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Host type and pricing on Airbnb: Seasonality and perceived market power*

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8th September 2021

Abstract

The literature on short-term rental emphasises the heterogeneity of the hosts population. Some argue that professional and opportunistic hosts differ in terms of their pricing strategy. This study highlights how differences in market perception and information create a price differential between professional and non-professional players. Proposing an original and accurate definition of professional hosts, we rely on a large dataset of almost 9,000 properties and 73,000 observations to investigate the pricing behaviour of Airbnb sellers in Corsica (France). Using OLS and the double-machine learning methods, we demonstrate that a price differential exists between professional and opportunistic sellers. In addition, we assess the impact of seasonality in demand on the size and direction of this price differential. We find that professionals perceive a higher degree of market power than others during the peak season and it allows them to enhance their revenues.

Declaration of interests: None

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The literature on short-term rental emphasises the heterogeneity of the hosts population. Some argue that professional and opportunistic hosts differ in terms of their pricing strategy. This study highlights how differences in market perception and information create a price differential between professional and non-professional players. Proposing an original and accurate definition of professional hosts, we rely on a large dataset of almost 9,000 properties and 73,000 observations to investigate the pricing behaviour of Airbnb sellers in Corsica (France). Using OLS and the double-machine learning methods, we demonstrate that a price differential exists between professional and opportunistic sellers. In addition, we assess the impact of seasonality in demand on the size and direction of this price differential. We find that professionals perceive a higher degree of market power than others during the peak season and it allows them to enhance their revenues.

1 Introduction

It is of interest to examine on-line rental platforms such as Airbnb from the economic viewpoint since they are markets in which differentiated goods are sold by heterogeneous sellers. That is, not only do different products coexist on the platform at different prices due to product differentiation but homogeneous products are also potentially sold at different prices due to heterogeneity between sellers. The literature emphasises that, like other markets of the ‘peer-to-peer economy’, the supply side often consists of both professional (experienced)

25 players practising a ‘profit-oriented supply’ economy and non-professional (inexperienced)
26 players oriented to a sharing-oriented supply (Ke 2017, Krause & Aschwanden 2020, Li et al.
27 2016)

28 As they differ both in their motivations and in their expertise, these two types of actors
29 may adopt very different behaviours. Some authors argue that professional hosts vary their
30 prices more (Gibbs, Guttentag, Gretzel, Yao & Morton 2018, Kwok & Xie 2019, Li et al.
31 2016), obtain Superhost status more easily (Gunter 2018), and have better occupancy rates
32 and better incomes (Kwok & Xie 2019, Li et al. 2016). Furthermore, Leoni (2020) and Li
33 et al. (2016) have empirically demonstrated that the most "expert" hosts (those who manage
34 the most listings or the oldest players in the market) have the highest survival rates. This
35 is thanks in particular to their managerial skills and especially to the implementation of
36 dynamic pricing. The relationship between prices and professionalisation seems to depend
37 on the market and context. In their study of five Canadian cities, Gibbs, Guttentag, Gretzel,
38 Morton & Goodwill (2018) reveal that professionals charge higher prices in Montreal alone.
39 Furthermore, over 33 cities worldwide, Wang & Nicolau (2017) found a positive relationship
40 between the price and the number of listings. Conversely, in the Hong Kong market (Cai
41 et al. 2019) or in New York City (Deboosere et al. 2019), professional hosts are shown to
42 charge lower prices than non-professionals. Finally, Li et al. (2016), who examined the
43 Airbnb market in Chicago, do not find a relationship between the price level and the degree
44 of professionalisation.

45 Besides the heterogeneity of actors on the supply side, the accommodation and tourism
46 industries are also marked by strong seasonality. However, as Magno et al. (2018) or Faye
47 (2021) argue, most empirical studies on pricing offer a static view. Only a few studies con-
48 sider the seasonality of demand. These latter studies show that prices charged by Airbnb
49 hosts are positively correlated with the level of market demand, being higher in peak sea-
50 sons (Aznar et al. 2018, Falk et al. 2019, Magno et al. 2018). Examining month-to-month
51 variation, Deboosere et al. (2019) find a significant impact of seasonality on the price per

52 night and revenue of Airbnb listings in NYC. The hosts adapt their prices to the holiday
53 calendar and therefore to seasonal demand, applying higher rates during the long summer
54 holidays than during shorter winter holiday periods. However, the response of Airbnb hosts
55 to seasonal fluctuations is not homogeneous. It has been observed that most hosts do not
56 practice dynamic pricing and therefore forego revenue opportunities (Chen & Xie 2017,
57 Gibbs, Guttentag, Gretzel, Yao & Morton 2018, Li et al. 2016). Indeed, hosts who adjust
58 their prices more frequently, upwards and/or downwards, improve the revenue performance
59 of their listings (Kwok & Xie 2019, Oskam et al. 2018).¹

60 Taking these two aspects into account, hosts heterogeneity, and seasonal variations in
61 demand, we focus on the pricing decision of Airbnb hosts and seek to understand to what ex-
62 tent professional players in the short-term rental market adopt significantly different pricing
63 strategies compared to the rest of the hosts population.

64 Pricing is certainly one of the most important business practices for hospitality profes-
65 sionals. While some sharing economy platforms, such as Uber or Lyft, impose their prices on
66 supplier-side users, short-term rental platforms leave the pricing to the host, possibly using
67 a pricing tool (Gibbs, Guttentag, Gretzel, Yao & Morton 2018). The possibility for the hosts
68 to set their own prices implies that they must summarise the characteristics of their accom-
69 modation, a relevant estimate of demand and, lastly, have a good knowledge of the market
70 in which they operate. As a result, prices and pricing strategies have been the subject of
71 increasing interest among scholars. According to the literature reviews in Dann et al. (2019)
72 and Guttentag (2019), more than 10% of the academic work on Airbnb is devoted to the
73 issue of pricing.

74 Our analysis relies on the hedonic pricing model (Rosen 1974), which is the workhorse
75 tool for analysing the determinants explaining market prices. In recent years, this model
76 has been mobilised by a few authors to examine the prices charged by Airbnb’s suppliers.

¹The efficiency of dynamic pricing strategies is a general feature of the accommodation industry. In their study on 17 european cities, Abrate et al. (2019) show that hotels practicing dynamic pricing significantly improve their revenue.

77 These studies focused on markets in North America (Benítez-Aurioles 2018, Chen & Xie
78 2017, Deboosere et al. 2019, Gibbs, Guttentag, Gretzel, Morton & Goodwill 2018, Lorde
79 et al. 2019, Wang & Nicolau 2017), Europe (Benítez-Aurioles 2018, Chica-Olmo et al. 2020,
80 Dudás et al. 2019, Lladós-Masllorens et al. 2020, Magno et al. 2018, Teubner et al. 2017,
81 Wang & Nicolau 2017), Oceania and Asia (Cai et al. 2019, Wang & Nicolau 2017). All
82 the hedonic studies have shown the permanence of certain price determinants, whatever the
83 market. The prices charged by hosts are systematically higher when the accommodation
84 offers greater privacy (accommodation rented in full and/or not shared with other guests),
85 when it is larger, or when it is located closer to the city centre or tourist attractions. The
86 amenities have an upward influence on the prices charged by hosts since better amenities
87 imply a higher price. However, their effect on prices varies according to the context and the
88 situation. The impact of free parking will be all the greater in metropolitan areas (Gibbs,
89 Guttentag, Gretzel, Morton & Goodwill 2018, Dudás et al. 2019). In the Caribbean, parking
90 is casual everywhere, and air conditioning is one of the amenities most frequently requested
91 by guests (Lorde et al. 2019).

92 Our approach improves on previous works in three main respects. First, we not only
93 estimate how prices differ with respect to the period and the host type, but also how the
94 difference in prices, if any, between opportunistic and professional hosts varies with the
95 period. We are not aware of any study performing that kind of estimation. The closest
96 analysis to ours (Deboosere et al. 2019) concentrates on the variations of prices between
97 hosts and seasons, but not on their interaction. Second, we provide a characterisation of
98 the host status that differs from the literature and can be argued to be more accurate.
99 To evaluate the degree of professionalism of an Airbnb market, many authors use a supply
100 indicator, the number of listings provided by the hosts. In most of destination market studies,
101 a host is considered as a professional when they list more than one listing (Dredge et al. 2016,
102 Gibbs, Guttentag, Gretzel, Morton & Goodwill 2018, Gurran & Phibbs 2017, Kwok & Xie
103 2019, Li et al. 2016, Magno et al. 2018, Oskam et al. 2018), others use a threshold of two

104 or three (Schneiderman 2014). To characterise professional hosts, rather than relying on
105 the number of listings marketed, we have compiled a dataset in which professional hosts
106 are those registered with the French Trade and Companies Register (RCS), which allows
107 to unequivocally ensure their professional status. Finally, on the methodological side, we
108 take advantage of a recent statistical method, double-machine learning (Chernozhukov et al.
109 2018), that provides more robust estimates to model misspecification than the standard
110 ordinary least squares (OLS) analysis, used in most of the aforementioned hedonic pricing
111 studies.

112 Using a large dataset of almost 9,000 properties and 73,000 observations of Airbnb sellers
113 in Corsica (France) in 2017, we test the hypothesis that a price differential exists between
114 professional and opportunistic sellers. Furthermore, we explore the source of this differential
115 by examining the impact of seasonality in demand on the size and direction of the price
116 differential.

117 Our findings reveal that, on average, professional sellers charge prices about 9% higher
118 than opportunistic hosts. Furthermore, accounting for seasonality, we demonstrate that this
119 positive price differential exists and is very large during the peak season, culminating at
120 +24% but vanishes off-peak. These results suggest that professional sellers perceive a higher
121 degree of market power than opportunistic sellers during the peak season, while perceived
122 market power falls dramatically during the low season. This difference in pricing strategies
123 translates into higher revenue for the professional hosts, who manage to generate almost
124 800€ more revenue in August for a comparable listing.

125 The remainder of this paper is organised as follows. Section 2 presents a simple theoretical
126 model and our hypotheses. Section 3 describes the dataset and our empirical strategy. The
127 results are detailed in sections 4 and 5. Section 6 proposes two robustness checks while section
128 7 draws some conclusions and discusses limitations and potential extensions of our work.

129 2 Theoretical background

130 A key feature of short-term rental platforms is the existence of a set of close substitutes
131 competing with the property offered by a given host. Hosts charging too high a price will
132 not be able to rent their property even once. Conversely, if hosts charge too low a price,
133 they will attract many consumers, but this behaviour is not economically efficient as they
134 could increase their profit by raising the rental price. In fact, the short-term rental market
135 structure clearly corresponds to monopolistic competition, as defined by Chamberlin (1933).
136 Hosts face a decreasing demand curve for their properties and, as a consequence, benefit
137 from a certain degree of market power that depends on the price elasticity of demand. A
138 host facing a highly elastic demand cannot set a high price because any small change in
139 price would cause a large decline in demand and profit. Conversely, a host facing a rather
140 inelastic demand curve is going to charge a higher price since the rise in price will only cause
141 a relatively small drop in demand. In this case, the host is going to charge a price that is
142 higher than the competitive price and enjoy an economic profit.

143 The demand curve faced by a given host is typically unobserved. When setting the rental
144 price, hosts must therefore imagine an expected demand curve relying on their knowledge
145 of the market and personal beliefs. Let us consider two different hosts, i and j , proposing
146 two perfectly identical properties and sharing the same marginal and average cost functions.
147 They differ in their perception of the demand side and are characterised by different expected
148 demand curves. Host i perceives the demand as more elastic than host j . Analysing the same
149 market as host i , host j perceives a higher degree of market power and will rent identical
150 properties at higher prices.²

151 We hypothesise that opportunistic hosts have a limited knowledge (sometimes no know-
152 ledge at all) of the market. As acknowledged by Airbnb itself on its website,³ setting a correct
153 price is a challenging task for a host due to the amount of information one has to gather

²Note that the coexistence of different prices for identical properties could also arise from a difference in marginal costs. The host characterised by the highest marginal cost will charge a higher price.

³<https://blog.airbnb.com/smart-pricing/>

154 and process to forge a satisfying representation of the market. This information acquisition
155 process is costly and casual hosts may not find it worth investing in.

156 Conversely, professional players are not looking for side revenues but need to generate
157 significant profits. It implies that they develop a more accurate personal knowledge of the
158 market than casual hosts and will use it to maximise their profit. Since the degree of
159 market knowledge of a professional is higher, their perception of demand is different. When
160 professionals perceive a higher degree of market power, they will charge higher prices and
161 conversely if they perceive that demand is very elastic, they will set lower prices.

162 Furthermore, when markets are characterised by important seasonal fluctuations in de-
163 mand, hosts have to adjust their expectations and pricing strategy accordingly. Typically,
164 during the peak season and due to the relative scarcity of supply, guests may have more
165 difficulties to find alternative opportunities of lodging, leading to a larger elasticity of de-
166 mand. This implies that both the size and the direction of the price differential between
167 professionals and non-professionals is likely to vary over time.

168 In this article, we aim at testing whether professional hosts indeed have a better per-
169 ception of the degree of market power than non-professionals. This should translate into
170 different prices on average. Furthermore, this differential should vary over the year, depend-
171 ing on the characteristics of demand. Finally, this difference in pricing strategies should
172 materialise into larger revenues for professionals. The remainder of the paper is therefore
173 based on the following three hypotheses:

174 H1: On average, a price differential exists between professional and non-professional
175 players.

176 H2: The size and direction of this price differential may vary according to seasonal
177 fluctuations in demand.

178 H3: This price differential allows professional hosts to generate more revenue.

179 3 Empirical strategy and data

180 We focus on the Mediterranean island of Corsica, France, which is a popular destination
181 with strong tourism seasonality. Corsica has 326,000 inhabitants and welcomes an estimated
182 2 million tourists annually. A total of two-thirds of the visitors come from France, the
183 remainder are mainly Italian and German. The island is one of the most popular tourist
184 destinations in France. Thus, according to official data (INSEE 2018), 3.27 million overnight
185 stays were registered in 2017 in the hotel sector, with total tourism expenditure amounting
186 to 2.5 billion euros a year, one-third of the regional GDP. Furthermore, tourism flow is highly
187 seasonal, as represented in Figure 1. Tourism frequentation is concentrated between April
188 and September, with a peak season in June, July, and August. According to the official
189 survey by the French Statistical Institute and Corsican Tourism Agency (INSEE 2018), the
190 island received, in 2017, 400,900 visitors during the peak day of the tourism season, more
191 than doubling its resident population.

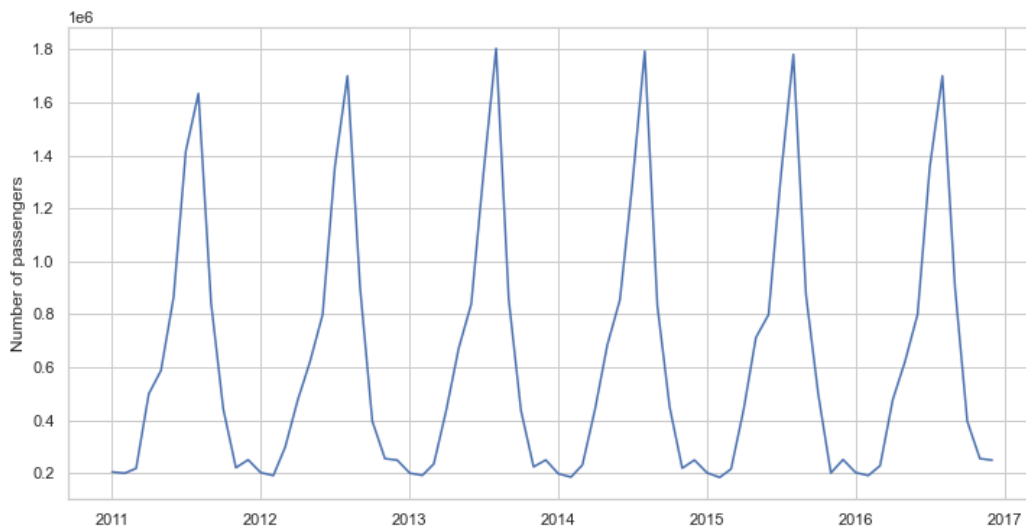


Figure 1: Monthly passengers flow in Corsica between 2011 and 2016, from ORTC 2016, <https://www.data.gouv.fr/en/datasets/trafic-mensuel-de-passagers-dans-les-ports-et-aeroports-corses-entrees-sorties-cors/>

192 **3.1 Description of the sample**

193 The main data are provided by AirDNA, a commercial company that collects short-term
194 vacation rental data. It covers the entire Airbnb listings population of Corsica for the period
195 from September 1, 2016 to August 31, 2017. The data for this study are aggregated at
196 the month level. After cleaning the original dataset, we obtain a sample of 72,986 prices
197 associated with 8,998 listings.⁴

198 In the following sections, we describe the variables used in our statistical analysis.

199 **3.1.1 Outcome and explanatory variables**

200 We seek to understand the difference in pricing between professional and non-professional
201 hosts, as well as the difference in revenue. The dependent variables in our regressions are
202 prices and revenue. Prices are given by the average daily rate (ADR), that is, the mean over
203 the month of the observed daily prices. Monthly revenues are obtained by taking the sum
204 of prices over the month for the days where a reservation occurred.

205 We define our main explanatory variable of interest, Pro, as a dummy variable that
206 takes the value 1 if the owner of a listing is a professional and 0 otherwise. We define
207 a professional as a host managing more than two listings and that is registered with the
208 French Trade and Companies Registry, the RCS. The method for identifying hosts registered
209 with the RCS first consists of an analysis of the host's Airbnb profile using the unique
210 host ID generated by Airbnb. Indeed, as Ke (2017) has already highlighted, professionals
211 frequently use the name of their company in the description of their profile and/or use the
212 logo of their company as a profile picture. In this way, hosts belonging to an identified
213 company are determined. The others were subject to a complementary search based on
214 the image recognition of their listings. This allowed, via their listing portfolio, to identify
215 the company's website and to exploit their legal informations. Finally, the company was

⁴Listings that did not carry out any transactions during the period under consideration have been removed. Furthermore, observations with no availability and no revenue in a given month, considered to be inactive, have also been dropped.

216 searched, on the basis of their name or registration number, in the public database of the
217 RCS via the institutional search tool Infogreffe. ([https://www.infogreffe.com/recherche-](https://www.infogreffe.com/recherche-siret-entreprise/chercher-siret-entreprise.html)
218 [siret-entreprise/chercher-siret-entreprise.html](https://www.infogreffe.com/recherche-siret-entreprise/chercher-siret-entreprise.html)).

219 The mean ADR across all listings and all months is €131.94 but, as shown in figure
220 2, it varies significantly over the year, denoting a clear seasonal phenomenon due to the
221 arrival of a large number of tourists during the summer season. The figure also displays
222 substantive differences between the prices charged by professionals and non-professionals,
223 with the former charging higher prices during the summer.

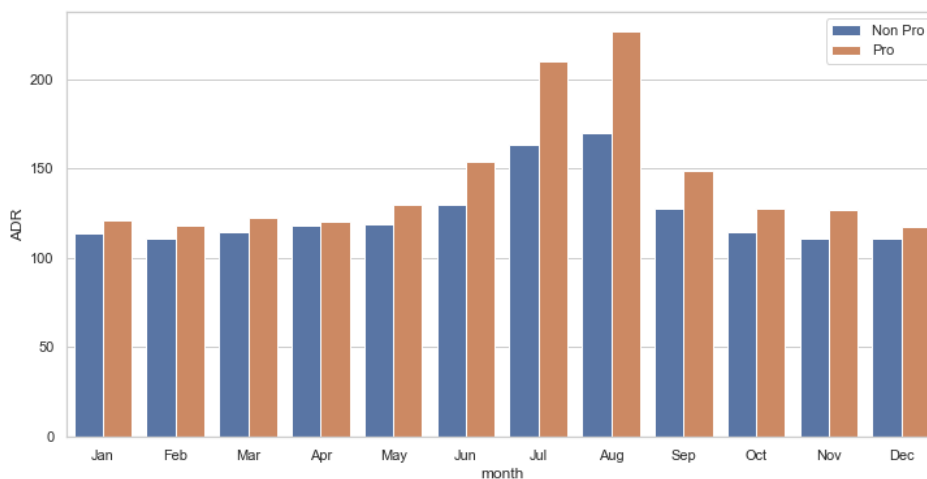


Figure 2: Average price per night and per month on Airbnb

224 3.1.2 Control variables

225 The dataset provides information related to both the listings and the hosts. A first set of
226 variables deals with attributes and reputation of the listings. A second set of variables is
227 related to host attributes. In addition, some variables make it possible to account for the
228 rental policy defined by the host. Finally, we have constructed a variable that provides
229 information about the location of the listing. These variables are summarised in Table 1 and
230 described below.

Listing attributes	Listing reputation	Hosts attributes	Rental policy	Location
ListingAge	OverallRating	ResponseRate	CancellationPolicy	Hex
PropertyType		ResponseTime	MinimumStay	
ListingType		Superhost	InstantbookEnabled	
Bedrooms				
Bathrooms				
MaxGuests				
NumberofPhotos				
Amenities				

Table 1: Control variables used in regressions

231 **Listing attributes and reputation** For each listing, identified by a property id, the
 232 following information is provided:

- 233 • The listing age (`ListingAge`), which is the difference measured in months between the
 234 scraping date and the date of creation of the listing.
- 235 • The property type (`PropertyType`), which indicates whether the property is an apart-
 236 ment, a house, or something else.
- 237 • The listing type (`ListingType`) distinguishes between entire homes or apartments,
 238 private rooms, and shared rooms.
- 239 • The number of bedrooms (`Bedrooms`) and bathrooms (`Bathrooms`).
- 240 • The maximum number of guests (`MaxGuests`) the listing can accommodate.
- 241 • The number of photos (`NumberofPhotos`) associated to the listing.
- 242 • The overall rating (`OverallRating`) of the listing, a scale variable from 1 to 5.
- 243 • A large set of dummy variables for the amenities.

244 **Hosts attributes** We use three variables for characterising the hosts. Information on how
245 fast and how often the host responds to a guest enquiry is provided by the response rate
246 (ResponseRate), the percentage of time a host responds to potential guests within 24 hours,
247 and the response time (ResponseTime), the average number of minutes it takes a host to
248 respond to a new booking enquiry. The dummy variable Superhost tells us if the host has
249 been awarded with this quality badge from Airbnb.

250 **Rental policy** The hosts may choose to use a number of options related to the rental
251 conditions of the property. For example, hosts may decide to impose a minimum number of
252 renting days to avoid too frequent a turnover between guests. This information is provided
253 by the minimum stay variable (MinimumStay). Furthermore, because Airbnb is a sharing
254 platform, the hosts can decide whether to accept or not a given guest. However, the hosts
255 have the possibility to automatically accept any guest enquiry by enabling the instant book-
256 ing option (InstantbookEnabled). This variable is a dummy that takes a value of 1 when
257 the option is enabled. Finally, a key rental variable is the cancellation policy (Cancellation-
258 Policy). Airbnb provides the hosts with three basic options: strict, flexible, and moderate.
259 When the chosen option is strict, the guest has the possibility to cancel the reservation for
260 free only during the first 48 hours and provided it is at least 14 days before the booking
261 dates. Under the moderate policy, it is possible to cancel the reservation up to five days
262 before the booked dates. Flexible policy makes it possible to cancel for free 24 hours up to
263 arrival. In addition, Airbnb proposes two very strict policies: Strict30 and Strict60. These
264 are offered to hosts connected to the platform via software, in general professional players.
265 Cancellation is possible only 30 or 60 days before arrival, and only 50% of the paid price is
266 refunded to the guest.

267 **Location** The original dataset contains variables that account for the location of the list-
268 ings. However, due to its peculiar insular geography, these variables may be insufficient in
269 the case of Corsica. For instance, if we used the city in which the listing is located to account

270 for the impact of space on price, we could observe inconsistent results due to the fact that, in
 271 the same city, some places are very attractive for tourists (the seaside) while others are not
 272 due to accessibility problems. We have therefore developed an original but simple solution.
 273 Using geographical information systems (GIS), the area of Corsica has been divided in 479
 274 hexagons of 10km², with each listing being associated to a unique hexagon, on the basis of
 275 geographical coordinates provided for each property ID. The qualitative variable *Hex* with
 276 479 levels has been added to our model to account for spatial fixed effects.

277 **3.2 Methodology of the study**

278 Regarding the methodology, since we examine the pricing strategy of professional hosts on
 279 Airbnb, a natural starting point is the hedonic price model proposed by Rosen (1974). The
 280 general idea of this model is that the price of a differentiated good, such as housing, is a
 281 function of its intrinsic (number of rooms, surface, etc.) and extrinsic (attractiveness of the
 282 neighbourhood, etc.) characteristics. This model is commonly used to estimate consumers'
 283 willingness to pay. We use this method to estimate the willingness to accept of Airbnb hosts
 284 since, as outlined in section 2, the price is chosen by the seller (the host). The originality of
 285 our approach lies in the fact that we focus on both the role of seasonality and the host type
 286 for the pricing strategy. To account for seasonality, we introduce the variable *Month*, that
 287 takes values ranging from 1 to 12.

288 The model we want to estimate takes the following general form:

$$Y_{im} = \theta_m Pro_i + g(ListAttr_i, HostAttr_i, RentPol_i, Hex_i, Month) + \epsilon_{im}. \quad (1)$$

289 where i corresponds to the property and m corresponds to the period (month), Y is the
 290 price (expressed in logarithm) or revenue, and $ListAttr_i, HostAttr_i, RentPol_i$ represent the
 291 listing attributes and reputation, the host attributes, as well as the rental policy variables,
 292 respectively. The effect of interest is captured by the term θ_m , which measures the impact

293 of the host status (professional vs. non-professional) on prices; dependence on m clarifies
294 that we allow this effect to vary with time. The function g is a general function, possibly
295 non-linear, of the control variables.

296 In a first specification, we assume that this function is linear:

$$g(.) = Cons + \beta_{la}ListAttr_i + \beta_{ha}HostAttr_i + \beta_{rp}RentPol_i + \gamma_{Hex_i} + \gamma_m.$$

297 Under this specification, equation (1) is estimated using OLS, with clustered standard errors
298 to account for serial correlation.

299 We consider two cases. In the first, $\theta_m = \theta$, that is, there is no variability in the effect
300 of the host status (professional vs. non-professional) on prices. This first model (Model 1)
301 provides us with an estimation of the effect, if any, of the host status on prices, so that
302 we obtain some answers to validate H1. However, the aim is to understand not only if the
303 pricing strategy of professional players differs from that of non-professional players (H1) but
304 also to understand if and how this difference is affected by seasonal fluctuations in demand
305 (H2). This is why we implement, in a second step, the estimation of a model in which θ_m is
306 allowed to vary with m (Model 2). It tells us how the difference in pricing changes over the
307 year between professional and non-professional hosts. Technically, this is done by creating
308 an interaction variable between the variables *Month* and *Pro*.

309 We then consider a second specification in which $g(.)$ is a general function of the control
310 variables. This allows us to check the robustness of the linear model.⁵ We adopt the double-
311 machine learning (DML) approach developed by [Chernozhukov et al. \(2018\)](#). Put simply,
312 this method consists of computing, in a first step, a prediction of the dependent (Y) and
313 treatment (*Pro*) variables through a machine learning (ML) algorithm. In a second step,
314 the residuals of the dependent variable (difference between the actual and predicted values
315 of this variable) are regressed on the residuals of the treatment variable.

⁵It is well known that the OLS estimator may be biased in the case where $g(.)$ is misspecified (see, e.g., [Robinson \(1988\)](#) and the references therein).

316 4 Effect of professionalisation on prices

317 This section presents the results of our econometric study to assess the validity of hypotheses
318 H1 and H2 presented in section 2. First, we detail the results of the baseline OLS specifica-
319 tion. Then, we discuss the impact of the inclusion of variable interacting time and the type
320 of host. Finally, we present the results obtained when adopting the DML approach.

321 4.1 OLS estimation

322 4.1.1 Results from the baseline model (Model 1)

323 As explained above, we start by estimating a simple OLS model in which the explained vari-
324 able is the natural logarithm of the average daily rate. Results from the baseline specification
325 are summarised in column ‘Model 1’ of tables 2 and 3 in appendix 7. The explanatory vari-
326 ables of interest are Pro and each of the twelve months of the year. Nonetheless, before
327 focusing on these variables, some general comments are necessary.

328 In this specification, the model includes a very large number of right-hand variables (555),
329 which are presented in section 3.1.2.

330 The global fit of the model is very good, with an R^2 of 0.693. This does not really come
331 at a surprise since the total number of explanatory variables is high. Nonetheless, it means
332 that our model accounts for most of the variability in rental prices.

333 It should also be noted that the most significant amenities (see Table 3) and those with
334 the larger positive effect on prices are, to some extent, related to luxury. For example, with
335 a coefficient of 0.190, the presence of a pool in the property increases the price by around
336 21% *ceteris paribus*. The same holds for the presence of a jacuzzi, which increases the price
337 by 13.3%, an air conditioner (+6%), or a dryer (+10.5%).⁶

338 Furthermore, as expected, entire homes are much more expensive than private rooms
339 (−20.4%) or shared rooms (−43.2%) *ceteris paribus*. Some property types are also shown to

⁶Since the price is in logarithm, the formula $e^\alpha - 1$ is applied to any coefficient α to obtain the effect in percentage points.

340 be more expensive than apartments. This is especially the case for guest houses (+26.7%)
341 and bed and breakfasts (+19.8%) that provide the guest with additional services. This is
342 also the case for houses and villas that are respectively 8.4% and 14.2% more expensive than
343 apartments *ceteris paribus*. The number of bedrooms and bathrooms are also proven to be
344 key determinants of the price since an additional bedroom raises the ADR by 15.5% and an
345 additional bathroom by 13.3%. The reputation has a significant positive impact on the rate
346 since an increment by one point of the rating of a listing leads to a 6% increase in the daily
347 rate. Interestingly, we find that being a Superhost is associated with a slightly lower price
348 (-4%).

349 Let us now consider the impact of seasonality on prices. Our results clearly show that
350 June, July, August, and September are by far the most significant determinants of prices.
351 This is no surprise but the impact of the peak season is proven to be very large. The same
352 property is 19.8% more expensive in June compared to January. The difference amounts
353 to +48.1% in July and peaks to +54.3% in August. It is noteworthy that the year can
354 be divided in two parts with February, March, November, and December being similar or
355 slightly cheaper than January and the rest of the months being more expensive.

356 Finally, looking at our main variable of interest, Pro, we see that on average, professional
357 hosts ask for higher prices. This variable has a strongly significant coefficient of 0.042: the
358 same property is 4.3% more expensive when listed by a professional host. This result supports
359 our first hypothesis, according to which a price differential exists between professional and
360 non-professional players. More precisely, since the price differential is positive, it suggests
361 that professional hosts tend to perceive a higher degree of market power on average over the
362 year.

363 **4.1.2 Results from the model with interactions (Model 2)**

364 Results from our baseline specification indicate that professional hosts ask for higher prices
365 and that the peak season is a key determinant of prices. However, at this stage, we do not

366 know if the pricing behaviour of professional hosts is affected by seasonality. As highlighted
367 in section 2, our hypothesis is that the size and direction of this price differential may vary
368 according to seasonal fluctuations in demand. In other words, the pricing behaviour of
369 professional and non-professional hosts should evolve differently over the year.

370 To assess the validity of this hypothesis, a set of interaction variables between Pro and
371 Month are introduced in the previous specification. Since the model is essentially the same,
372 results for most of the coefficients are only slightly modified.

373 We now focus on our variables of interest, Pro and Month. In the baseline specification,
374 Pro was positive and significant. Looking at column ‘Model 2’ of table 2, it now appears to
375 be negative. This result must not be misunderstood. It means that professional hosts charge
376 lower prices than non-professionals *for the month of January*. To determine if the behaviour
377 of a professional differs from the behaviour of a non-professional and by how much, one has
378 to add up the coefficient associated with Pro and that associated with the interaction term
379 of a given month (other than January).

380 Monthly effects of the professional status on prices are depicted in Figure 3, together
381 with 95% confidence intervals.

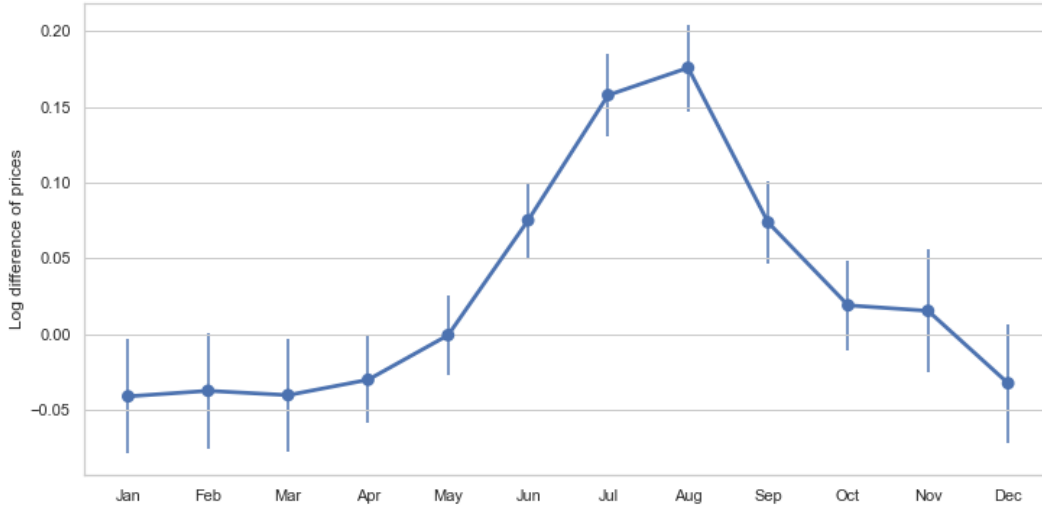


Figure 3: Log difference of prices between professionals and non-professionals in the OLS specification

382 According to the results of the OLS regression, professional players ask for higher prices
 383 than non-professionals between June and September, and for (slightly) lower prices in Janu-
 384 ary, February, March, April, and December. In May, October, and November, the prices
 385 are similar. Specifically and as examples, in August, professional hosts ask for prices that
 386 are 19.2% higher for the same property. In March, they ask for prices that are 4% lower.⁷

387 These results support the idea that professional hosts adjust their pricing behaviour
 388 across the year and react in a different way to the opportunity created by the peak season.
 389 When a high demand is expected, professionals perceive the existence of a potential gain since
 390 the extent of their market increases. This is due to the fact that guests face a relatively scant
 391 offer and must accept having to pay higher prices. Non-professionals also perceive this reality
 392 of the market, but since their knowledge of the market and their objectives are different, they
 393 do not set a price that would allow them to extract the totality of what one could call the
 394 ‘seasonal rent’. These results confirm that the price differential between professionals and

⁷These percentages are obtained by adding up the coefficients associated to Pro and ProXMonth and then applying the formula given in footnote 7.

395 non-professionals evolves over time. More precisely, the price differential between professional
396 and non-professional hosts depends positively on the evolution of demand.

397 4.2 DML estimation

398 As emphasised in section 3.2, newer methods have recently been developed, which allows
399 for a better identification of the causal impact of the professional status on prices. The
400 estimation results of Model 2 with the so-called DML approach are represented in Figure 4.

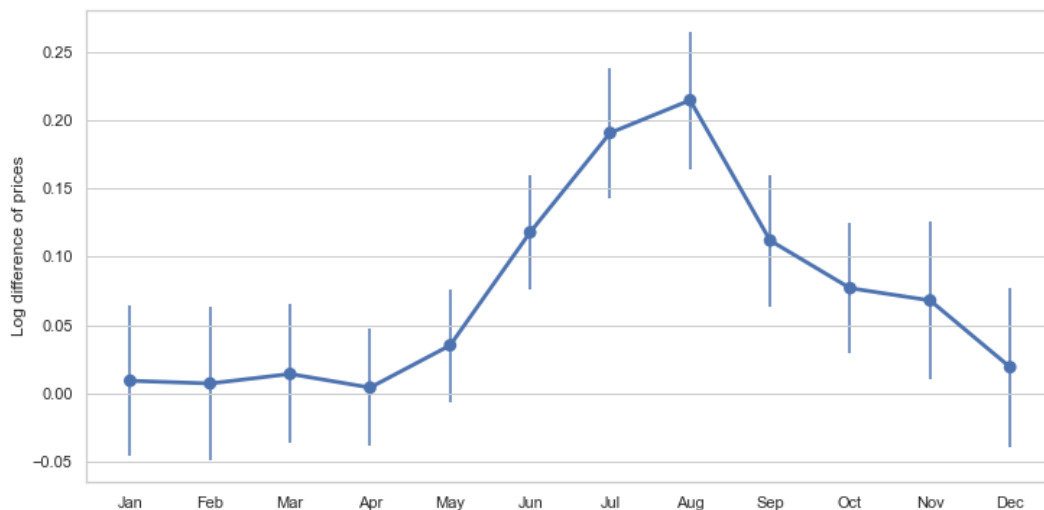


Figure 4: Log difference of prices between professionals and non-professionals in the DML specification

401 Figure 4 has a similar shape to Figure 3, with the important difference that the price
402 differential between professionals and non-professionals is now larger. For example, the price
403 differential in August is 24% instead of 19.2%. In June and September, professional hosts
404 charge prices more than 11% higher than non-professionals, whereas the OLS estimation re-
405 vealed a price differential less than 8%. Furthermore, the negative price differential obtained
406 in January, February, March, April, and December, is not robust to the application of the
407 DML method. This latter indeed concludes that *professionals never charge lower prices than*

408 *non-professionals*. They happen to choose similar prices in January, February, March, April,
409 and December. Otherwise the price differential is always strictly positive.

410 These results are confirmed by the DML estimation of Model 1, which reveals an average
411 price differential equal to 8.8%, twice as much as that determined via the OLS (4.3%).

412 We can conclude that prices are generally higher for professionals, except in the winter
413 and the beginning of spring. Specifically, it is dubious to consider that professionals ask for
414 lower prices off-peak, as suggested by the OLS analysis.

415 5 Impact on revenue

416 We have observed that professionals tend to propose higher prices than non-professionals (for
417 comparable listings). We now turn to the question of whether these higher prices translate
418 into higher revenue (H3). For this purpose, we estimate the model (1), with the dependent
419 variable now being the revenue earned, instead of the logarithm of the price. Estimates
420 obtained via the DML method are shown in Figure 5.

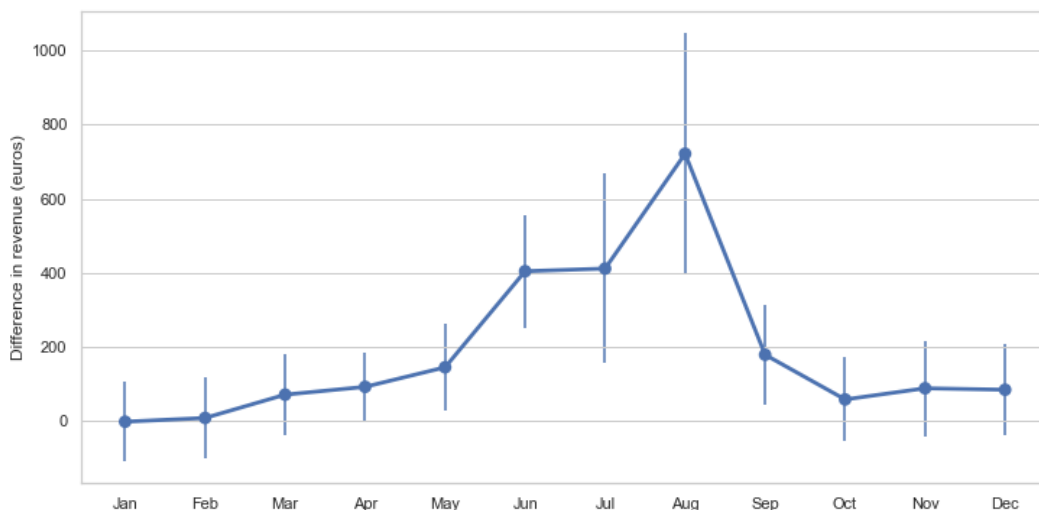


Figure 5: Difference in revenue between professionals and non-professionals in the DML specification

421 Results are very clear-cut. The higher prices adopted by professional hosts in the summer
422 translate into higher revenue, meaning that the drop in demand, if any, is not sufficient to
423 offset the price differential. Observe that the revenue differential may be quite large, peaking
424 at almost €800 per listing in August.

425 However, we do not observe such an effect in Autumn (October and November), despite
426 the professionals proposing higher prices than non-professionals. This could be explained by a
427 sensitivity of demand to prices during this season greater than expected by the professionals.
428 Faced with a limited market power, these latter would therefore be unable to transform higher
429 prices into larger revenues.

430 Finally, despite adopting similar prices, professional hosts tend to generate more revenue
431 than non-professionals in the spring (March, April, and May). This effect could have two
432 possible explanations. Due to the correlation of the professional status with unobserved
433 listing characteristics, it could be the case that professionals tend to rent more easily for a
434 given level of prices. Another, simpler, explanation could well be that professionals make
435 their listings more available, on average, than non-professionals during this period of the
436 year.

437 **6 Robustness checks**

438 We propose two robustness checks. We first contrast our results with what would be obtained
439 under an alternative characterisation of professional hosts, more in line with the usual as-
440 sumption made in the literature. Then we implement our methodology on a dataset collected
441 two years later in order to assess the temporal consistency of our results.

442 **6.1 Alternative characterisation of professional hosts**

443 The common characterisation of professional hosts encountered in the literature is based on
444 the number of listings managed. A host is considered a professional player as soon as they

445 manage more than a given number of listings. In the literature, thresholds are commonly
 446 between one and three listings. We assume in this alternative specification that a host has
 447 a professional activity as soon as they manage (strictly) more than two listings. Adopting
 448 the DML methodology, estimation results in this setting are represented in Figure 6.

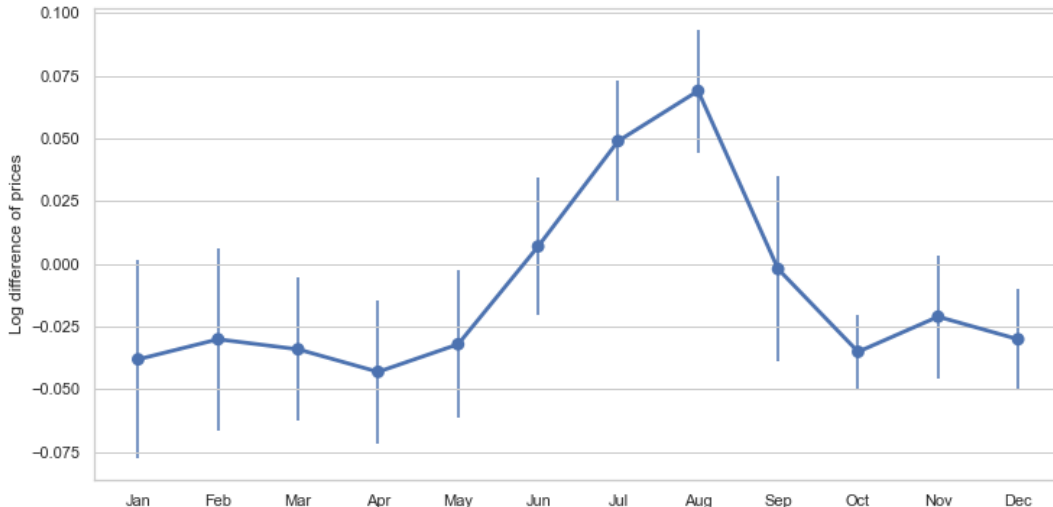


Figure 6: Log difference of prices in the DML specification under the alternative characterisation of professionalisation

449 The variations of the price differential according to the period of the year follow a similar
 450 pattern as with our characterisation of professional hosts. However, two important differ-
 451 ences arise. First, the magnitude of the price differential is much lower. It now peaks
 452 at approximately 8% in August, compared with more than 20% in our baseline scenario.
 453 Second, and contrary to our results, professional hosts now propose lower prices off-peak.
 454 When combining these two phenomena, we find that professional and non-professional hosts
 455 tend to propose, under this alternative characterisation of professionalisation, similar prices
 456 on average. This illustrates the importance of adopting a sound characterisation of the
 457 professional activity on the short-term rental market.

458 **6.2 Temporal consistency of the results**

459 In November 2015, Airbnb launched their pricing tool called Smart Pricing to help guests set
460 their prices to maximise their revenue. Smart pricing algorithm uses 70 different variables to
461 provide hosts with pricing suggestions. They can either choose to follow the piece of advise
462 or not. (Airbnb 2017 <https://blog.airbnb.com/smart-pricing/>).

463 Our data has been collected between September 2016 and August 2017, in a period in which
464 the smart pricing tool was not widely used yet. One could argue that the diffusion of this
465 practice among the hosts is likely to make our results already obsolete.

466 To deal with this potential issue, we have gathered the same dataset on airbnb sales for the
467 period ranging from September 2018 to August 2019 and run the analysis again considering
468 the same sample of hosts than for 2017. Results about the difference in prices are reported on
469 Figure 7. Comparing Figure 7 with Figure 4, one can observe that, two years later, the price
470 gap between professionals and non-professionals has become larger in both low and peak
471 season. For example, in 2017 the price gap was not significantly different for the months
472 between January and April. In 2019, instead, it lies above 10%. This suggests not only that
473 our previous results are not obsolete but that the price differential is likely to increase with
474 time and experience.

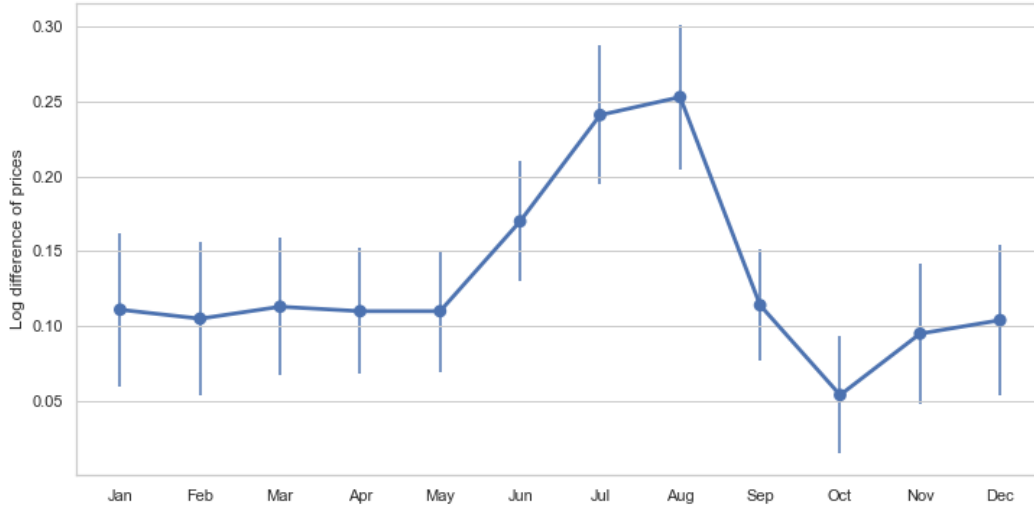


Figure 7: Log difference of prices in the DML specification for the period September 2018-August 2019

475 As for the difference in revenue, the results obtained with the data collected between
 476 September 2018 and August 2019 are depicted in Figure 8. Comparing this Figure with
 477 Figure 5, we still observe that professionals generate significantly more revenue during the
 478 summer, with a gap peaking at more than €1000 in August. However, it appears that they
 479 only perform slightly better in June and July 2019. For instance, while we have obtained
 480 a gap in revenue per listing of €400 in July 2017, it is merely above €200 in July 2019.
 481 This could be explained by a misperception of the market by professionals, who failed to
 482 adjust sufficiently their prices to an increase in the elasticity of demand in July, as compared
 483 to 2017. Data from the observatory of transports of Corsica indicate that the number of
 484 tourists in 2019 was 5% lower compared to 2018. Furthermore, the number of tourists in
 485 July was 25% below the number of tourists in August. These observations suggest that the
 486 demand in July 2019 was likely to be more elastic than in July 2017, hence explaining the
 487 drop in professionals performance with respect to 2017. The same reasoning applies for the
 488 month of June.

489 Results for the other months are comparable, with slight differences. In June, the gap

490 between professionals and non-professionals, around €250, appears smaller than in our main
491 analysis. Furthermore, the revenue generated by professionals is now (slightly) larger in
492 Autumn and Winter.

493 Overall, we can say that our results are fairly robust and that the increased diffusion of
494 the smart pricing tool did not have too much of an impact on the pricing behaviour of the
495 hosts. Interestingly enough, however, we note that even though the difference in prices in
496 July is of the same order with the 2019 data, professionals failed to generate more revenue
497 during this month.

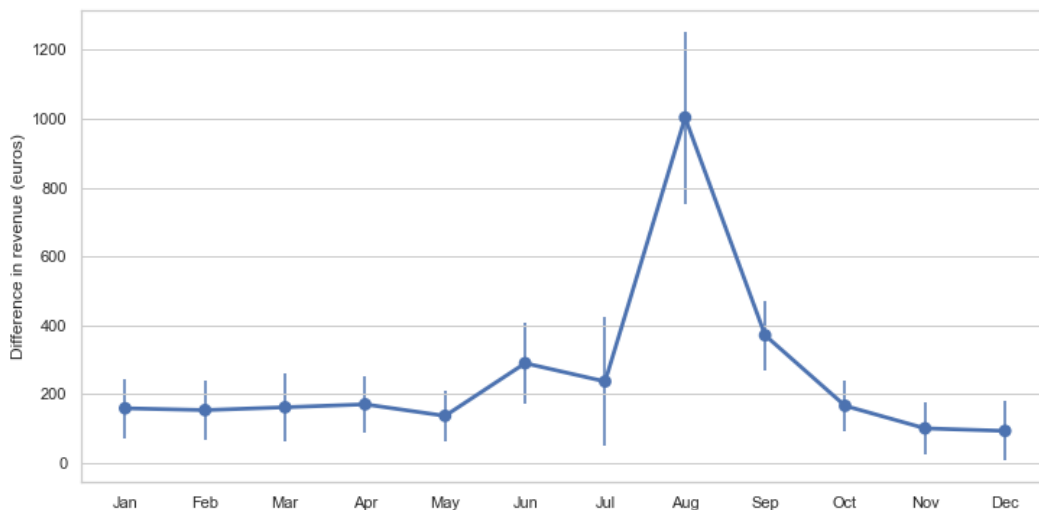


Figure 8: Difference in revenue between professionals and non-professionals in the DML specification for the period September 2018-August 2019

498 7 Discussion and conclusion

499 To date, the literature related to the pricing behaviour of Airbnb hosts has highlighted some
500 interesting features that differentiate professional players from casual hosts. According to
501 [Deboosere et al. \(2019\)](#), despite the fact that the price asked by professional hosts does not
502 differ on average from the price asked by casual hosts, the former obtain a higher level of

503 revenue on average. This enhanced capacity to generate revenue could be partially explained
504 by the fact that professional players practice dynamic pricing and change their prices more
505 often to cope with changes in demand, as argued by [Oskam et al. \(2018\)](#). Nonetheless, even
506 if changing the asked price more often is a key to understand why professional players are
507 more efficient in the generation of revenue, there is a need to understand when and in which
508 direction professionals adjust the prices in more depth. The proposed methodology makes
509 it possible to understand the difference in the pricing strategy of professionals with respect
510 to non-professionals.

511 Furthermore, our approach relies on a clear definition of the professional host. In the
512 aforementioned studies, hosts are characterised by the number of listings that they manage.
513 It raises a number of potential issues due to the fact that these hosts could be very heterogen-
514 eous in terms of objective and characteristics. Some of them are obviously not professionals.
515 By considering only businesses as professional players, we obtain clearer results, indicating
516 that the difference in revenue, as already revealed by [Deboosere et al. \(2019\)](#), is associated
517 to a price differential. In addition, we demonstrate that this price differential depends on
518 time and the intensity of demand.

519 This study is the first to measure a month-by-month price differential between profes-
520 sional and non-professional hosts. The results indicate that the price differential exists during
521 the peak season. More precisely, asked prices are similar between January and May and they
522 start to differ in June. In July and August, the peak in demand, professional hosts are more
523 than 20% more expensive. This positive price differential slowly decreases as the demand
524 slows in September, October, and November, and vanishes in December. This provides addi-
525 tional evidence that professionals practice dynamic pricing, as suggested by [Deboosere et al.](#)
526 [\(2019\)](#) and [Oskam et al. \(2018\)](#).

527 Professionals tend to adopt a different behaviour only when demand is high. It means
528 that they have a different perception of the economic opportunities associated with the
529 seasonal increase in demand. Their enhanced knowledge of the market, related to experience

530 or the existence of loyal customers, for example, makes them aware of the fact that during
531 the peak season, a fringe of customers is characterised by a quite low price elasticity of
532 demand. They simply use this temporary market power to raise their prices and increase
533 their revenue. We should stress that professional hosts behave as suggested by the textbook
534 model of monopolistic competition while this is not (or less frequently) the case for casual
535 hosts. Both casual and professional hosts increase their prices during the peak season but,
536 on average, professionals perceive a larger degree of market power and tend to increase their
537 rates more to enhance their revenue.

538 Our results emphasise that an economic incentive exists for short-term rental platforms
539 to attract a significant number of professionals in destinations marked by an important
540 seasonality, as the revenue of the platform is a fraction of the host's revenue. Since we
541 show that professional hosts perform better in the presence of seasonality, it means that
542 the platform will enhance its profit if the share of professional hosts is sufficiently large.
543 Furthermore, another managerial implication for the platform is related to its ability to
544 train casual hosts. The development of an accurate pricing tool such as smart pricing could
545 be a way for the platform to reduce the gap in market knowledge between professional and
546 casual hosts. By closing this gap, the platform will probably experience a significant increase
547 in profits. Nonetheless, one has to keep in mind that a key attraction factor for the platform is
548 the capacity to provide relatively cheap accommodation to some guests. That is, the correct
549 mix between casual and professional hosts in the portfolio of the platform is destination
550 specific and will partly depend on seasonality.

551 Finally, it should be kept in mind that the pricing decision may depend, in addition to the
552 numerous explanatory variables included in our model, on some other, unmeasured, variables.
553 In particular, some recent literature has emphasised the importance of human relationships
554 between guests and hosts ([Stofberg & Bridoux 2019](#), [Ert & Fleischer 2020](#)). Guests are shown
555 to value having in-person interactions or the quality of hosts' photographs. Assuming that
556 professional hosts are less likely to provide these "services" than casual hosts, we conjecture

557 that the pricing gap between these two types of hosts would be even larger than the one
558 found in this article. Our econometric specification indeed implies that professionals charge
559 higher prices, despite offering less human relationships. If we could control for the quality
560 of human interactions, a *ceteris paribus* analysis would compare professional to casual hosts
561 providing the same quality of human interactions. It would therefore conclude to a larger
562 price differential since guests, who value positively human relationships, would be willing
563 to pay more to professionals for an increase in this service. A precise development of this
564 informal statement should, however, be the subject of future research.

565 References

- 566 Abrate, G., Nicolau, J. L. & Viglia, G. (2019), ‘The impact of dynamic price variability on
567 revenue maximization’, *Tourism Management* **74**, 224–233.
568 **URL:** <https://www.sciencedirect.com/science/article/pii/S0261517719300627>
- 569 Aznar, J. P., Sayeras, J. M., Segarra, G. & Claveria, J. (2018), ‘Airbnb landlords and price
570 strategy: Have they learnt price discrimination from the hotel industry? Evidence from
571 Barcelona’, *International Journal of Tourism Sciences* **18**(1), 16–28.
- 572 Benítez-Aurioles, B. (2018), ‘Why are flexible booking policies priced negatively?’, *Tourism
573 Management* **67**, 312–325.
- 574 Cai, Y., Zhou, Y., Ma, J. & Scott, N. (2019), ‘Price Determinants of Airbnb Listings:
575 Evidence from Hong Kong’, *Tourism Analysis* **24**, 227–242.
- 576 Chamberlin, E. (1933), *The Theory of Monopolistic Competition*, Harvard University Press.
- 577 Chen, Y. & Xie, K. (2017), ‘Consumer Valuation of Airbnb Listings: A Hedonic Pricing
578 Approach’, *International Journal of Contemporary Hospitality Management* **29**.
- 579 Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W. &

- 580 Robins, J. (2018), ‘Double/debiased machine learning for treatment and structural para-
581 meters’, *The Econometrics Journal* **21**(1), C1–C68.
- 582 Chica-Olmo, J., González-Morales, J. G. & Zafra-Gómez, J. L. (2020), ‘Effects of location
583 on Airbnb apartment pricing in Málaga’, *Tourism Management* **77**, 103981.
- 584 Dann, D., Teubner, T. & Weinhardt, C. (2019), ‘Poster child and guinea pig – insights
585 from a structured literature review on Airbnb’, *International Journal of Contemporary
586 Hospitality Management* **31**(1), 427–473.
- 587 Deboosere, R., Kerrigan, D. J., Wachsmuth, D. & El-Geneidy, A. (2019), ‘Location, location
588 and professionalization: A multilevel hedonic analysis of Airbnb listing prices and revenue’,
589 *Regional Studies, Regional Science* **6**(1), 143–156.
- 590 Dredge, D., Gyimóthy, S., Birkbak, A., Jensen, T. E. & Madsen, A. K. (2016), *The Impact of
591 Regulatory Approaches Targeting Collaborative Economy in the Tourism Accommodation
592 Sector: Barcelona, Berlin, Amsterdam and Paris*.
- 593 Dudás, G., Kovalcsik, T., Vida, G., Boros, L. & Nagy, G. (2019), *Price Determinants of
594 Airbnb Listing Prices in Lake Balaton Touristic Region, Hungary*.
- 595 Ert, E. & Fleischer, A. (2020), ‘What do airbnb hosts reveal by posting photographs on-
596 line and how does it affect their perceived trustworthiness?’, *Psychology & Marketing*
597 **37**(5), 630–640.
598 **URL:** <https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21297>
- 599 Falk, M., Larpin, B. & Scaglione, M. (2019), ‘The role of specific attributes in determining
600 prices of Airbnb listings in rural and urban locations’, *International Journal of Hospitality
601 Management* **83**, 132–140.
- 602 Faye, B. (2021), ‘Methodological discussion of Airbnb’s hedonic study : A review of the

603 problems and some proposals tested on Bordeaux City data’, *Annals of Tourism Research*
604 **86**, 21.

605 Gibbs, C., Guttentag, D., Gretzel, U., Morton, J. & Goodwill, A. (2018), ‘Pricing in the
606 sharing economy: A hedonic pricing model applied to Airbnb listings’, *Journal of Travel*
607 *& Tourism Marketing* **35**(1), 45–56.

608 Gibbs, C., Guttentag, D., Gretzel, U., Yao, L. & Morton, J. (2018), ‘Use of dynamic pricing
609 strategies by Airbnb hosts’, *International Journal of Contemporary Hospitality Manage-*
610 *ment* **30**(1), 2–20.

611 Gunter, U. (2018), ‘What makes an Airbnb host a superhost? Empirical evidence from San
612 Francisco and the Bay Area’, *Tourism Management* **66**, 26–37.

613 Gurran, N. & Phibbs, P. (2017), ‘When Tourists Move In: How Should Urban Planners
614 Respond to Airbnb?’, *Journal of the American Planning Association* **83**(1), 80–92.

615 Guttentag, D. (2019), ‘Progress on Airbnb: A literature review’, *Journal of Hospitality and*
616 *Tourism Technology* **10**(4), 814–844.

617 INSEE (2018), Bilan annuel du tourisme - 2017, Insee Dossier Corse 9.

618 Ke, Q. (2017), Sharing Means Renting?: An Entire-marketplace Analysis of Airbnb, *in*
619 ‘Proceedings of the 2017 ACM on Web Science Conference - WebSci ’17’, ACM Press,
620 Troy, New York, USA, pp. 131–139.

621 Krause, A. & Aschwanden, G. (2020), ‘To Airbnb? Factors Impacting Short-Term Leasing
622 Preference’, *Journal of Real Estate Research* p. 25.

623 Kwok, L. & Xie, K. L. (2019), ‘Pricing strategies on Airbnb: Are multi-unit hosts revenue
624 pros?’, *International Journal of Hospitality Management* **82**, 252–259.

625 Leoni, V. (2020), ‘Stars vs lemons. Survival analysis of peer-to peer marketplaces: The case
626 of Airbnb’, *Tourism Management* **79**, 104091.

- 627 Li, J., Moreno, A. & Zhang, D. (2016), Pros vs Joes: Agent Pricing Behavior in the Sharing
628 Economy, SSRN Scholarly Paper ID 2708279, Social Science Research Network, Rochester,
629 NY.
- 630 Lladós-Masllorens, J., Meseguer-Artola, A. & Rodríguez-Ardura, I. (2020), ‘Understanding
631 Peer-to-Peer, Two-Sided Digital Marketplaces: Pricing Lessons from Airbnb in Barcelona’,
632 *Sustainability* **12**(13), 5229.
- 633 Lorde, T., Jacob, J. & Weekes, Q. (2019), ‘Price-setting behavior in a tourism sharing eco-
634 nomy accommodation market: A hedonic price analysis of AirBnB hosts in the caribbean’,
635 *Tourism Management Perspectives* **30**, 251–261.
- 636 Magno, F., Cassia, F. & Ugolini, M. M. (2018), ‘Accommodation prices on Airbnb: Effects
637 of host experience and market demand’, *The TQM Journal* .
- 638 Oskam, J., van der Rest, J.-P. & Telkamp, B. (2018), ‘What’s mine is yours—but at what
639 price? Dynamic pricing behavior as an indicator of Airbnb host professionalization’,
640 *Journal of Revenue and Pricing Management* **17**(5), 311–328.
- 641 Robinson, P. M. (1988), ‘Root-N-Consistent Semiparametric Regression’, *Econometrica*
642 **56**(4), 931.
- 643 Rosen, S. (1974), ‘Hedonic Prices and Implicit Markets: Product Differentiation in Pure
644 Competition’, *Journal of Political Economy* **82**(1).
- 645 Schneiderman, E. T. (2014), Airbnb in the City, Technical report, Office of the New-York
646 State Attorney General.
- 647 Stoffberg, N. & Bridoux, F. (2019), ‘Consumers’ choice among peer-to-peer sharing platforms:
648 The other side of the coin’, *Psychology & Marketing* **36**(12), 1176–1195.
649 **URL:** <https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21265>

650 Teubner, T., Hawlitschek, F. & Dann, D. (2017), 'Price Determinants on Airbnb: How Reputa-
651 tion Pays Off in the Sharing Economy', *Journal of Self-Governance and Management*
652 *Economics* **5**, 53–80.

653 Wang, D. & Nicolau, J. L. (2017), 'Price determinants of sharing economy based accommod-
654 ation rental: A study of listings from 33 cities on Airbnb.com', *International Journal of*
655 *Hospitality Management* **62**, 120–131.

OLS Results

Table 2: OLS Results

	Model 1		Model 2	
Pro	0.041667**	(3.205)	-0.041228*	(-2.144)
<i>Month</i> (ref. Jan)				
Feb	-0.022464***	(-8.709)	-0.022955***	(-8.276)
Mar	0.021615***	(6.130)	0.021945***	(5.962)
Apr	0.041383***	(9.875)	0.040896***	(9.177)
May	0.073532***	(16.555)	0.068979***	(14.765)
Jun	0.181323***	(37.399)	0.166463***	(32.718)
Jul	0.393524***	(69.445)	0.368368***	(62.399)
Aug	0.434069***	(73.192)	0.406592***	(65.937)
Sep	0.154286***	(33.233)	0.139805***	(28.993)
Oct	0.031714***	(7.867)	0.024239***	(5.821)
Nov	-0.015830***	(-4.438)	-0.022960***	(-6.325)
Dec	-0.014841***	(-5.049)	-0.016550***	(-5.287)
Pro X Feb			0.003663	(0.515)
Pro X Mar			0.000803	(0.070)
Pro X Apr			0.010964	(0.842)
Pro X May			0.040409**	(2.821)
Pro X Jun			0.116231***	(7.539)
Pro X Jul			0.198898***	(10.975)
Pro X Aug			0.216955***	(11.531)
Pro X Sep			0.114847***	(7.458)
Pro X Oct			0.060108***	(4.305)
Pro X Nov			0.056468***	(4.288)
Pro X Dec			0.008653	(0.987)
ListingAge	0.001954***	(6.474)	0.001928***	(6.388)

<i>PropertyType</i> (ref. Apartment)				
Bed_Breakfast	0.180840***	(6.573)	0.181498***	(6.587)
Bungalow	-0.042481	(-1.146)	-0.041989	(-1.136)
Chalet	0.028553	(0.626)	0.029146	(0.639)
Condominium	-0.024916	(-1.148)	-0.025170	(-1.159)
Guesthouse	0.236824***	(7.084)	0.234529***	(7.019)
House	0.080729***	(7.953)	0.080793***	(7.960)
Other	0.046692	(1.649)	0.045001	(1.585)
Vacation_home	0.102848***	(3.339)	0.107183***	(3.453)
Villa	0.132657***	(7.389)	0.132275***	(7.367)
<i>ListingType</i> (ref. Entire Home)				
Private_room	-0.227561***	(-10.402)	-0.227307***	(-10.388)
Shared_room	-0.759416***	(-6.245)	-0.758081***	(-6.339)
Bedrooms	0.143918***	(15.845)	0.143885***	(15.856)
Bathrooms	0.124604***	(10.270)	0.124407***	(10.254)
MaxGuests	0.029508***	(5.993)	0.029567***	(6.002)
NumberofPhotos	0.002682***	(6.293)	0.002682***	(6.298)
Superhost	-0.039978**	(-3.029)	-0.040525**	(-3.073)
ResponseTime	0.000000	(1.561)	0.000000	(1.517)
ResponseRate	-0.000127	(-0.404)	-0.000123	(-0.393)
OverallRating	0.058553***	(5.666)	0.059029***	(5.704)
<i>CancellationPolicy</i> (Ref: Flexible)				
Moderate	-0.052426***	(-4.118)	-0.052614***	(-4.133)
Strict	0.002457	(0.242)	0.002217	(0.218)
Strict_30	0.018812	(0.377)	0.019979	(0.405)
Strict_60	0.131867	(1.506)	0.106986	(1.221)
MinimumStay	0.000267	(0.903)	0.000269	(0.904)
InstantbookEnabled	-0.027489***	(-3.417)	-0.027802***	(-3.455)
Constant	3.647006***	(57.070)	3.657152***	(57.272)
<hr/>				
Observations	72986		72986	
R^2	0.693		0.695	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: OLS Results for amenities

	Model 1		Model 2	
amenity_kitchen	-0.097777***	(-4.720)	-0.098421***	(-4.753)
amenity_internet	-0.031605	(-1.463)	-0.032460	(-1.500)
amenity_tv	0.040041**	(3.279)	0.039563**	(3.238)
amenity_heating	-0.037649***	(-3.910)	-0.037732***	(-3.919)
amenity_ac	0.058508***	(7.096)	0.058703***	(7.120)
amenity_washer	-0.002933	(-0.227)	-0.002732	(-0.211)
amenity_dryer	0.099710***	(8.727)	0.100336***	(8.783)
amenity_free_parking	-0.013122	(-1.157)	-0.012359	(-1.087)
amenity_wireless_internet	0.036387***	(4.198)	0.036392***	(4.198)
amenity_cable	0.035097***	(3.388)	0.035037***	(3.381)
amenity_breakfast	-0.007901	(-0.492)	-0.007533	(-0.469)
amenity_allows_pets	-0.052749*	(-2.410)	-0.052271*	(-2.383)
amenity_family_friendly	0.025295	(1.604)	0.025325	(1.604)
amenity_event_friendly	0.021278	(0.648)	0.021018	(0.638)
amenity_allows_smoking	-0.016397	(-0.796)	-0.016872	(-0.818)
amenity_wheelchair_accessible	0.136288**	(3.064)	0.135760**	(3.048)
amenity_elevator	0.037092**	(2.952)	0.037217**	(2.964)
amenity_fireplace	0.078426***	(6.208)	0.078339***	(6.199)
amenity_buzzer	-0.012256	(-0.376)	-0.013543	(-0.416)
amenity_doorman	0.162710	(1.721)	0.162783	(1.720)
amenity_pool	0.190425***	(17.565)	0.190240***	(17.549)
amenity_jacuzzi	0.125441***	(4.752)	0.125631***	(4.752)
amenity_gym	0.057221	(1.279)	0.056985	(1.278)
amenity_bedroom_step_free_access	0.581829**	(2.929)	0.591521**	(2.979)
amenity_bathroom_step_free_access	0.331481	(1.021)	0.315784	(0.978)
amenity_home_step_free_access	-0.357330*	(-2.073)	-0.364094*	(-2.121)
amenity_common_space_step_free_a	-0.254069	(-0.820)	-0.238686	(-0.772)
amenity_bedroom_wide_doorway	0.148071	(0.399)	0.184763	(0.496)
amenity_home_wide_doorway	0.181656	(0.761)	0.186079	(0.784)

amenity_bathroom_wide_doorway	0.468759	(1.535)	0.477076	(1.559)
amenity_changing_table	0.028576	(0.931)	0.028469	(0.927)
amenity_childrens_books_and_toys	0.005353	(0.379)	0.005218	(0.370)
amenity_iron	-0.025709*	(-2.402)	-0.025501*	(-2.384)
amenity_common_space_wide_doorwa	-0.467646	(-1.703)	-0.485591	(-1.776)
amenity_wide_clearance_to_shower	0.408242	(1.175)	0.410585	(1.184)
amenity_fireplace_guards	0.026033	(0.756)	0.026228	(0.764)
amenity_accessible_height_toilet	-0.246174	(-0.789)	-0.255545	(-0.817)
amenity_private_living_room	-0.014194	(-0.330)	-0.016137	(-0.376)
amenity_childrens_dinnerware	0.020375	(0.771)	0.020943	(0.793)
amenity_fire_extinguisher	0.029733*	(2.387)	0.029797*	(2.392)
amenity_bathtub	0.007012	(0.398)	0.007455	(0.424)
amenity_flat_smooth_pathway_to_f	-0.480815	(-1.643)	-0.496317	(-1.691)
amenity_crib	0.058535***	(4.627)	0.058289***	(4.609)
amenity_street_parking	-0.041580**	(-3.275)	-0.041664**	(-3.282)
amenity_table_corner_guards	0.054211	(0.645)	0.056505	(0.671)
amenity_shampoo	0.015533	(1.566)	0.015342	(1.546)
amenity_laptop_friendly	0.002784	(0.320)	0.002776	(0.319)
amenity_carbon_monoxide_detector	0.007587	(0.573)	0.007704	(0.583)
amenity_private_entrance	-0.014792	(-1.481)	-0.014169	(-1.419)
amenity_grab_rails_in_shower_and	0.000000	(.)	0.000000	(.)
amenity_stair_gates	-0.093638**	(-3.127)	-0.093961**	(-3.136)
amenity_window_guards	-0.075419	(-1.518)	-0.076479	(-1.535)
amenity_safety_card	-0.029486	(-0.606)	-0.028223	(-0.581)
amenity_smoke_detector	-0.022282**	(-2.648)	-0.022488**	(-2.673)
amenity_game_console	0.023496	(0.448)	0.024180	(0.460)
amenity_pack_n_play_travel_crib	-0.031209**	(-2.931)	-0.031086**	(-2.921)
amenity_wide_hallway_clearance	-0.121817	(-0.613)	-0.123960	(-0.629)
amenity_lock_on_bedroom_door	-0.033587	(-1.404)	-0.034398	(-1.438)
amenity_room_darkening_shades	-0.041267*	(-2.013)	-0.041463*	(-2.023)
amenity_outlet_covers	0.046484	(1.331)	0.047107	(1.349)
amenity_handheld_shower_head	0.115496	(0.374)	0.118062	(0.383)

amenity_baby_bath	-0.066564***	(-3.780)	-0.066681***	(-3.788)
amenity_wide_clearance_to_bed	-0.637618	(-1.086)	-0.667595	(-1.132)
amenity_paid_parking	0.009683	(0.372)	0.009913	(0.381)
amenity_accessible_height_bed	0.000000	(.)	0.000000	(.)
amenity_disabled_parking_spot	0.472426	(1.333)	0.494744	(1.387)
amenity_baby_monitor	0.067483	(1.289)	0.067375	(1.288)
amenity_first_aid_kit	-0.017050	(-1.319)	-0.016684	(-1.293)
amenity_path_to_entrance_lit_at_	0.043922	(0.262)	0.041852	(0.250)
amenity_hair_dryer	0.009855	(1.019)	0.009956	(1.030)
amenity_essentials	0.073390***	(7.855)	0.073795***	(7.901)
amenity_24hr_checkin	-0.059891	(-1.225)	-0.059173	(-1.211)
amenity_babysitter_recommendatio	0.044604*	(2.059)	0.044517*	(2.056)
amenity_high_chair	-0.052234***	(-4.086)	-0.052313***	(-4.095)
amenity_hangers	-0.011367	(-0.917)	-0.011767	(-0.950)

t statistics in parentheses

Only significant coefficients at the 0.05 level are reported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$