(0.018)	(0.023)
Time×Social distancing size	$\mathbf{-0.024}^{*}$	**0.006**	$\mathbf{-0.053}^{***}$
	(0.009)	(0.009)	(0.012)
Time×Social distancing kitchen	$\mathbf{0.098}^{**}$	$\mathbf{-0.051}$	$\mathbf{0.080}^{*}$
	(0.030)	(0.030)	(0.035)
Time×Social distancing room type	**0.019**	**0.036**	$\mathbf{-0.150}^{***}$
	(0.036)	(0.036)	(0.041)
Smooth terms			
EDF: f(Longitude,Latitude)	35.011^{***}	35.478^{***}	45.315^{***}
	(43.354)	(43.799)	(50.875)
EDF: f(Number of reviews)	3.122^{***}	3.575^{***}	4.665^{*}
	(3.927)	(4.472)	(5.728)
EDF: f(Review scores rating)	3.282^{***}	3.387^{***}	3.990^{***}
	(4.116)	(4.241)	(4.916)
EDF: f(Age)	5.734^{***}	4.585^{***}	4.134^{*}
	(6.913)	(5.666)	(5.157)
EDF: f(Host listings count)	7.894^{***}	7.625^{***}	8.793^{***}
	(8.622)	(8.321)	(8.985)
R^2	0.680	0.756	0.692
Num. obs.	2900	2010	3201

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ Zip code fixed effects are included but not shown for the linear specifications. Errors clustered by zip code. EDF stands for *Estimated Degrees of Freedom*, as they capture wiggliness of predictors. Significance of smooth terms based on a test of deviation from a flat or null function constant at 0 over all observed Z_i. The first dimension of the PCA for *Social distancing size* accounts for nearly 85% of the explained variance.
**Time* is a time dummy variable that takes the value of 1 in September 2020 and 0 in September 2019 in Robustness check 1, 1 in August 2019 and 0 in August 2018 in Robustness check 2 and 1 in August 2020 and 0 in August 2019 in Robustness check 3.

Table IV: Robustness check results.

Finally, our main findings are still valid when we consider Barcelona in August 2019 and August 2020, as from the third column of Table IV. Listings with a well-equipped kitchen increase implicit prices up to 8 percentage points and larger listings are relatively cheaper. On top of that, the price differential between entire apartments versus shared/private increases in Barcelona.

6 Conclusions and implications

The COVID-19 crisis has severely affected the hospitality sector. However, the impact has not been equal for all. A relatively better performance of short-term rentals throughout the hotel industry can be explained by the possibility of preserving social distancing better than in traditional hotels. After reviewing previous studies, we identify several attributes that allow potential customers to minimize the risk and keep social distancing in peer-to-peer accommodations. After the adoption of a semi-parametric hedonic regression model, we quantify how much social distancing attributes change in the first summer after the COVID-19 outbreak, and we observe a shift in the guests' preferences. We do find that Airbnb users prefer smaller listings with a well-equipped kitchen. Eventually, we do not find evidence that guests changed their attitude towards shared or private rooms. We argue that the latter result can be a combination of competing demand and supply side factors.

6.1 Academic implications

The present study makes meaningful contributions to the literature of travel pattern behavior during pandemics and hedonic modeling applied to peer-to-peer accommodations. On the one hand, although the link between COVID-19 and peer-to-peer accommodations has recently been investigated (Farmaki et al., 2020; Hossain, 2020), this study represents the first attempt to examine the impacts of COVID-19 from the side of the guests. In this regard, by using a semi-parametric hedonic modeling framework, we are able to check whether the implicit prices for a selection of structural social distancing attributes changed during the COVID-19 summer season. The main findings show that guests prefer smaller, well-equipped kitchen listings to preserve social distancing during this time. This last result may contribute to explaining an evident overperformance for peer-to-peer accommodation with respect to the traditional hospitality industry during the COVID-19 crisis. This last issue is of special relevance as the peer-to-peer accommodation sector has been shown to be a substitute for the traditional hospitality industry (Guttentag and Smith, 2017; Zervas et al., 2017).

Also, this study contributes to the literature of hedonic pricing models in peer-to-peer accommodation by proposing a new method with which estimate hedonic price models: the Generalized Additive Model. The use of the GAM can help prospective researchers to identify the effect of the price determinants correctly by considering non-linearities in the characteristics and correcting for the recurrent problem of spatial autocorrelation in the error term in the context of cities, where the modeling of the urban structure has always posed a challenge to solving this type of problem.

6.2 Practical implications

We believe that our results may help the hospitality sector understand how to better serve travelers who wish to follow protocols of social distancing. This is relevant because one can expect that such a desire might outlive the ongoing pandemic with long-lasting effects on the demand for accommodations, because guests may continue to perceive a high risk in travelling. In this context, the battle between star-rated hotels and peer-to-peer accommodations is far from over. Although peer-to-peer accommodations seem better endowed with attributes that help preserve social distancing, they are becoming less group-friendly, thereby losing one of their most valued attributes. However, it seems to us inevitable that the future supply of accommodations will have to ensure a safer and healthier environment, including better sanitation and hygiene (Naumov et al., 2020), possibly relying on contactless services whenever it is possible.

6.3 Limitations and further research

Finally, some weaknesses of this study should be mentioned. We have focused on analyzing the change in guests' preferences for the demand side, whereas home-sharing hosts may also have reacted by modifying the Airbnb supply to meet those changes in customers' tastes. By analyzing listings which do not modify their attributes which were present before and during the COVID-19 crisis, we are removing composition effects in the Airbnb supply. However, it may be the case that the peer-to-peer accommodations are already adapting to this new tourism scenario. Further research is needed to check whether newcomers or current listings are changing their listings characteristics by providing new attributes that allow social distancing. In the same way, the reduction of apartments from the platform may be caused by a lack of adaptation to this new reality in which social distancing has been mandated. As Farmaki et al. (2020) point out, it is vital that peer-to-peer accommodation platforms adopt measures in order to avoid the risk of losing members. As such, peer-to-peer accommodations are developing cleaning protocols for hosts (e.g, 24-hour vacancies between bookings in Airbnb) in an effort to adapt to the COVID-19 travel environment. Also, hosts might incur higher costs by offering accommodations adapted for social distancing mandates during the COVID-19 crisis. This can be studied in future research by considering, for instance, cleaning costs in the final price rate.

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A Appendix

Reference	Country/City	Period	Data	Technique
Dudás et al. (2020)	Hungary (Lake Balaton)	July 2018	Own web scraper	OLS and QR
Tong and Gunter (2020)	Spain (Madrid, Barcelona and Seville)	17 August 2015 to 2 August 2016	AirDNA	WLS and QR
Chica-Olmo et al. (2020)	Spain (Málaga)	November 2017	Inside Airbnb	OLS, SAR, SEM
Voltes-Dorta and Sánchez-Medina (2020)	UK (Bristol)	February 9th and July 14th, 2019	Inside Airbnb	OLS and GWR
Suárez-Vega and Hernández (2020)	Spain (Canary Islands)	January 2018	Own web scraper	OLS and GWR
Deboosere et al. (2019)	USA (New York City)	August 2014 and September 2016	AirDNA	Multilevel Regression
Tang et al. (2019)	USA (10 cities)	November 2017	Own web scraper	GWR
Chattopadhyay and Mitra (2019)	USA (11 cities)	April, 2018	Inside Airbnb	OLS, RF, Conditional Decision trees
Falk et al. (2019)	Switzerland	2016 to 2018	Own web scraper	Random Effects and QR
Cai et al. (2019)	China (Hong Kong)	August 7, 2016	Inside Airbnb	OLS
Gibbs et al. (2018)	Canada	June 2016	Own web scraper	OLS
Benítez-Aurioles (2018)	Multiple countries (44)	November 2015	Inside Airbnb	OLS
Magno et al. (2018)	Italy (Verona)	Tuesday, 12 July 2016, 21 September 2016, 24 October 2016	Own web scraper	OLS
Perez-Sanchez et al. (2018)	Spain (Valencia, Alicante, Castellón and Elche)	March 2018	AirDNA	WLS and QR
Wang and Nicolau (2017)	Multiple countries	2015-2016	Inside Airbnb	OLS and QR
Zhang et al. (2017)	USA (Nashville)	7 August 2017	Own web scraper	OLS and GWR
Teubner et al. (2017)	Germany (86 largest German cities)	August 2017	Own web scraper	OLS
Chen et al. (2020)	USA (Austin, Texas)	2017	Own web scraper	OLS

OLS (Ordinary Least Squares), QR (Quantile Regression) WLS (Weighted Least Squares), SAR (Spatial Autoregressive Model), SEM (Spatial Error Model), GWR (Geographically Weighted Regression), RF (Random Forest)

Table AI: Literature review for peer-to-peer accommodation studies.

Linear terms	Accommodates	Beds	Bedrooms	Sum of kitchen amenities
(Intercept)	3.774***	3.960***	3.947***	4.281***
	(0.026)	(0.022)	(0.021)	(0.017)
Aug2020×Accommodates	−0.025**			
	(0.008)			
Aug2020×Beds		−0.028**		
		(0.011)		
Aug2020×Bedrooms			−0.032*	
			(0.016)	
Aug2020×Social distancing kitchen sum				0.031**
				(0.012)
R^2	0.680	0.661	0.672	0.681
Num. obs.	3190	3190	3190	3190

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. The GAM specifications are as in (4), but we omit all other variables from the table for the sake of exposition. *Social distancing kitchen sum* identifies the number of kitchen amenities of a listing, i.e., oven, dishwasher, refrigerator and oven.

Table AII: Alternative measures for the social distancing variables using the restricted sample GAM specification for Madrid (only listings that are active on the platform in August 2019 and August 2020).

Linear terms	GAM Aug 2020	GAM Aug 2019	Linear Aug 2020	Linear Aug 2019
(Intercept)	3.952***	4.291***	3.485***	4.144***
	(0.009)	(0.005)	(0.151)	(0.114)
Social distancing size	**0.127***	**0.154***	**0.125***	**0.152***
	(0.005)	(0.003)	(0.006)	(0.006)
Social distancing kitchen	**0.167***	**0.064***	**0.184***	**0.074***
	(0.015)	(0.010)	(0.019)	(0.010)
Social distancing room type	**−0.685***	**−0.609***	**−0.690***	**−0.611***
	(0.019)	(0.010)	(0.040)	(0.022)
Number of reviews			−0.001***	−0.001***
			(0.000)	(0.000)
Review scores rating			0.007***	0.005***
			(0.002)	(0.001)
Age			0.041***	−0.002
			(0.008)	(0.004)
Host Listings Count			0.000	−0.000**
			(0.001)	(0.000)
Smooth terms				
EDF: f(Longitude,Latitude)	29.702***	49.455***		
	(37.867)	(55.049)		
EDF: f(Number of reviews)	4.092***	5.539***		
	(5.047)	(6.552)		
EDF: f(Review scores rating)	4.704***	5.403***		
	(5.675)	(6.374)		
EDF: f(Age)	3.886***	1.500***		
	(4.862)	(1.855)		
EDF: f(Host Listings Count)	4.285**	8.807***		
	(5.096)	(8.987)		
R^2	0.637	0.624	0.6004	0.599
Num. obs.	2998	11423	2998	11423

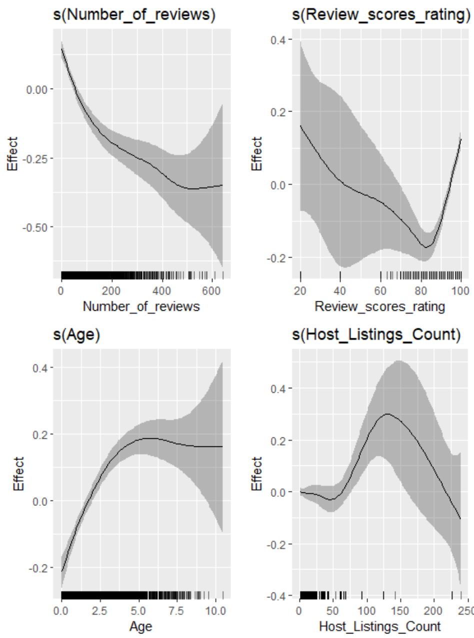
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Zip code fixed effects are included but not shown for the linear specifications. Errors were clustered at the zip code level to account for residual spatial correlation. EDF stands for *Estimated Degrees of Freedom*. They capture the level of wiggliness in the variable. The significance of the smooth terms is a test of deviation from a flat or null function that is constant at 0 over all observed Z_i.

Table AIII: Whole cross-sectional sample hedonic models, Madrid, August 2020 and 2019.

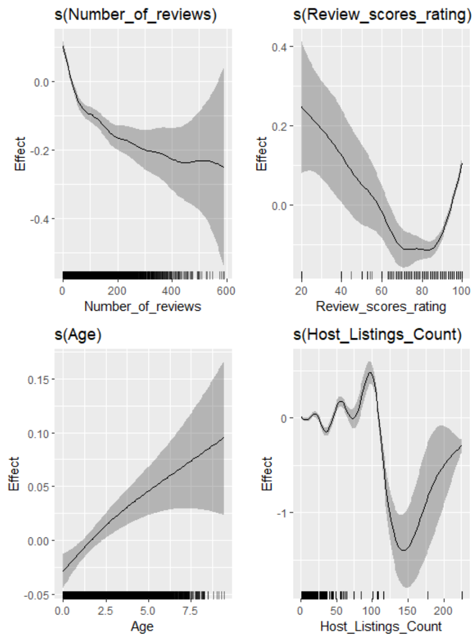
Linear terms	GAM Aug 2020	GAM Aug 2019	Linear Aug 2020	Linear Aug 2019
(Intercept)	3.974***	4.286***	2.424***	3.887***
	(0.012)	(0.012)	(0.323)	(0.227)
Social distancing size	**0.125***	**0.152***	**0.126***	**0.149***
	(0.006)	(0.006)	(0.008)	(0.008)
Social distancing kitchen	**0.162***	**0.090***	**0.155***	**0.080***
	(0.020)	(0.021)	(0.024)	(0.029)
Social distancing room type	**−0.706***	**−0.672***	**−0.686***	**−0.692***
	(0.025)	(0.025)	(0.055)	(0.041)
Number of reviews			−0.001***	−0.001***
			(0.000)	(0.000)
Review scores rating			0.020***	0.007**
			(0.004)	(0.002)
Age			0.043***	−0.003
			(0.010)	(0.009)
Host Listings Count			−0.000	0.001
			(0.001)	(0.001)
Smooth terms				
EDF: f(Longitude,Latitude)	21.623***	32.434***		
	(28.234)	(40.715)		
EDF: f(Number of reviews)	3.318***	2.641***		
	(4.151)	(3.321)		
EDF: f(Review scores rating)	3.732***	3.980***		
	(4.649)	(4.824)		
EDF: f(Age)	3.004***	1.001		
	(3.785)	(1.001)		
EDF: f(Host Listings Count)	4.798**	8.340***		
	(5.701)	(8.844)		
R^2	0.678	0.702	0.6574	0.657
Num. obs.	1595	1595	1595	1595

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Zip code fixed effects are included but not shown for the linear specifications. Errors were clustered at the zip code level to account for residual spatial correlation. EDF stands for *Estimated Degrees of Freedom.* They capture the level of wiggliness in the variable. The significance of the smooth terms is a test of deviation from a flat or null function that is constant at 0 over all observed Z_i.

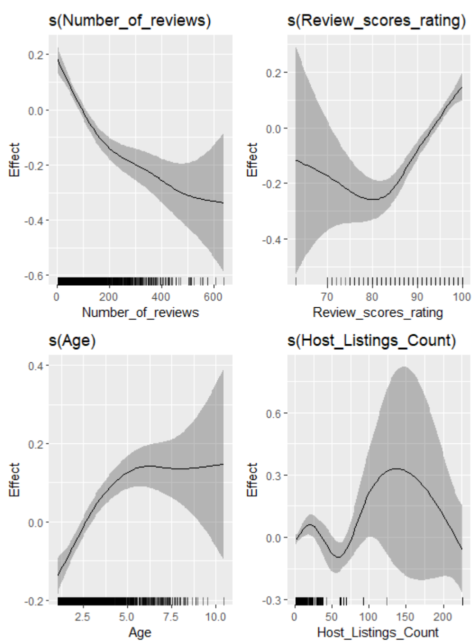
Table AIV: Restricted cross-sectional sample hedonic models, Madrid, August 2020 and 2019.



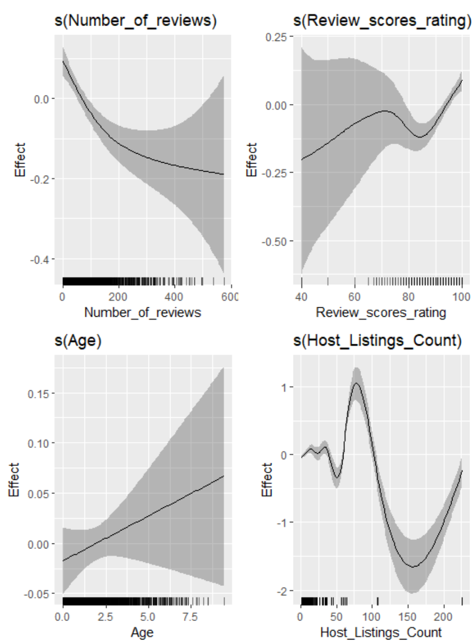
(a) Whole Aug 2020



(b) Whole Aug 2019



(c) Restricted Aug 2020



(d) Restricted Aug 2019

Figure II: Partial plots for the restricted cross-sectional sample hedonic models, Madrid, August 2020 and 2019. The response variable is logarithm of the price. Each component function is vertically centered about zero. The shaded regions indicate approximately 95% pointwise confidence intervals. The tick marks indicate the values of the predictors.

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