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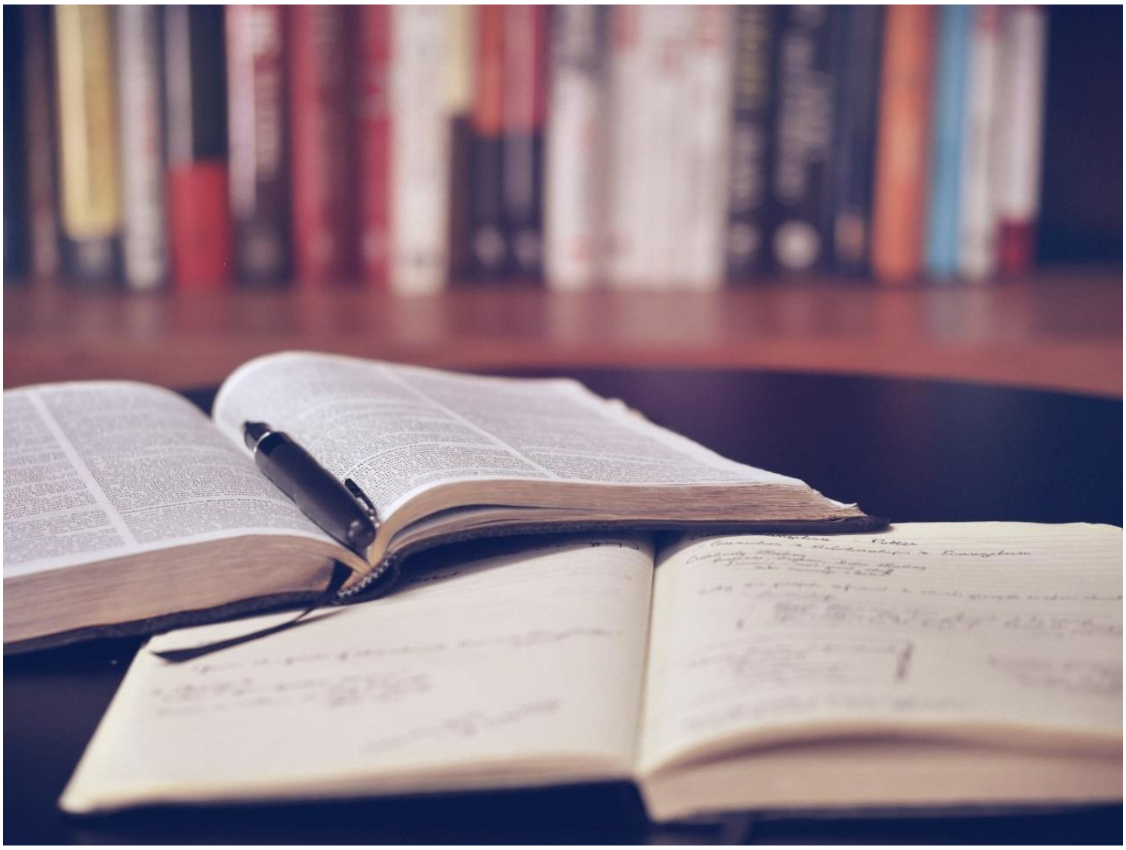

Host type and pricing on Airbnb: Seasonality and perceived market power

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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. 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.

*We thank seminar participants at the University of Corsica (LISA) and University of Leeds for their comments.

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

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

Besides the heterogeneity of actors on the supply side, the accommodation and tourism industries are also marked by strong seasonality. However, as Magno et al. (2018) or Faye (2021) argue, most empirical studies on pricing offer a static view. Only a few studies consider the seasonality of demand. These latter studies show that prices charged by Airbnb hosts are positively correlated with the level of market demand, being higher in peak seasons (Aznar et al. 2018, Falk et al. 2019, Magno et al. 2018). Examining month-to-month variation, Deboosere et al. (2019) find a significant impact of seasonality on the price per night and revenue of Airbnb listings in NYC. The hosts adapt their prices to the holiday calendar and therefore to seasonal demand, applying higher rates during the long summer holidays than during shorter winter holiday periods. However, the response of Airbnb hosts to seasonal fluctuations is not homogeneous. It has been observed that most hosts do not practice dynamic pricing and therefore forego revenue opportunities (Chen & Xie 2017, Gibbs, Guttentag, Gretzel, Yao & Morton 2018, Li et al. 2016). Indeed, hosts who adjust their prices more frequently, upwards and/or downwards, improve the revenue performance of their listings (Kwok & Xie 2019, Oskam et al. 2018).

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

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

Our analysis relies on the hedonic pricing model (Rosen 1974), which is the workhorse tool for analysing the determinants explaining market prices. In recent years, this model has been mobilised by a few authors to examine the prices charged by Airbnb's suppliers. These studies focused on markets in North America (Benítez-Aurioles 2018, Chen & Xie 2017, Deboosere et al. 2019, Gibbs, Guttentag, Gretzel, Morton & Goodwill 2018, Lorde et al. 2019, Wang & Nicolau 2017), Europe (Benítez-Aurioles 2018, Chica-Olmo et al. 2020, Dudás et al. 2019, Lladós-Masllorens et al. 2020, Magno et al. 2018, Teubner et al. 2017, Wang & Nicolau 2017), Oceania and Asia (Cai et al. 2019, Wang & Nicolau 2017). All the hedonic studies have shown the permanence of certain price determinants, whatever the market. The prices charged by hosts are systematically higher when the accommodation offers greater privacy (accommodation rented in full and/or not shared with other guests), when it is larger, or when it is located closer to the city centre or tourist attractions. The amenities have an upward influence on the prices charged by hosts since better amenities imply a higher price. However, those that affect prices will vary according to the context and the situation. The impact of free parking will be all the greater as availability is typically low in metropolitan areas (Gibbs, Guttentag, Gretzel, Morton & Goodwill 2018, Dudás et al. 2019). In the Caribbean, parking is casual everywhere, and air conditioning is one of the amenities most frequently requested by guests (Lorde et al. 2019).

Our approach improves on previous works in three main respects. First, we not only estimate how prices differ with respect to the period and the host type, but also how the difference in prices, if any, between opportunistic and professional hosts varies with the period. We are not aware of any study performing that kind of estimation. The closest analysis to ours (Deboosere et al. 2019) concentrates on the variations of prices between hosts and seasons, but not on their interaction. Second, we provide a characterisation of the host status that differs from the literature and can be argued to be more accurate. To evaluate the degree of professionalism of an Airbnb market, many authors use a supply indicator, the number of listings provided by the hosts. In most of destination market studies, a host is considered as a professional when they list more than one listing (Dredge et al. 2016, Gibbs, Guttentag, Gretzel, Morton & Goodwill 2018, Gurran & Phibbs 2017, Kwok & Xie 2019, Li et al. 2016, Magno et al. 2018, Oskam et al. 2018), others use a threshold of two or three (Schneiderman 2014). To characterise professional hosts, rather than relying on the number of listings marketed, we have compiled a dataset in which professional hosts are those registered with the French Trade and Companies Register (RCS) to unequivocally ensure their professional status. Finally, on the methodological side, we take advantage of a recent statistical method, double-machine learning Chernozhukov et al. (2018), that provides more robust estimates to model misspecification than the standard ordinary least squares (OLS) analysis, used in most of the aforementioned hedonic pricing studies.

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

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

The remainder of this paper is organised as follows. Section 2 presents a simple theoretical model and our hypotheses. Section 3 describes the dataset and our empirical strategy. The results are detailed in sections 4 and 5. Finally, section 6 draws some conclusions and discusses limitations and potential extensions of our work.

2 Theoretical background

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

The demand curve faced by a given host is typically unobserved. When setting the rental price, hosts must therefore imagine an expected demand curve relying on their knowledge of the market and personal beliefs. To understand the importance of this market property in the context of this study, let us consider two different hosts, i and j, proposing two perfectly identical properties and sharing the same marginal and average cost functions. They differ in their perception of the demand side and are characterised by different expected demand curves. Host i perceives the demand as more elastic than host j. As a consequence, after equalling their marginal revenue to their marginal cost, host i will charge a lower price P_i than host j, who charges P_j for exactly the same property. This is simply due to the fact that analysing the same market as host i, host j perceives a higher degree of market power. Due to this difference in demand perception, hosts will rent identical properties at different prices.[1]

[1]Note that the coexistence of different prices for identical properties could also arise from a difference in

We hypothesise that opportunistic hosts have a limited knowledge (sometimes no knowledge at all) of the market. As acknowledged by Airbnb itself on its website,[2] setting a correct price is a challenging task for a host due to the amount of information one has to gather and process to forge a satisfying representation of the market. This information acquisition process is costly and casual hosts may not find it worth investing in.

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

Furthermore, when markets are characterised by important seasonal fluctuations in demand, hosts have to adjust their expectations and pricing strategy accordingly. It means that both the size and the direction of the price differential between professionals and non-professionals is likely to vary over time.

The remainder of our paper is based on the following three hypotheses:

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

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

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

3 Empirical strategy and data

We focus on the Mediterranean island of Corsica, France, which is a popular destination with strong tourism seasonality. Corsica has 326,000 inhabitants and welcomes an estimated

marginal costs. The host characterised by the highest marginal cost will charge a higher price.

[2] https://blog.atairbnb.com/smart-pricing/

2 million tourists annually. A total of two-thirds of the visitors come from France, the remainder are mainly Italian and German. The island is one of the most popular tourist destinations in France. Thus, according to official data (INSEE 2018), 3.27 million overnight stays were registered in 2017 in the hotel sector, with total tourism expenditure amounting to 2.5 billion euros a year, one-third of the regional GDP. Furthermore, tourism flow is highly seasonal, as represented in Figure 1. Tourism frequentation is concentrated between April and September, with a peak season in June, July, and August.[3] According to the official survey by the French Statistical Institute and Corsican Tourism Agency (INSEE 2018), in 2017 the island received 400,900 visitors during the peak day of the tourism season, more than doubling its resident population.

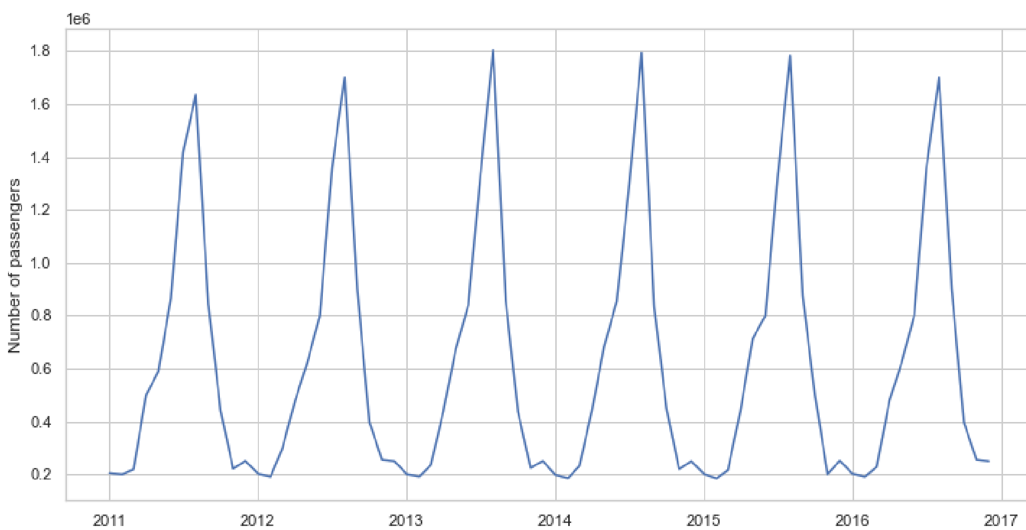

Figure 1: Monthly passengers flow in Corsica between 2011 and 2016

3.1 Description of the sample

The main data are provided by AirDNA, a commercial company that collects short-term vacation rental data. It covers the entire Airbnb listings population for the French island of Corsica for the period from September 1, 2016 to August 31, 2017. The data for this study

[3] https://dre20.pagesperso-orange.fr/ORTNET/Sommaire.htm

are aggregated at the month level. After cleaning the original dataset, we obtain a sample of 72,986 prices associated with 8,998 listings.[4]

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

3.1.1 Outcome and explanatory variables

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

We define our main explanatory variable of interest, Pro, as a dummy variable that takes the value 1 if the owner of a listing is a professional and 0 otherwise. We define a professional as a host managing more than two listings and that is registered with the French Trade and Companies Registry, the RCS.[5]

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

[4] Listings 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.

[5] The method for identifying hosts registered with the RCS first consists of an analysis of the host's Airbnb profile. Indeed, as Ke (2017) has already highlighted, professionals frequently use the name of their company in the description of their profile and/or use the logo of their company as a profile picture. In this way, hosts belonging to an identified company are determined. The others were subject to a complementary search based on the image recognition of their listings. This allowed the identification of their company's websites. Finally, the company was searched for in the RCS via the Infogreffe institutional search tool (https://www.infogreffe.com/recherche-siret-entreprise/chercher-siret-entreprise.html).

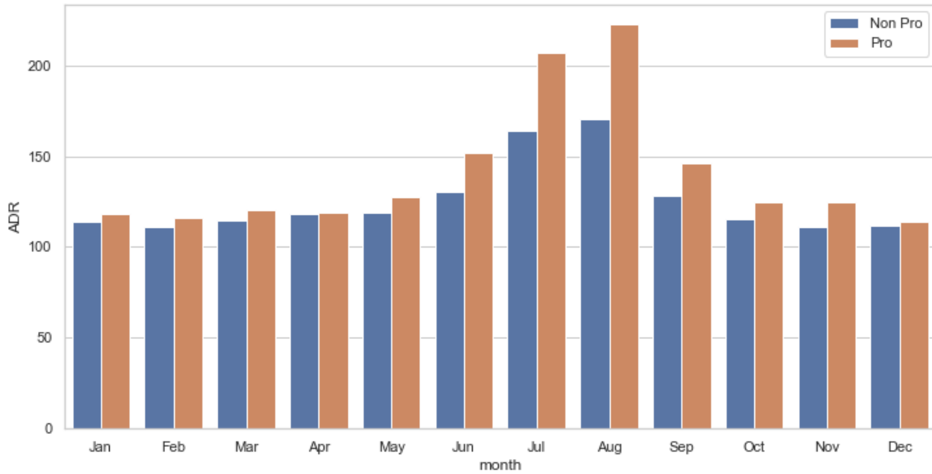

Figure 2: Average price per night and per month on Airbnb

3.1.2 Control variables

The dataset provides information related to both the listings and the hosts. A first set of variables deals with attributes and reputation of the listings. A second set of variables is related to host attributes. In addition, some variables make it possible to account for the rental policy defined by the host. Finally, we have constructed a variable that provides information about the location of the listing. These variables are summarised in Table 1 and described below. Summary graphs are presented in Figures 7 and 8 in the Appendix A.

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

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

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

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

Rental policy The hosts may choose to use a number of options related to the rental conditions of the property. For example, hosts may decide to impose a minimum number of renting days to avoid too frequent a turnover between guests. This information is provided by the minimum stay variable (MinimumStay). Furthermore, because Airbnb is a sharing platform, the hosts can decide whether to accept a given guest. However, the hosts have the possibility to automatically accept any guest enquiry by enabling the instant booking (InstantbookEnabled) option. This variable is a dummy that takes a value of 1 when the option is enabled. Finally, a key rental variable is the cancellation policy (CancellationPolicy). Airbnb provides the hosts with three basic options: strict, flexible, and moderate. When the chosen option is strict, the guest has the possibility to cancel the reservation for free only during the first 48 hours and provided it is at least 14 days before the booking dates. Under the moderate policy, it is possible to cancel the reservation up to five days before the booked dates. Flexible policy makes it possible to cancel for free 24 hours up to arrival. In addition, Airbnb two very strict policies: Strict30 and Strict60. These are offered to hosts connected to the platform via software, in general professional players. Cancellation is possible only 30 or 60 days before arrival, and only 50% of the paid price is refunded to the guest.

Location The original dataset proposes variables that account for the location of the listings. However, due to its peculiar insular geography, these variables may be insufficient in the case of Corsica. For instance, if we used the city in which the listing is located to account for the impact of space on price, we could observe inconsistent results due to the fact that, in the same city, some places are very attractive for tourists (the seaside) while others are not due to accessibility problems. We have therefore developed an original but simple solution. Using geographical information systems (GIS), the area of Corsica has been divided in 479 hexagons of 10km^2. Each listing is associated to a unique hexagon and the qualitative variable Hex with 479 levels is added to our model to account for spatial fixed effects.

3.2 Methodology of the study

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

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

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

where i corresponds to the property and m corresponds to the period (month), Y is the price (expressed in logarithm) or revenue, and $ListAttr_i, HostAttr_i, RentPol_i$ represent the listing attributes and reputation, the host attributes, as well as the rental policy variables, respectively. The effect of interest is represented by the term θ_m, which measures the impact of the host status (professional vs. non-professional) on prices; dependence on m clarifies that we allow this effect to vary with time. The function g is a general function, possibly non-linear, of the control variables.

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

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

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

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

We then consider a second specification in which $g(.)$ is a general function of the control variables. This allows us to check the robustness of the linear model.[6] We adopt the double-machine learning (DML) approach developed by Chernozhukov et al. (2018). Put simply, this method consists of computing, in a first step, a prediction of the dependent (Y) and treatment (Pro) variables through any machine learning (ML) algorithms. In a second step, the residuals of the dependent variable (difference between the actual and predicted values of this variable) are regressed on the residuals of the treatment variable.

4 Effect of professionalisation on prices

This section presents the results of our econometric study to assess the validity of hypotheses H1 and H2 presented in section 2. First, we detail the results of the baseline OLS specification. Then, we discuss the impact of the inclusion of variable interacting time and type of host. Finally, we present the results obtained when adopting the DML approach. We also contrast our results with what would be obtained under an alternative characterisation of professional hosts, more in line with the usual assumption made in the literature.

[6] It 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).

4.1 OLS estimation

4.1.1 Results from the baseline model (Model 1)

As explained above, we start by estimating a simple OLS model in which the explained variable is the natural logarithm of the average daily rate. Results from the baseline specification are summarised in column 'Model 1' of tables 2 and 3 in the appendix B. The explanatory variables of interest are Pro and each of the twelve months of the year. Nonetheless, before focusing on these variables, some general comments are necessary.

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

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

It should also be noted that the most significant amenities (see Table 3) and those with the larger positive effect on prices are, to some extent, related to luxury. For example, with a coefficient of 0.190, the presence of a pool in the property increases the price by around 21% *ceteris paribus*. The same holds for the presence of a jacuzzi, which increases the price by 13.3%, an air conditioner (+6%), or a dryer (+10.5%).[7]

Furthermore, as expected, entire homes are much more expensive than private rooms (−20.4%) or shared rooms (−43.2%) *ceteris paribus*. Some property types were also shown to be more expensive than apartments. This is especially the case for guest houses (+26.7%) and bed and breakfasts (+19.8%) that provide the guest with additional services. This is also the case for houses and villas that are respectively 8.4% and 14.2% more expensive than apartments *ceteris paribus*. The number of bedrooms and bathrooms are also proven to be key determinants of the price since an additional bedroom raises the ADR by 15.5% and an additional bathroom by 13.3%. The reputation has a significant positive impact on the rate

[7] Since the price is in logarithms, the formula $e^{\alpha} - 1$ is applied to any coefficient α to obtain the effect in percentage points.

since an increment by one point of the rating of a listing leads to a 6% increase in the daily rate. Interestingly, we find that being a Superhost is associated with a slightly lower price (-4%).

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

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

4.1.2 Results from the model with interactions (Model 2)

Results from our baseline specification indicate that professional hosts ask for higher prices and that the peak season is a key determinant of prices. However, at this stage, we do not know if pricing behaviour of professional hosts is affected by seasonality. As highlighted in section 2, our hypothesis is that the size and direction of this price differential may vary according to seasonal fluctuations in demand. In other words, the pricing behaviour of professional and non-professional hosts should evolve differently over the year.

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

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

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

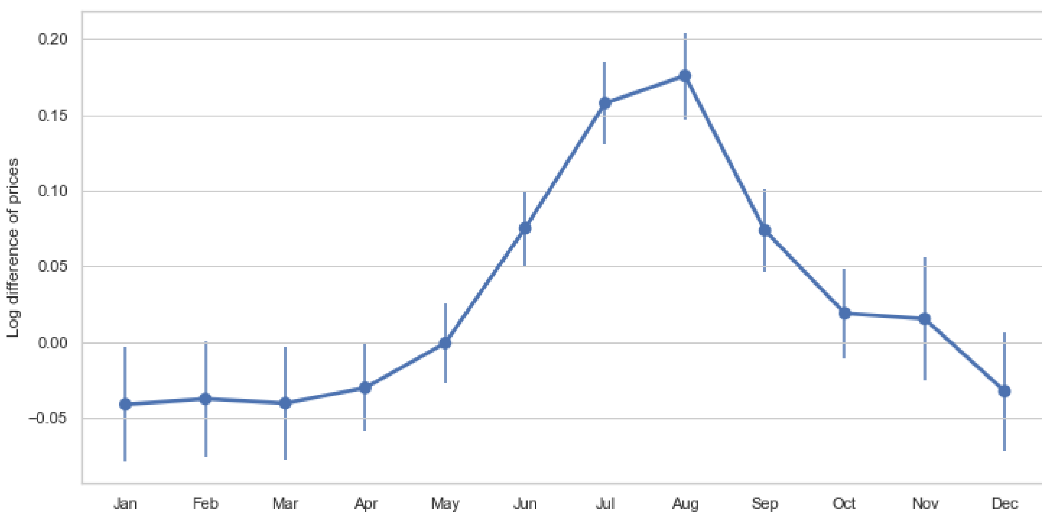

Figure 3: Log difference of prices between professionals and non-professionals in the OLS specification

According to the results of the OLS regression, professional players ask for higher prices than non-professionals between June and September, and for (slightly) lower prices in January, February, March, April, and December. In May, October, and November, the prices are similar. Specifically and as examples, in August, professional hosts ask for prices that are 19.2% higher for the same property. In March, they ask for prices that are 4% lower.[8]

[8]These percentages are obtained by adding up the coefficients associated to Pro and ProXMonth and

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

4.2 DML estimation

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

then applying the formula given in footnote 7.

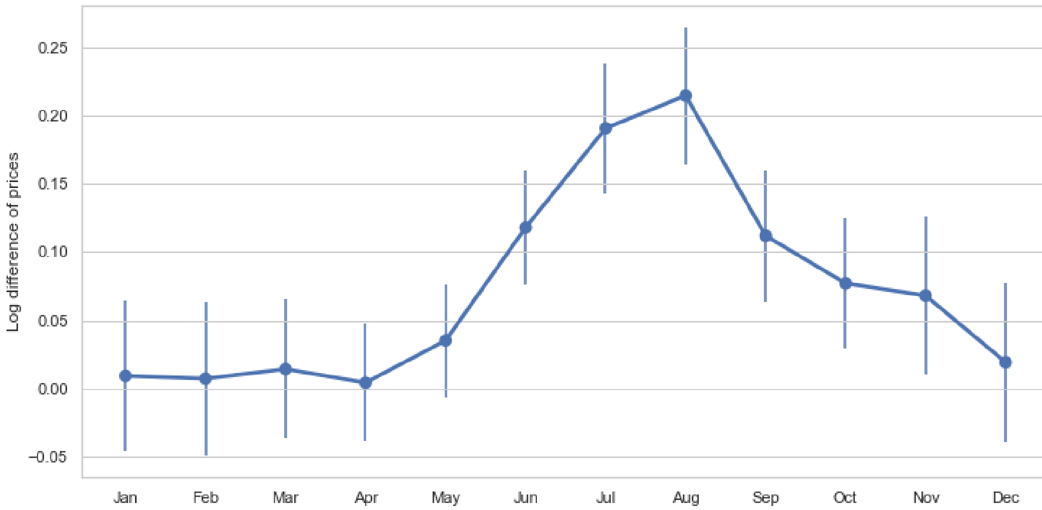

Figure 4: Log difference of prices between professionals and non-professionals in the DML specification

Figure 4 has a similar shape to Figure 3, with the important difference that the price differential between professionals and non-professionals is now larger. For example, the price differential in August was 24% instead of 19.2%. In June and September, professional hosts charge prices more than 11% higher than non-professionals, whereas the OLS estimation revealed a price differential less than 8%. Furthermore, the negative price differential obtained in January, February, March, April, and December, is not robust to the application of the DML method. This latter indeed concludes that *professionals never charge lower prices than non-professionals*. They happen to choose similar prices in January, February, March, April, and December. Otherwise the price differential is always strictly positive.

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

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

4.3 Alternative characterisation of professional hosts

The common characterisation of professional hosts encountered in the literature is based on the number of listings managed. A host is considered a professional player as soon as they manage more than a given number of listings. In the literature, thresholds are commonly between one and three listings. We assume that a host has a professional activity as soon as they manage (strictly) more than two listings. Adopting the DML methodology, estimation results in this setting are represented in Figure 5.

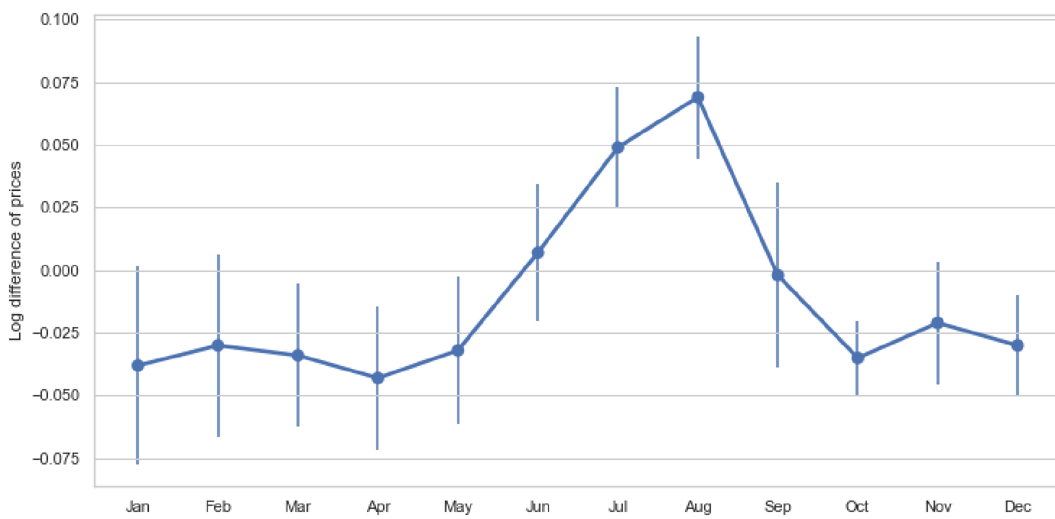

Figure 5: Log difference of prices in the DML specification under the alternative characterisation of professionalisation

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

5 Impact on revenue

We have observed that professionals tend to propose higher prices than non-professionals (for comparable listings). We now turn to the question of whether these higher prices translate into higher revenue (H3). For this purpose, we estimate the model (1), with the dependent variable now being the revenue earned, instead of the logarithm of the price. Estimates obtained via the DML method are shown in Figure 6.

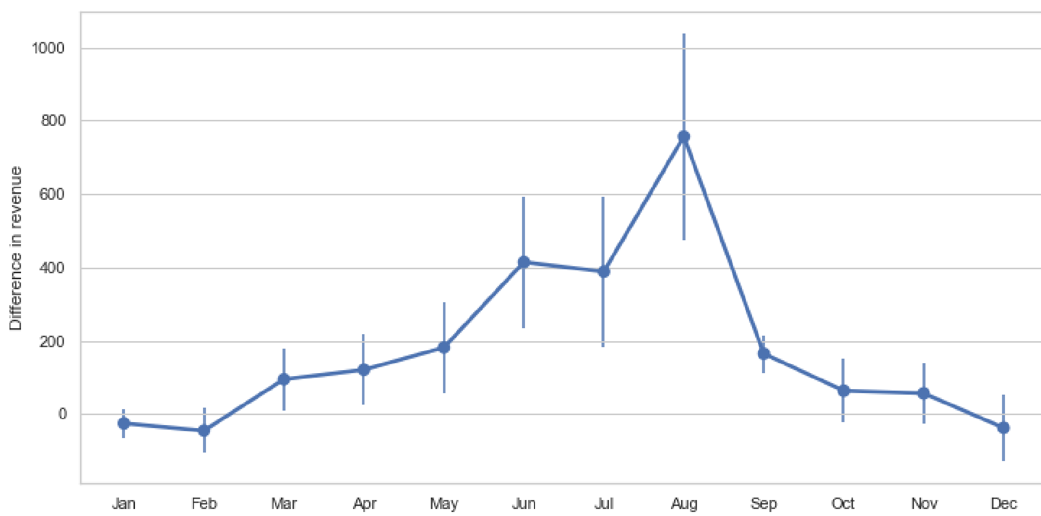

Figure 6: Difference in revenue between professionals and non-professionals in the DML specification

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

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

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

6 Discussion and conclusion

To date, the literature related to the pricing behaviour of Airbnb hosts has highlighted some interesting features that differentiate professional players from casual hosts. According to Deboosere et al. (2019), despite the fact that the price asked by professional hosts does not differ on average from the price asked by casual hosts, the former obtain a higher level of revenue on average. This enhanced capacity to generate revenue could be partially explained by the fact that professional players practice dynamic pricing and change their prices more often to cope with changes in demand, as argued by Oskam et al. (2018). Nonetheless, even if changing the asked price more often is a key to understand why professional players are more efficient in the generation of revenue, there is a need to understand when and in which direction professionals adjust the prices in more depth. The proposed methodology makes it possible to understand when and in which direction professionals modify their prices while the rest of the host population does not.

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

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

Professionals tend to adopt a different behaviour only when demand is high. It means that they have a different perception of the economic opportunities associated with the seasonal increase in demand. Their enhanced knowledge of the market, related to experience or the existence of loyal customers, for example, makes them aware of the fact that during the peak season, a fringe of customers is characterised by a quite low price elasticity of demand. They simply use this temporary market power to raise their prices and increase their revenue. We should stress that professional hosts behave as suggested by the textbook model of monopolistic competition while this is not (or less frequently) the case for casual hosts. Both casual and professional hosts increase their prices during the peak season but, on average, professionals perceive a larger degree of market power and tend to increase their rates more to enhance their revenue.

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

References

Aznar, J. P., Sayeras, J. M., Segarra, G. & Claveria, J. (2018), 'Airbnb landlords and price strategy: Have they learnt price discrimination from the hotel industry? Evidence from Barcelona', *International Journal of Tourism Sciences* **18**(1), 16–28.

Benítez-Aurioles, B. (2018), 'Why are flexible booking policies priced negatively?', *Tourism Management* **67**, 312–325.

Cai, Y., Zhou, Y., Ma, J. & Scott, N. (2019), 'Price Determinants of Airbnb Listings: Evidence from Hong Kong', *Tourism Analysis* **24**, 227–242.

Chamberlin, E. (1933), *The Theory of Monopolistic Competition*, Harvard University Press.

Chen, Y. & Xie, K. (2017), 'Consumer Valuation of Airbnb Listings: A Hedonic Pricing Approach', *International Journal of Contemporary Hospitality Management* **29**.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W. & Robins, J. (2018), ‘Double/debiased machine learning for treatment and structural parameters’, *The Econometrics Journal* **21**(1), C1–C68.

Chica-Olmo, J., González-Morales, J. G. & Zafra-Gómez, J. L. (2020), ‘Effects of location on Airbnb apartment pricing in Málaga’, *Tourism Management* **77**, 103981.

Dann, D., Teubner, T. & Weinhardt, C. (2019), ‘Poster child and guinea pig – insights from a structured literature review on Airbnb’, *International Journal of Contemporary Hospitality Management* **31**(1), 427–473.

Deboosere, R., Kerrigan, D. J., Wachsmuth, D. & El-Geneidy, A. (2019), ‘Location, location and professionalization: A multilevel hedonic analysis of Airbnb listing prices and revenue’, *Regional Studies, Regional Science* **6**(1), 143–156.

Dredge, D., Gyimóthy, S., Birkbak, A., Jensen, T. E. & Madsen, A. K. (2016), *The Impact of Regulatory Approaches Targeting Collaborative Economy in the Tourism Accommodation Sector: Barcelona, Berlin, Amsterdam and Paris*.

Dudás, G., Kovalcsik, T., Vida, G., Boros, L. & Nagy, G. (2019), *Price Determinants of Airbnb Listing Prices in Lake Balaton Touristic Region, Hungary*.

Falk, M., Larpin, B. & Scaglione, M. (2019), ‘The role of specific attributes in determining prices of Airbnb listings in rural and urban locations’, *International Journal of Hospitality Management* **83**, 132–140.

Faye, B. (2021), ‘Methodological discussion of Airbnb’s hedonic study : A review of the problems and some proposals tested on Bordeaux City data’, *Annals of Tourism Research* **86**, 21.

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

Gibbs, C., Guttentag, D., Gretzel, U., Yao, L. & Morton, J. (2018), 'Use of dynamic pricing strategies by Airbnb hosts', *International Journal of Contemporary Hospitality Management* **30**(1), 2–20.

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

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

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

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

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

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

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

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

Li, J., Moreno, A. & Zhang, D. (2016), Pros vs Joes: Agent Pricing Behavior in the Sharing Economy, SSRN Scholarly Paper ID 2708279, Social Science Research Network, Rochester, NY.

Lladós-Masllorens, J., Meseguer-Artola, A. & Rodríguez-Ardura, I. (2020), 'Understanding Peer-to-Peer, Two-Sided Digital Marketplaces: Pricing Lessons from Airbnb in Barcelona', *Sustainability* **12**(13), 5229.

Lorde, T., Jacob, J. & Weekes, Q. (2019), 'Price-setting behavior in a tourism sharing economy accommodation market: A hedonic price analysis of AirBnB hosts in the caribbean', *Tourism Management Perspectives* **30**, 251–261.

Magno, F., Cassia, F. & Ugolini, M. M. (2018), 'Accommodation prices on Airbnb: Effects of host experience and market demand', *The TQM Journal* .

Oskam, J., van der Rest, J.-P. & Telkamp, B. (2018), 'What's mine is yours—but at what price? Dynamic pricing behavior as an indicator of Airbnb host professionalization', *Journal of Revenue and Pricing Management* **17**(5), 311–328.

Robinson, P. M. (1988), 'Root-N-Consistent Semiparametric Regression', *Econometrica* **56**(4), 931.

Rosen, S. (1974), 'Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition', *Journal of Political Economy* **82**(1).

Schneiderman, E. T. (2014), Airbnb in the City, Technical report, Office of the New-York State Attorney General.

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

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

Wu, A. A. E. (2016), Learning in Peer-to-Peer Markets: Evidence from Airbnb, Economy, Fundação Getulio Vargas, Escola de Pós-Graduação em Econom, Rio de Janeiro.

APPENDIX

A Summary graphs

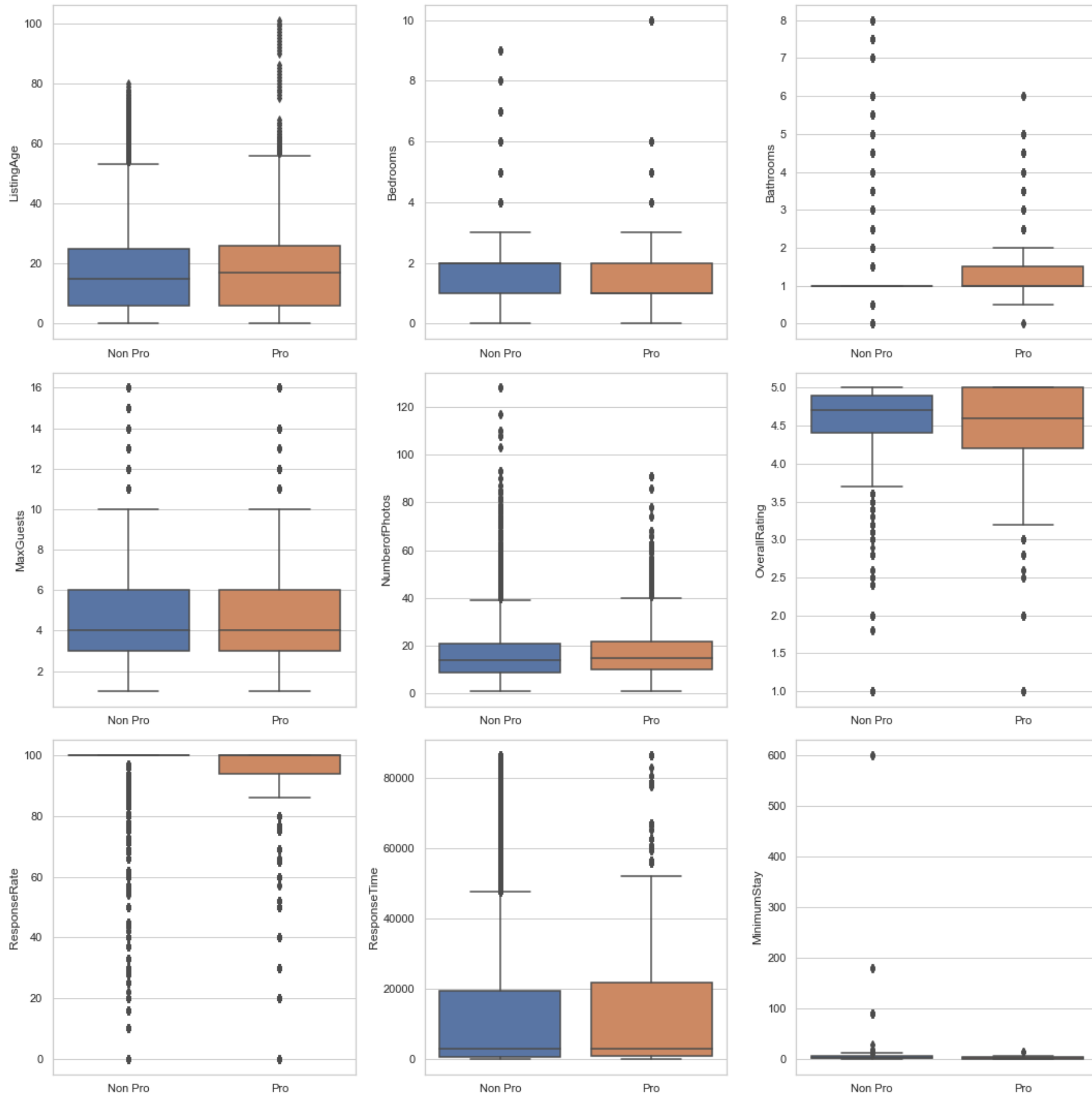

Figure 7: Summary graphs for numerical variables

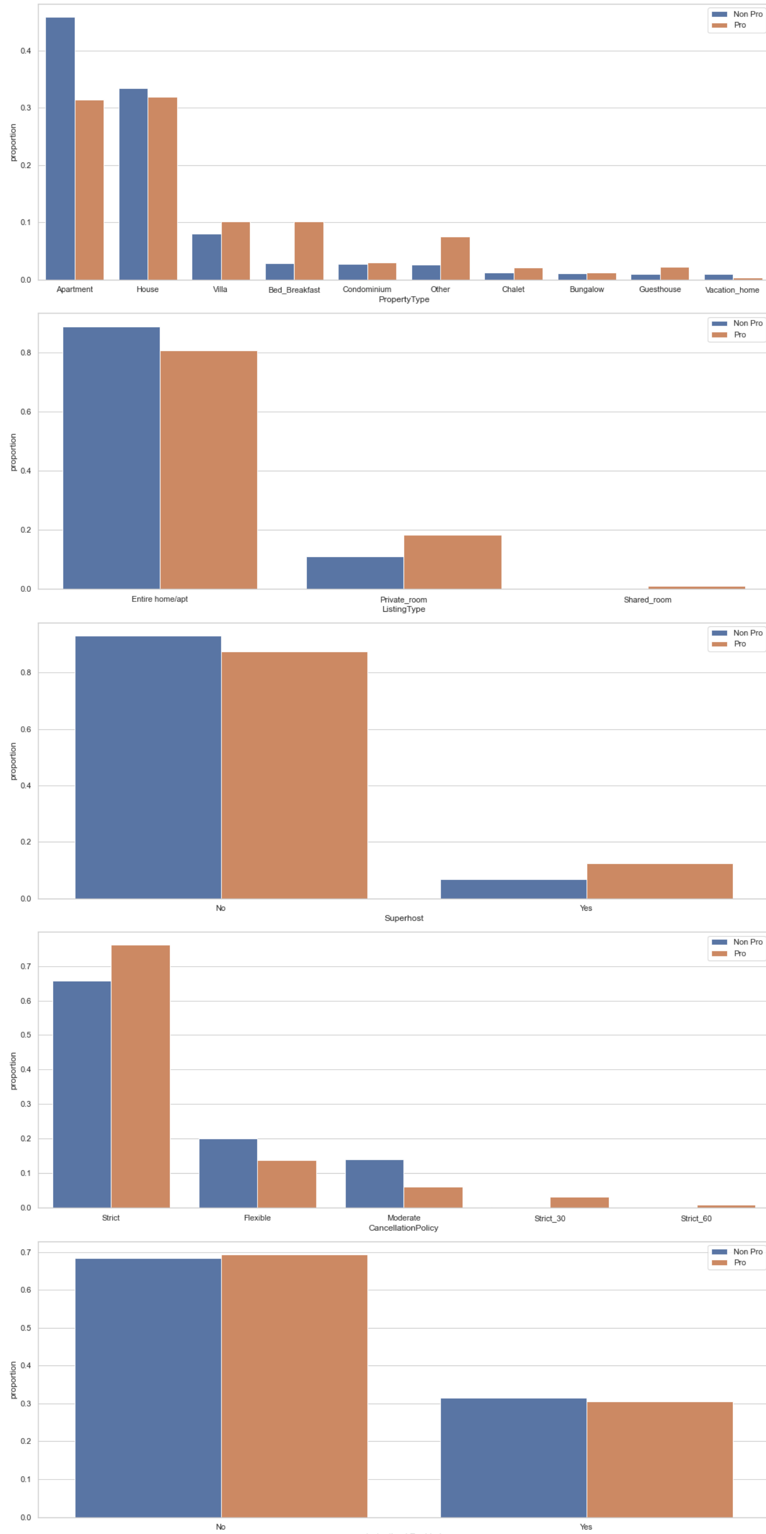

Figure 8: Summary graphs for categorical variables

B OLS Results

Table 2: OLS Results

	Model 1		Model 2	
Pro	0.041667**	(3.205)	-0.041228*	(-2.144)
Month (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)
PropertyType (ref. Apartment)				
Bed_Breakfast	0.180840***	(6.573)	0.181498***	(6.587)
Guesthouse	0.236824***	(7.084)	0.234529***	(7.019)

House	0.080729***	(7.953)	0.080793***	(7.960)
Vacation_home	0.102848***	(3.339)	0.107183***	(3.453)
Villa	0.132657***	(7.389)	0.132275***	(7.367)
ListingType (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)
OverallRating	0.058553***	(5.666)	0.059029***	(5.704)
CancellationPolicy (Ref: Flexible)				
Moderate	-0.052426***	(-4.118)	-0.052614***	(-4.133)
InstantbookEnabled	-0.027489***	(-3.417)	-0.027802***	(-3.455)
Constant	3.647006***	(57.070)	3.657152***	(57.272)
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_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_dryer	0.099710***	(8.727)	0.100336***	(8.783)
amenity_wireless_internet	0.036387***	(4.198)	0.036392***	(4.198)
amenity_cable	0.035097***	(3.388)	0.035037***	(3.381)
amenity_allows_pets	-0.052749*	(-2.410)	-0.052271*	(-2.383)
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_pool	0.190425***	(17.565)	0.190240***	(17.549)
amenity_jacuzzi	0.125441***	(4.752)	0.125631***	(4.752)
amenity_bedroom_step_free_access	0.581829**	(2.929)	0.591521**	(2.979)
amenity_home_step_free_access	-0.357330*	(-2.073)	-0.364094*	(-2.121)
amenity_iron	-0.025709*	(-2.402)	-0.025501*	(-2.384)
amenity_fire_extinguisher	0.029733*	(2.387)	0.029797*	(2.392)
amenity_crib	0.058535***	(4.627)	0.058289***	(4.609)
amenity_street_parking	-0.041580**	(-3.275)	-0.041664**	(-3.282)
amenity_smoke_detector	-0.022282**	(-2.648)	-0.022488**	(-2.673)
amenity_pack_n_play_travel_crib	-0.031209**	(-2.931)	-0.031086**	(-2.921)
amenity_room_darkening_shades	-0.041267*	(-2.013)	-0.041463*	(-2.023)
amenity_baby_bath	-0.066564***	(-3.780)	-0.066681***	(-3.788)
amenity_essentials	0.073390***	(7.855)	0.073795***	(7.901)
amenity_babysitter_recommendatio	0.044604*	(2.059)	0.044517*	(2.056)
amenity_high_chair	-0.052234***	(-4.086)	-0.052313***	(-4.095)

t statistics in parentheses

Only significant coefficients at the 0.05 level are reported

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