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Research note

Heterogeneous price adjustments among Airbnb hosts amid COVID-19: Evidence from Barcelona

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ABSTRACT

COVID-19-induced travel restrictions have led to a sharp drop in Airbnb bookings. Confronted with a decrease in demand, hosts have implemented heterogeneous price responses. This study evaluates the different price adjustments developed by professional and non-professional hosts. Considering the city of Barcelona as the case study, I exploit monthly longitudinal data for 24,000 different Airbnb listings observed between June 2020 and April 2021. Using hedonic regressions with listing and neighbourhood fixed effects, I show that professional hosts have reduced prices to a greater extent, especially during the worst months of the pandemic. The findings support intertemporal price discrimination among professional hosts, which seem to adjust prices faster to meet demand and better adapt to market conditions.

1. Introduction

The Airbnb rental market has been severely affected by COVID-19. The pandemic has produced important income losses for Airbnb hosts (Chen et al., 2021), mainly due to travellers' reluctance to book shared flats on Airbnb when physical distance is needed (Bresciani et al., 2021).[1] An emerging body of literature has started to analyse hosts' practices and behavioural adaptation to the uncertainties that surround COVID-19. Existing evidence points to some hosts considering exiting the platform and switching to residential renting (Farmaki et al., 2020), whereas others are willing to innovate to adapt their dwellings to the new circumstances (Zhang et al., 2021). However, little is known yet about hosts' adaptation in terms of price adjustments during COVID-19.

This paper studies the heterogeneous variations in Airbnb listings' prices amid COVID-19. The literature on Airbnb pricing has documented important differences in price setting between professional (i.e., those who hold several properties and behave close to business operators) and non-professional hosts (Xie et al., 2021; Casamatta et al., 2022). Professional hosts have been shown to better exploit economies of scale (Li and Srinivasan, 2019), to earn more revenues through practising intertemporal price discrimination (Leoni and Nilsson, 2021) and to imitate to a lower extent the prevailing prices in the neighbourhood (Boto-García et al., 2021). Dolnicar and Zare (2020) suggest that super-shocks like COVID-19 affect hosts heterogeneously depending on their professionalism. These authors predict that professional hosts with several properties suffer greater budget constraints (e.g., facing mortgage payments) during the pandemic if they have their properties unoccupied than non-professionals, which incentivizes them to set lower prices. Therefore, we expect the way prices are adjusted to deal with demand drops to differ by host type. Furthermore, price adjustments are likely to vary over time depending on the severity of the epidemiological circumstances.

Taking the city of Barcelona as the case study, I exploit longitudinal monthly data on almost 24,000 different Airbnb listings observed between June 2020 and April 2021 (208,223 observations). I estimate hedonic price equations (Rosen, 1974) to examine how prices vary over the course of the pandemic and the heterogeneity in price drops between professional and non-professional hosts. Since I control for listing and neighbourhood fixed effects, the regressions provide a clean estimate of the time variation in prices that is net of unobserved heterogeneity and locational circumstances.

2. Data and methods

2.1. Dataset

A longitudinal monthly dataset of Airbnb listings for the city of Barcelona (Spain) between June 2020 and April 2021 is drawn from Inside Airbnb (http://insideairbnb.com/). This free-access website periodically web-scraps detailed information about the available listings

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[1] Nevertheless, the hotel industry has been relatively more affected in terms of revenue losses (Ozdemir et al., 2021).

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in Airbnb website. After data cleaning, there is valid information for 23,997 distinct listings. Since not all the listings are observed over the whole study period, the database is an unbalanced panel with 208,223 observations. Table 1 outlines the dates when the data was scrapped. Table 2 reports the distribution of the number of panel periods the listings are observed. Table 3 presents descriptive statistics of some variables.

Fig. 1 plots a histogram of the distribution of prices (in €). The distribution is highly right-skewed, with a low share of listings having really high prices per night (luxury ones). Fig. 2 presents the mean prices per month, separately for professional and nonprofessional hosts. Professional status is defined as those who hold more than 10 listings on property. This threshold is chosen based on evidence presented in Deboosere et al. (2019) and Boto-García et al. (2021) showing that 10 properties is a suitable cutoff to distinguish host professionalism. As can be seen, professional hosts charge greater prices, on average. Relative to June and July of 2020, both types of hosts have reduced prices from August 2020 onwards. The price drop is greater for professionals, even though their average prices are always above those by non-professionals. Since the quality and characteristics of the listings might differ depending on host professionalism, a proper understanding of their distinct intertemporal price adaptation is performed using regression analysis.

2.2. Econometric modelling

In line with related applications in the Airbnb rental market (e.g., Falk et al., 2019; Sainaghi et al., 2021), I propose a log-linear hedonic price regression as follows:

$$\ln P_{ijt} = \alpha + \beta T_t + \gamma Professional_i + \delta T_t x Professional_i + \theta X_{it} + \mu_i + \omega_j + \epsilon_{ijt} \quad (1)$$

where i indexes listings, j refers to neighbourhoods within the city and t to the period (month); α is the constant term; T_t is a set of monthly dummies (with June 2020 being the reference category), $Professional_i$ is the dummy for being a professional host; X_{it} are listing controls that vary over time; μ_i and ω_j are listing and neighbourhood fixed effects; β, γ, δ and θ are parameters to be estimated; and ϵ_{ijt} is the error term, varying across listings, neighbourhoods and periods.

One archetypical problem in price hedonic studies is the bias the emanates from omitted variables. Even though scholars include all available information about listing characteristics, unobserved quality that is correlated with explanatory variables is likely to bias the estimated shadow prices. By exploiting longitudinal data, this problem is avoided; the inclusion of listing fixed effects in the regression captures any time-invariant heterogeneity (either observed or unobserved). Note that listing structural characteristics like property type or the number of days available per year are omitted from the specification because of being captured by the fixed effects.

Similarly, the inclusion of neighbourhood fixed effects is necessary for several reasons. First, it captures location advantages depending on accessibility to transportation hubs, the city centre or sightseeing spots (Deboosere et al., 2019). Second, Barcelona is nowadays divided into four areas with different municipality policies regarding the number of Airbnb listings that can legally operate (see on this Benítez-Aurioles, 2021). Finally, Jang et al. (2021) indicate that the revenue losses caused by COVID-19 differ across areas so that price responses might exhibit a geographical pattern.

To avoid the price changes over time being confounded by other characteristics, we also control for the following variables: (1) the number of listings the host has on property (which vary across properties), (2) the number of reviews per month, and (3) a dummy indicator for whether the listing has no reviews (varying across months).

Table 1
Dates the dataset is scrapped and number of observations.

Date	Observations	%
13/06/2020	19,439	9.34
17/07/2020	19,815	9.52
24/08/2020	20,039	9.62
12/09/2020	19,778	9.50
12/10/2020	19,363	9.30
06/11/2020	19,332	9.28
16/12/2020	19,105	9.18
12/01/2021	18,097	8.69
09/02/2021	18,015	8.65
05/03/2021	17,825	8.56
12/04/2021	17,415	8.36
Total	208,233	100

Table 2
Number of panel periods and number of observations.

Periods	Observations	%
2	2752	1.32
3	3309	1.59
4	5228	2.51
5	6215	2.98
6	7890	3.79
7	9576	4.60
8	6248	3.00
9	10,566	5.07
10	11,910	5.72
11	144,529	69.41
Total	208,233	100

Table 3
Descriptive statistics of the sample.

Continuous Variables	Definition	Mean	SD	Min	Max
P	Price per night (in €)	81.66	97.36	10	1000
Num.listings	Number of listings owned by the host	15.61	32.09	1	197
Availability	Number of days the listing is available per year	182.11	144.01	2	365
Avg. Reviews	Number of reviews divided by the number of months in the platform	0.76	1.13	0	24.05
Dummy variables	Definition	%			
Professional	= 1 if host has more than 10 properties	27.00			
Entire	= 1 if entire apartment	48.84			
Private	= 1 if private room	49.98			
Shared	= 1 if shared room	1.16			
NB1	= 1 if Ciutat Vella neighbourhood	23.51			
NB2	= 1 if Eixample neighbourhood	33.81			
NB3	= 1 if Gràcia neighbourhood	8.32			
NB4	= 1 if Horta-Guinardó neighbourhood	3.26			
NB5	= 1 if Les Corts neighbourhood	2.11			
NB6	= 1 if Nou Barris neighbourhood	1.37			
NB7	= 1 if Sant Andreu neighbourhood	1.66			
NB8	= 1 if Sant Martí neighbourhood	10.21			
NB9	= 1 if Sants-Montjuïc neighbourhood	11.38			
NB10	= 1 if Sarrià-Sant Gervasi neighbourhood	4.32			

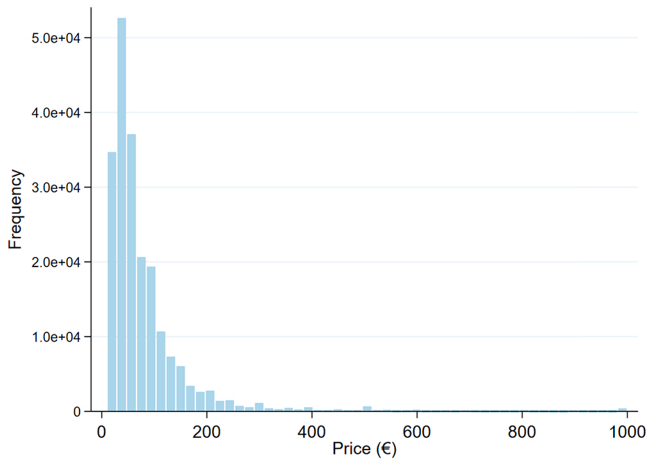

Fig. 1. Histogram of price.

Fig. 2. Mean prices per month and host type.

3. Results

Table 4 presents the estimation results. Column 1 presents the estimates of a naïve model that does not consider listing fixed effects, estimated using OLS. Column 2 reports the parameter for the fixed effects regression in (1). Standard errors have been clustered at the district level to control for potential cross-sectional dependence in the residuals of listings that share the same environment that would bias the standard errors (Boto-García, 2021).

Consistent with descriptive evidence presented in Fig. 2, hosts in Barcelona have significantly reduced prices amid COVID-19 pandemic relative to the price levels at the base period (June 2020). Interestingly, this pattern differs between professionals and non-professionals. The drop in prices has been significantly greater in magnitude among professionals between August 2020 and January 2021. From the latter period onwards, the price setting of both types has been about the same. Interestingly, the price decline over time appears to be U-shaped. The partial derivatives for the FE regression indicate the greatest price drops took place in October (−11.4%), November (−13.1%) and December 2020 (−9.6%) and in January 2021 (−11.5%). This corresponds with the months of higher COVID-19 incidence in Spain and in Catalonia.

To better understand this pattern, it is important to indicate that no entry restrictions for tourists existed in Barcelona between June 2020 and October 2020. However, on 25th October, the Spanish government dictated a second State of Alarm (which lasted until 9th May 2021) that allowed autonomous communities to close their borders to contain COVID-19 spread. By the end of October, Catalonia was closed to people outside the region, and further within region mobility restrictions were imposed.

Table 4
Estimation results from hedonic regressions.

Dependent variable: *ln price*	(1) OLS	(2) FE
Explanatory variables	Coeff	Coeff
July2020	-0.006 * *	-0.006 * **
	(0.003)	(0.001)
August2020	-0.085 * **	-0.074 * **
	(0.015)	(0.016)
September2020	-0.104 * **	-0.096 * **
	(0.013)	(0.015)
October2020	-0.114 * **	-0.108 * **
	(0.012)	(0.014)
November2020	-0.119 * **	-0.119 * **
	(0.012)	(0.014)
December2020	-0.091 * **	-0.091 * **
	(0.011)	(0.011)
January2021	-0.120 * **	-0.106 * **
	(0.010)	(0.011)
February2021	-0.110 * **	-0.099 * **
	(0.010)	(0.010)
March2021	-0.095 * **	-0.088 * **
	(0.010)	(0.010)
April2021	-0.068 * **	-0.066 * **
	(0.010)	(0.009)
July2020#Professional	0.010	0.006
	(0.007)	(0.004)
August2020#Professional	-0.067 * *	-0.081 * **
	(0.029)	(0.028)
September2020#Professional	-0.055 *	-0.072 * **
	(0.029)	(0.027)
October2020#Professional	-0.022	-0.050 *
	(0.027)	(0.027)
November2020#Professional	-0.070 * **	-0.082 * **
	(0.025)	(0.023)
December2020#Professional	-0.036 *	-0.035 *
	(0.021)	(0.019)
January2021#Professional	-0.058 * *	-0.061 * **
	(0.025)	(0.018)
February2021#Professional	-0.025	-0.018
	(0.021)	(0.016)
March2021#Professional	-0.007	-0.002
	(0.027)	(0.017)
April2021#Professional	0.026	0.027
	(0.028)	(0.018)
Professional	0.353 * **	0.027
	(0.052)	(0.033)
Num.listings	0.001 * *	-0.001 *
	(0.000)	(0.001)
Avg. Reviews	0.017 *	-0.024
	(0.009)	(0.018)
Zero reviews	-0.042 * *	0.032
	(0.020)	(0.022)
Listing fixed effects	NO	YES
Neighbourhood fixed effects	YES	YES
Constant	3.976 * **	4.161 * **
	(0.031)	(0.025)
R-squared	0.894	0.376
VIF	2.37	2.37
Observations	208,223	
Number of id	23,997	

Clustered standard errors at the district level in parentheses.
***$p < 0.01$, **$p < 0.05$, * $p < 0.1$.

Fig. 3 plots the OLS and FE coefficient estimates and confidence intervals for the monthly dummy variables and their interactions with the indicator of being a professional host. As shown, in March and April 2021 the prices charged by professional hosts become very similar to the base levels in June 2020, when the first State of Alarm was withdrawn. It appears that once the epidemiological circumstances improved and the end of mobility restrictions were closer in time, professional hosts reacted faster and increased listing's rates. Interestingly, quality seems

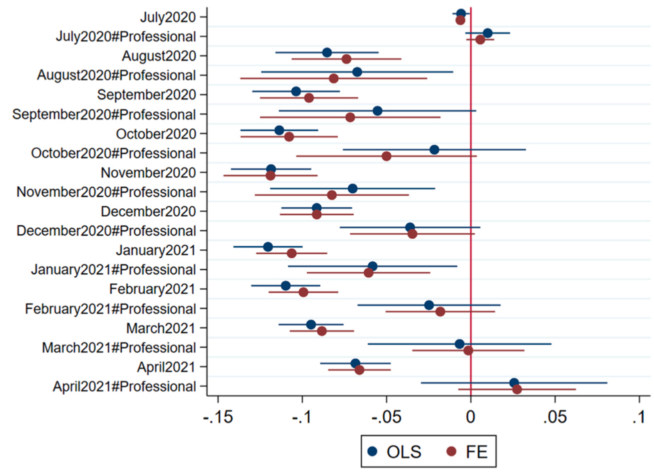

Fig. 3. Coefficient estimates per month and confidence intervals (OLS and FE).

to be a relevant confounder according to the differences in point estimates between OLS and FE, particularly during the second semester of 2020. A F test rejects the null hypothesis that the property fixed effects are globally zero (F=67.6, p-value<0.001), which indicates that the estimates are more precise in the FE regression than in the naïve OLS. This supports the importance of controlling for listing quality heterogeneity when analysing Airbnb price dynamics.

As a robustness check, the analysis was repeated considering alternative thresholds for the definition of professional hosts. Rather than more than 10 properties, the professional status was defined based on having more than 1, 5 and 12 listings. The estimation results are presented in Supplementary Material. Overall, the results using alternative definitions for professionalism are consistent with our main findings. We only notice that professional hosts based on having more than 1 or 5 properties still set relatively lower prices, ceteris paribus, also in February and March 2021.

4. Conclusions

This research studies the heterogeneous price responses of professional and non-professional Airbnb hosts amid COVID-19 in the city of Barcelona. Using monthly panel data for almost 24,000 listings observed during 11 months with and without mobility restrictions, hedonic price equations with listing and neighbourhood fixed effects are estimated. The estimations indicate that professional hosts have decreased their listings' prices during the pandemic significantly more than non-professionals, even though the average prices charged by professionals remain higher.

The findings suggests that professionals are more proficient at practising intertemporal price discrimination when demand drops, conditional on quality. Plausibly, since their motivation to host appears to be driven by income, these hosts are less willing to have their rooms unoccupied, so they decrease prices to meet demand. Importantly, the greater price drops among professional hosts are found to vanish from February 2021 onwards. This suggests that the improvement in epidemiological conditions that fosters demand makes professional hosts to quickly adapt and raise daily rates again. Therefore, professional hosts' price adaptation has been asymmetric and U-shaped.

These results have important implications for the recovery of the Airbnb rental market. Dolnicar and Zare (2021) predict the proportion of professional hosts will decline after COVID-19, moving Airbnb back towards its original sharing conceptualization. However, in line with Leoni and Nilsson (2021), it appears that professional hosts might benefit more from dynamic pricing depending on circumstances. Overall, it seems that 'nothing has change' and, contrary to the predictions by Dolnicar and Zare (2021), professional hosts might continue representing a large share of the market since they react faster to market shocks.

From a methodological viewpoint, the documented differences between OLS and FE regressions highlight the importance of controlling for listing quality when analysing the distinct behaviour of professional and non-professional Airbnb hosts. Since professionals usually face a trade-off between quality and quantity (Xie et al., 2021), future studies concerned about price, revenue or length of stay differences by host type must control for quality heterogeneity in their analyses. In addition to this, our results points to non-negligible seasonality in professionals' pricing behaviour, in line with Casamatta et al. (2022). Incoming works on the topic should also acknowledge seasonal differences in pricing strategies.

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Declaration of interest

None.

Data availability

Data will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijhm.2022.103169.

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